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Adaptive Neuro Fuzzy Inference System (ANFIS) for Prediction of Maximum Power in a PV System using Historical Data

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Abstract: India, the fifth largest consumer of energy in the world will become the third largest consumer of energy by 2030. Much of its energy needs are met by fossil sources which are depleting and are in huge demand. In view of the present scenario and to satisfy its future energy needs India is looking towards renewable energy as a viable alternative. The issues with renewable energy sources in general and PV energy systems in particular are their susceptibility to varying environment conditions. In order to harvest maximum energy tracking of maximum power point is an important task. In this work, an Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed for tracking the maximum power. The system has been formulated and trained to predict with the help of historic data. The data pertains to Global horizontal irradiance; Global diffused irradiance, Ambient Temperature and Surface Temperature. The performance of the proposed system is discussed and the results have been validated by using different performance measures like, Pearson correlation coefficient and Normalized Root Mean Square Error (NRMSE).

Keywords: ANFIS, Global horizontal irradiance; Global diffused irradiance, Pearson correlation coefficient, NRMSE.

1. INTRODUCTION

The increasing demand for electricity and ever increasing gap between demand and supply, has forced India to target 20GW of Solar Power by 2022 [1]. India's energy basket is dominated by coal with 54 % of the total installed electricity generation capacity are coal based power plants. Other renewable such as wind, geothermal, solar, and hydroelectric represent a 2 percent share of the Indian fuel mix. Nuclear holds a one percent share [2]. The Indian government has undertaken lots of policy initiative to tap in to the natural resources. In view of its geographic location, India is endowed with rich solar energy resources. With average annual that ranges from 25°C – 27.5°C India has huge potential for solar power generation. In addition to this, the average solar radiation received in India is 200 MW/km^2 over 250-300 sunny days. The country receives close t0 5000 tnKwh/Year and most regions in the country receive close to 4-7 Kwh per square metre per day [3].

The primary aspect in tapping solar energy is that the PV panel is a variable power source. This is the critical issue in connecting them to the grid or using them as standalone systems. It is theoretically proved that many factors like Temperature, humidity, wind speed, air pressure, air temperature, solar collector area etc. influence the outcome in terms of performance. PV power forecasting has been widely studied and mainly includes two categories: physical methods and statistical methods. Physical methods use physical equation for forecasting the PV power. They take in to account the generation process in combination with forecast weather data [4, 5]. On the other hand statistical employs inherent laws to predict the output power of PV power plants based on historical power data [6-9].

Each and every of these methods have their own advantages and disadvantages. The convergence and properties of these above methods are severally limited by the non-stationary characteristics of PV

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power. Earth's rotation and revolution imparts periodicity and non-stationary characteristics to the solar irradiance received at the surface. The power generated data of PV plants show one day periodicity. Output power data of PV plants shows one day periodicity. In other words, the power output fluctuates having an increasing trend before noon and shows a declining trend after noon. In order to guarantee precise forecasting an effective method to reduce the non-stationary characteristics of PV output power has to be adopted. Conventional power prediction methods cannot guarantee the precision of forecasting results, or even the convergence of the method [10]. Relevant research has achieved good results in wind power prediction [11].Artificial Neural Network (ANN) has been viewed as a convenient way to forecast solar radiation intensity and power output of PV system, which can be trained to overcome the limitations of traditional methods to solve complex problems, and to solve difficult problems which are hard to model and analyze [12].

Similarly Adaptive Neuro Fuzzy Inference System (ANFIS) is a very effective modeling approach which combines the attributes of both the fuzzy inference system and neural network. The amalgamation of fuzzy logic with architectural design of neural network led to creation of neuro- fuzzy systems. These systems derive benefit from feed forward calculation of output coupled with back propagation learning capability of neural networks. While doing so, they keep the interpretability of fuzzy system unaltered. In this research work an Adaptive Neuro Fuzzy Inference System (ANFIS) has been formulated for predicting the Maximum Power that shall be delivered by a PV system. This prediction is based on historical data. The prediction is based on 4 Parameters namely, Global horizontal irradiance; Global diffused irradiance, Ambient Temperature and Surface Temperature. The data set is collected from a 10 MW power plant and scaled down to 10 KW for ease of analysis. The ANFIS is trained using both hybrid approach and back propagation approach and the results analyzed. The results of the proposed work are also evaluated with the help of Pearson correlation coefficient and Normalized Root Mean Square Error (RMSE) [18].

2. INPUT VARIABLES FOR THE POWER FORECASTING MODEL

Generally, sufficiently accurate solar irradiance data can be input into a formula to derive predicted output power. Predicting power output from renewable energies is closely related to weather forecast predictions. To predict the amount of solar irradiance or power generated, various environmental factors, such as solar irradiance, cloud cover, atmospheric pressure, and temperature, along with the conversion efficiency of PV panels, installation angles, dust on a PV panel, and other random factors must be considered. All these factors affect PV system output. Hence, in choosing input variables for a prediction model, one should consider deterministic factors strongly correlated with power generation. Additionally, time-series data for PV power generation are strongly auto correlated and therefore these historical data should be the input data of the forecasting model. Table 1 provides the Pearson product-moment correlation coefficient [13] between PV output and environmental factors under typical weather conditions. The value of PPMCC falls between −1 to +1, with total positive correlation indicated by 1, a no correlation indicated by 0 and negative correlation indicated by −1.

Table 1
Pearson product-moment correlation coefficient between PV output and environmental factors

Weather Condition	*Pearson Product-Moment Correlation Coefficient*			
	Irradiance	*Temperature*	*Humidity*	*Wind Speed*
Clear	0.966	0.322	–0.527	–0.229
Cloudy	0.891	0.441	–0.511	–0.025
Overcast	0.987	0.409	–0.478	0.125
Rainy	0.923	0.410	0.039	–0.178

It can be seen from Table 1 that the correlation coefficient between the power output of a PV power generator and solar irradiance is greater than 0.9, which means they are highly correlated, while the correlation coefficient between PV power generation output and temperature is greater than 0.3, which means these factors are positively and low-level correlated. The correlation coefficient of humidity indicates a low but negative correlation. The correlation between PV power generation output and wind speed is small. It can be inferred from the data that two factors namely solar irradiance and temperature strongly affects the performance of PV cells. Even though manufacturers specify most important electrical characteristics, they are specified under Standard Temperature Conditions (STC). It is imperative to model the performance of the PV cells under normal operating conditions.

3. MODELING OF PV CELL

Multiple models explaining the behavior of PV cells based on the I-V (Current- Voltage) characteristics of the PN junction in the PV Cell. The models harp on photocurrent that is generated by electron-hole pairs and the recombination current attributed to the diffusion of electrons and holes across the junction. These models also usually incorporate series and parallel electrical resistances to internal losses owing to the interconnection of the individual cells to form a PV array. An Ideal PV cell model neglects the effects of electrical resistances and considers only the effect of photo current and recombination current. Typical PV cell models are modeled with single diode or a double diode. Two diode model is more popular and extensively employed to model the behavior of PV cells.

In Two diode model, two diodes are attached in parallel to the circuit of single-diode model. The second additional diode is included to provide a more accurate I-V characteristic curve that accounts for the difference in the flow of circuit at low current values. This can be attributed to the combination of charges in the depletion region. The mathematical form of the model is given by Eq. (1).

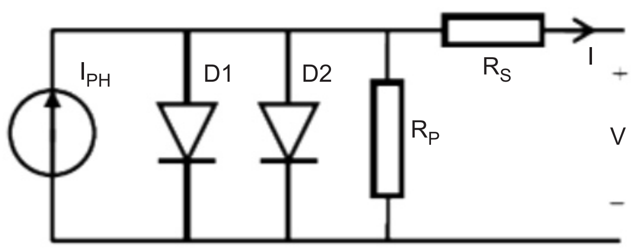

Figure 1: Lumped-circuit, two-diode model of a PV cell

$$V = \sum_{i=1}^{35} V_{\text{ill cell}} + V_{\text{sh}_{\text{cell}}} \tag{1}$$

Where, V is the total PV module voltage, and V_{ill_cell} and V_{sh_cell} are the voltages across the illuminated cells and the shaded one, respectively. The current I of the cell has four different components depicted using the equation (2). These components are the photo generated current (I_{PH}), the current through the shunt resistance (I_P), the diffusion-diode current (I_{D1}), and the recombination-diode current (I_{D2}). The parameters that are unknown and are extracted using different approaches 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. In accordance to the diffusion theory of *p-n* junction [14] n_1 is assumed to be 1, while n_2 is assumed to be 2 according to the theory of recombination.

The thermal voltage is given by $V_T = k_B T/qe$, where T is the *p-n* junction temperature, k_B is Boltzmann's constant, and qe is the elementary charge. These parameters used in the two diode model are heavily influenced by the cell temperature and irradiance [16]. Figure 2 represents the model and the current voltage relationship can be expressed with the help of following equations.

$$I_L = -I_{ph} + I_{D1} + I_{D2} + I_{sh} \quad (2)$$

$$I_{D1} = I_{SD1}\ [\exp(q(V_L - I_L R_S)/n_1 K_t)] - 1 \quad (3)$$

$$I_{D2} = I_{SD2}\ [\exp(q(V_L - I_L R_S)/n_2 k_t)] - 1 \quad (4)$$

And

$$I_{sh} = V_L - I_L R_S / R_{sh} \quad (5)$$

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

$$= I_{PH} - V + IR_{S/RP} - I_{SD1}[\exp^{V + I R_S/n_1 V_r} - 1] - I_{SD2}[\exp^{V + I R_S/n_1 V_r} - 1] \quad (6)$$

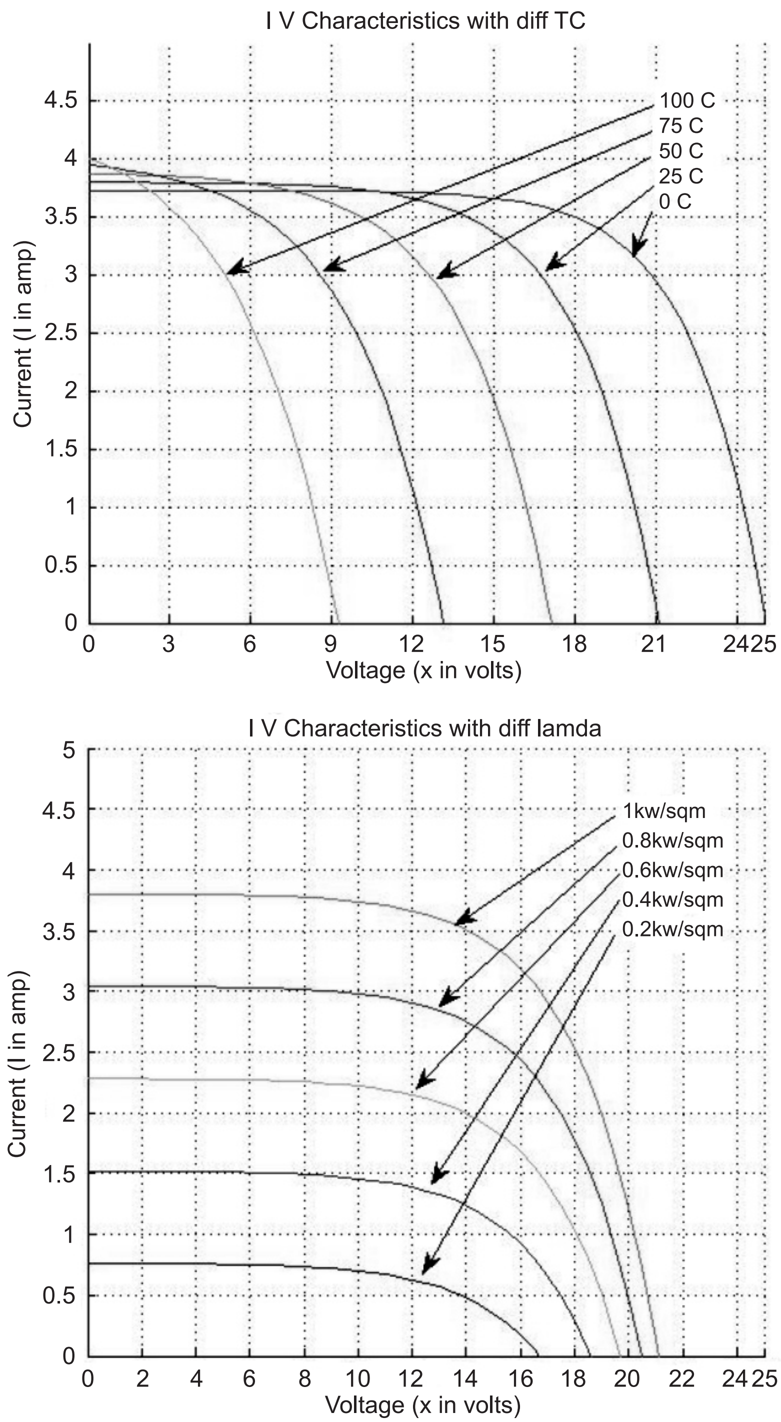

Figure 2: I-V Characteristics for Changes in Temperature and Insolation

Figure 2 depicts the I-V characteristics when the insolation is maintained constant and the temperature is varied. Similarly it also depicts the relationship between current and voltage when the temperature is maintained constant and the insolation is varied.

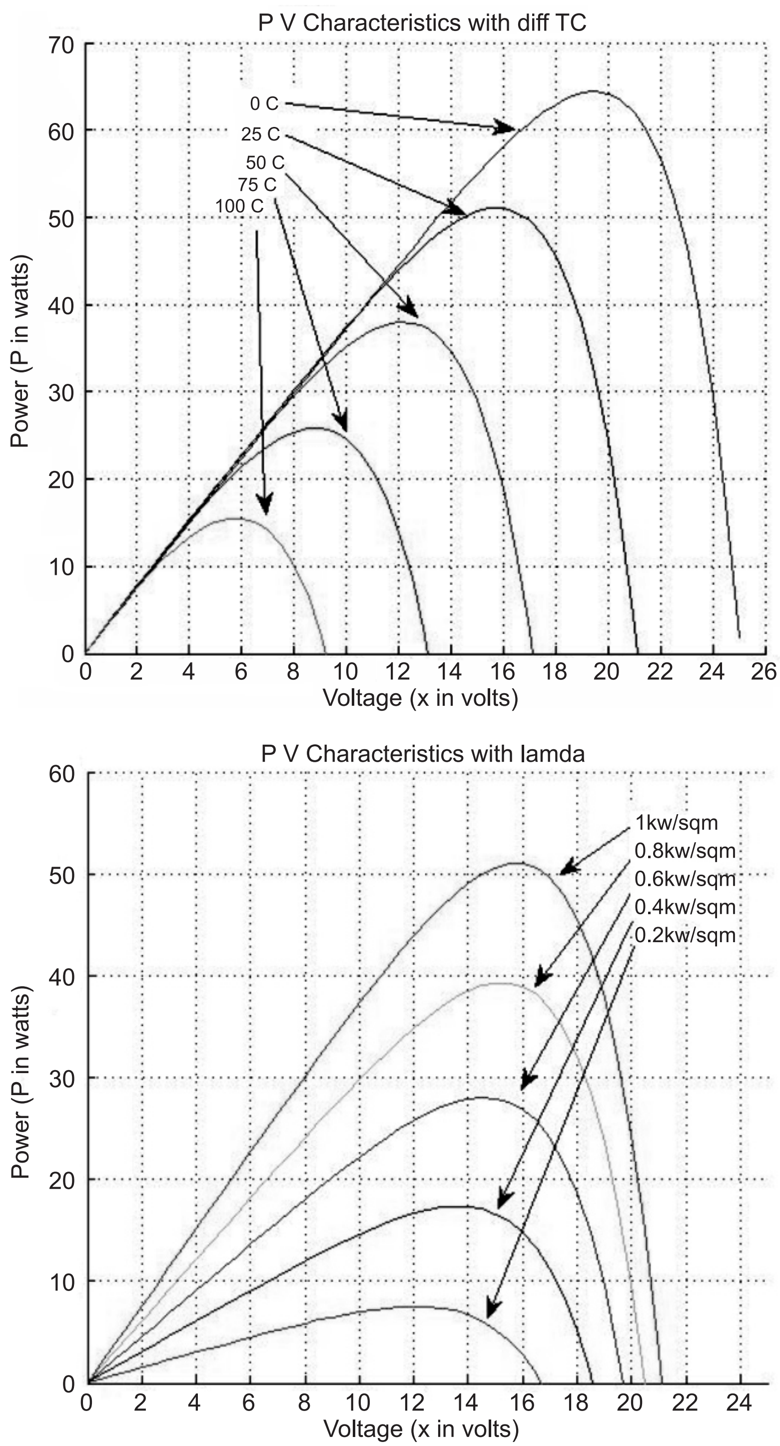

Figure 3: P-V Characteristics for Changes in Temperature and Insolation

Figure 3 illustrates the P-V curves when the insolation and temperature are varied alternately with one being maintained constant. Both Figure 2 and Figure 3, illustrates the significance of temperature and isolation on the inherent characteristics of the PV cell. The figures also demonstrate the non linear relationship that exists between the PV cell parameters and the significance of Maximum Power Point Tracking (MPPT).

4. ANFIS STRUCTURE

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of adaptive network that is equivalent functionally to fuzzy inference system. In the case of Sugeno type ANFIS [17], the approach uses a hybrid learning algorithm to deliver parameters of Sugeno-type fuzzy inference system. It considers a combination of the least squares method and the back propagation gradient descent method. This consideration is for training FIS membership function parameters to emulate a given training data set. An ANFIS functions by applying neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS). The network is comprised of nodes (Figure 4) with specific functions collected in layers. ANFIS is able to construct a network realization of IF / THEN rules. ANFIS normally has 5 layers of neurons of which neurons in the same layer are of the same function family.

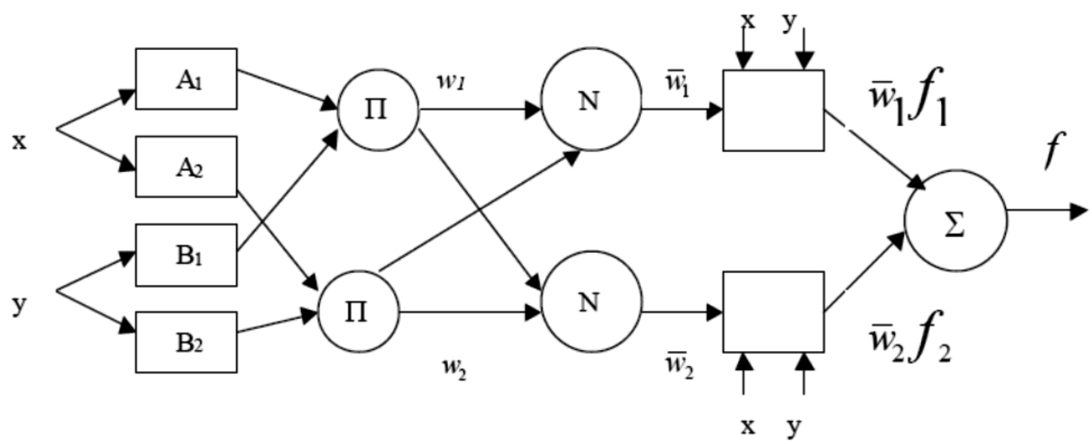

Figure 4: Structure of the ANFIS network.

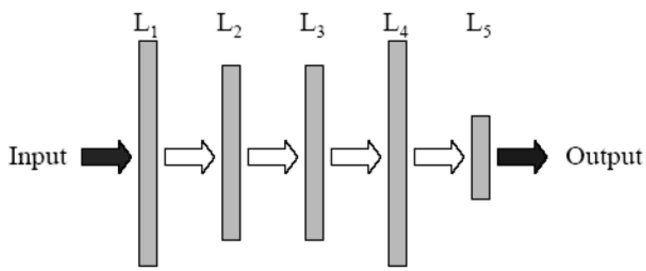

Figure 5: ANFIS Architecture

The ANIFS network comprises of five different layers (Figure 5) with each node in the very first layer being an adaptive square node with a function. The structure comprises units and connections laid out as five connected layers.

Layer 1: This layer has the inputs variables and their representing membership functions through inputs. A triangular or a bell membership function can be used and this layer is used to supply the inputs values to the next layer.

Layer 2: This layer which forms the membership layer verifies for the weights of each MFs. It takes the input from the 1^{st} layer and uses the MFs to depict fuzzy sets of the respective input variables. It also calculates the membership values and determines the degree to which a particular variable belongs to fuzzy set, which acts as the inputs to the next layer.

Layer 3: This is the rule layer where each node computes the activation level of each rule with the number of layers being equal to the total number of fuzzy rules in the rule base. In effect this layer performs the precondition matching of the fuzzy rules. The nodes also calculate the normalized weights for each of this layer.

Layer 4: Referred to as the defuzzification layer delivers the resultant output by inferring the rules. Fuzzy singleton functions which connect the layers layer 3 and layer 4 through weights represent one set of parameters which form the basis for neuro fuzzy network.

Layer 5: The last layer is the output layer that adds all the inputs from the preceding layer transforms the classification in to a crisp output. The structure is tuned by least square estimation and also at times using the back propagation algorithm.

5. PROPOSED FORECASTING SYSTEM

Some of the important features of ANFIS include ease of implementation, fast learning, good generalization and capability to incorporate both linguistic and numeric knowledge for problem solving. According to this approach, a neural network complements the fuzzy system. It functions by formulating the structure and parameter identification of the fuzzy rule base by defining, adapting and optimizing the topology and the parameters of the corresponding neuro-fuzzy network. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data, and as a connectionist architecture provided with linguistic meaning. Global horizontal irradiance; Global diffused irradiance, Ambient Temperature and Surface Temperature form the input vectors for the network. In the proposed work both Backpropogation and Hybrid methods of optimization are employed. The Surface Viewer, (Figure 6) helps in visualizing a three-dimensional curve that represents the mapping between the inputs and the outputs.

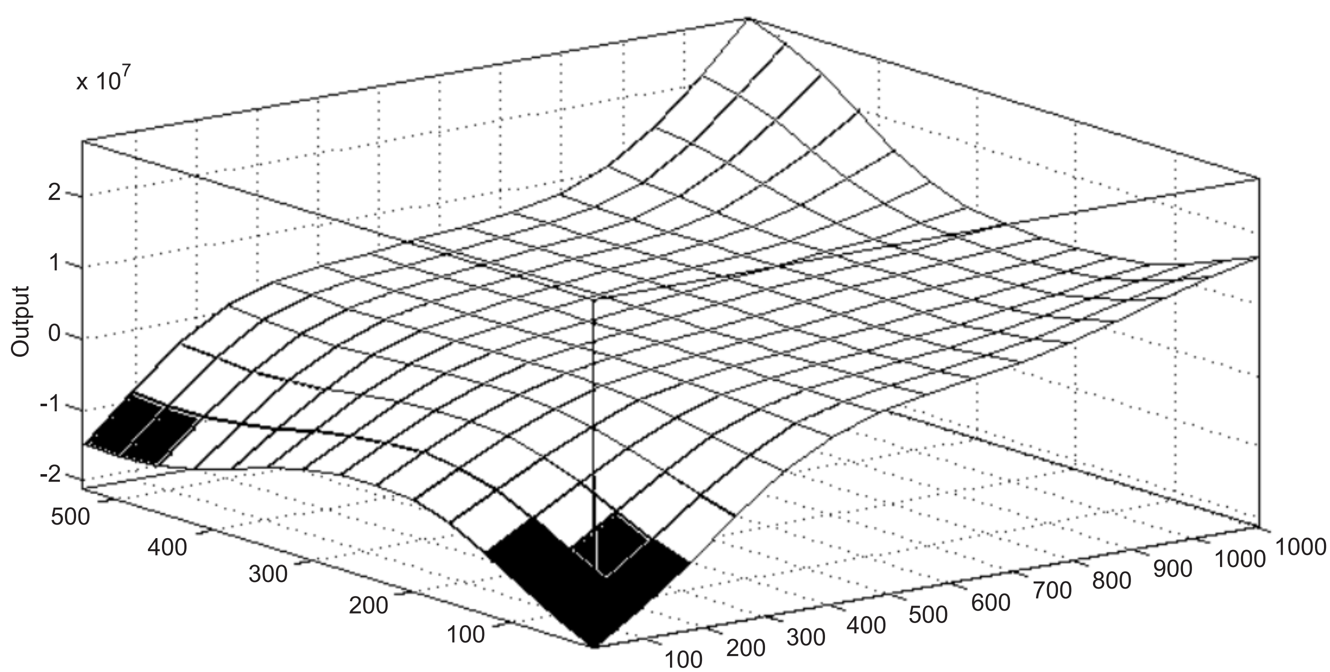

Figure 6: Surface Plot of the ANFIS Rules

The ANFIS model structure that is generated for the analysis of output power for PV energy system is presented in the Figure 7.

The output for different inputs during the training of ANIS is illustrated in the Figure 8.

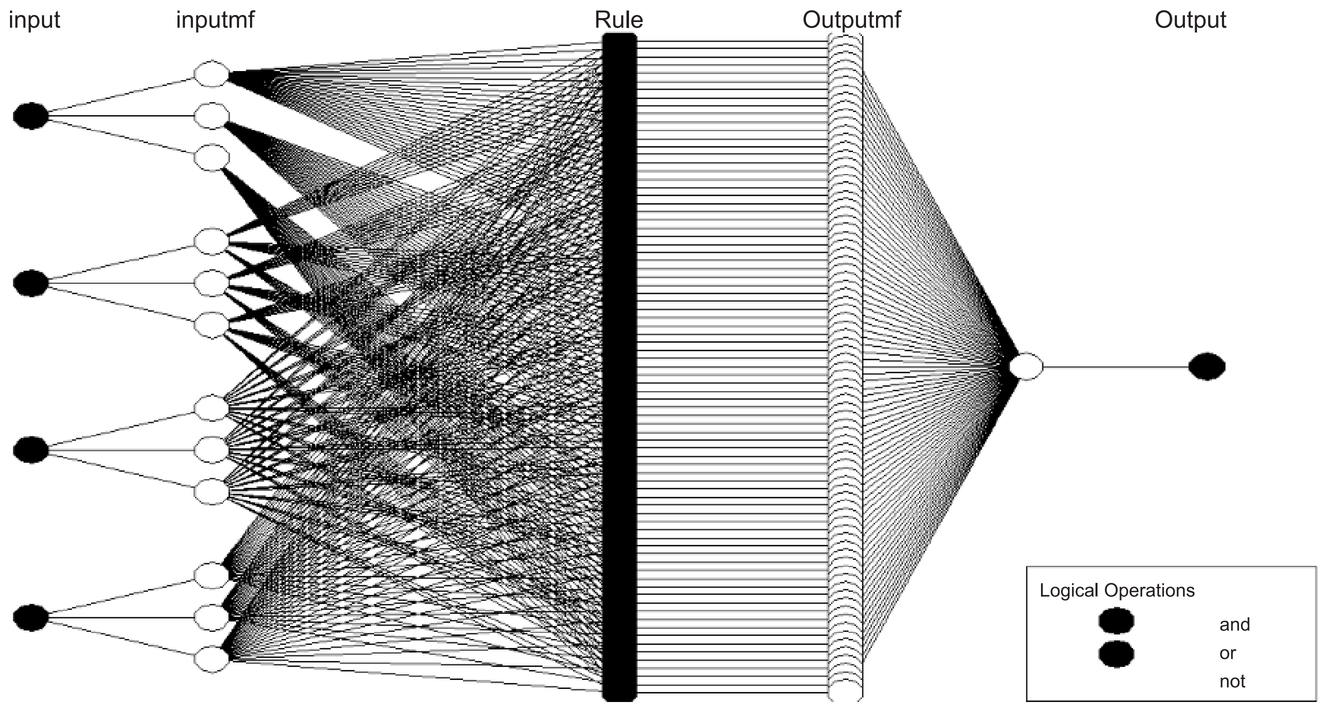

Figure 7: ANFIS Model Structure to Forecast Power

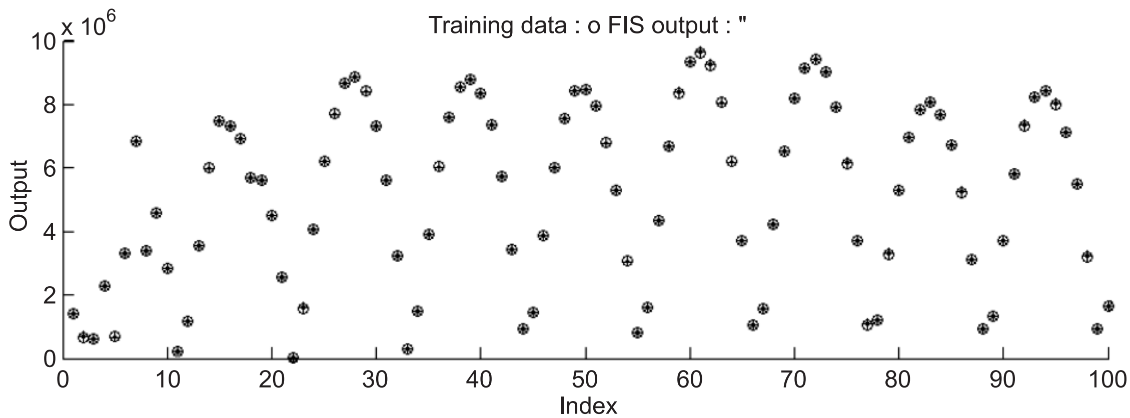

Figure 8: Plot of training data against FIS output

The details about the ANFIS system are illustrated with the help of Table 2.

Table 2
Information about the ANFIS employed

S.No.	*ANFIS INFO*	
1	Number of nodes	193
2	Number of linear parameters	81
3	Number of nonlinear parameters	36
4	Total number of parameters	117
5	Number of fuzzy rules	81
6	Type of Membership function	Triangular

6. RESULTS AND ANALYSIS

The Data set used for training and testing pertains to 10 MW solar plant, which is scaled down to 10 KW for simplification of analysis The Data format considered to train the proposed model comprises of 100 individual data sets sampled from hourly data for 365 days .The data hour is considered from 7 am to 6 pm.

Table 3
Sample data set used in training the ANFIS forecast model

G_Gh (Global Horizontal)	18	123	339	547	705	810	836	790	677
G_Dh (Global Diffused)	18	40	64	86	121	134	147	138	115
Ambient Temperature	26.8	19.9	22.1	24.4	26.5	28.3	29.7	30.6	30.9
Surface Temperature	26.4	20.7	25.3	29.7	32.2	35.2	36.1	37.6	37.7

ANFIS Forecast I is arrived at by having Hybrid optimization and ANFIS Forecast II is arrived by having Backpropogation optimization. The ANFIS system for solar forecast considers 4 factors like (Global diffused and normal irradiance, ambient temperature and surface temperature). In order to validate the results of the proposed work, the forecast is tested against 5 data points for both PV and Wind energy. The data points being considered for validation are sampled to represent high, medium and low values of the parameters being considered in the forecast model and are depicted with the help of table 4.

Table 4
Data Points used in the validation for PV forecast

	D1	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*
G_Gh (Global Horizontal)	76	264	532	671	797	866	888	905
G_Dh (Global Diffused)	76	123	134	352	156	85	97	91
Ambient Temperature	24.7	28.8	24.4	28.6	27.5	29.5	28.9	28.5
Surface Temp	24.9	31	29.8	34.5	35.9	35.7	38.3	35.5
Actual Generation Scaled to 10 KW (KWh)	0.66	2.83	5.993	6.94	8.55	9.22	9.43	9.62

Table 5
Forecast for PV Generation by ANFIS – Forecast I

Data Point	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*
Actual Value	0.66	2.83	5.993	6.94	8.55	9.22	9.43	9.62
Predicted Value	0.52	2.24	5.38	6.36	7.62	8.66	8.79	9.27
% Error	21.21	20.85	10.23	8.36	10.87	6.07	6.79	3.64

Table 6
Forecast for PV Generation by ANFIS – Forecast II

Data Point	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*
Actual Value	0.66	2.83	5.993	6.94	8.55	9.22	9.43	9.62
Predicted Value	0.52	2.23	5.40	6.37	7.62	8.69	8.82	9.30
% Error	21.21	21.20	9.89	8.21	10.88	5.75	6.47	3.33

From the Table 5 and Table 6 following observations can be inferred

(a) For very low insolation values both the approaches results in very high error percentage, this can be evident from the fact that high error percentage of 21.21 % being delivered by the both ANIS I and ANFIS II predictions.

(b) As there is increase in the insolation values, there is substantial and appreciable increase in the prediction accuracy and subsequently a decrease in the error percentage.

(c) It can be observed that the least error percentage stands at 3.33 for D8 as predicted ANFIS – Forecast I

The plot of error percentage illustrated using the Figure 9 also shows that there is a considerable increase in the prediction accuracy as the insolation value increases. Similarly it can be observed from the Figure 9 that the error percentage produced by ANFIS–II which is based on back propagation based optimization is slightly better when compared to the forecast delivered by ANFIS–I based on hybrid optimization.

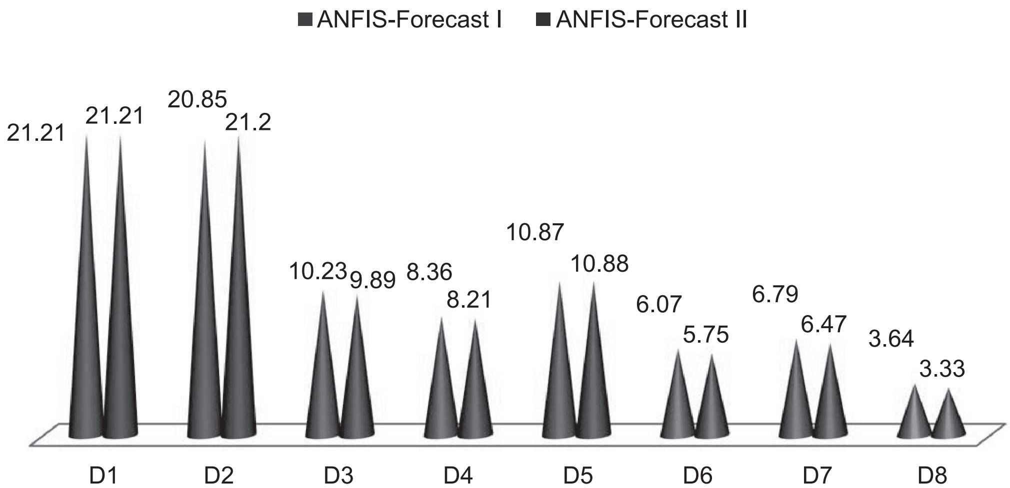

Figure 9: The plot of error % for different forecast methods

The performance of the proposed approach is evaluated using Pearson correlation coefficient (*r*) Correlation – often measured as a correlation coefficient – indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). The Pearson product-moment correlation coefficient (also called Pearson correlation coefficient or the sample correlation coefficient), is obtained by dividing the covariance of the two variables by the product of their standard deviations. The Pearson product-moment correlation coefficient can be used to estimate the correlation between model and observations. The Pearson product-moment correlation is represented using equation (12).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\cdot(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{11}$$

The correlation is +1 in the case of a perfect increasing linear relationship, and −1 in case of a decreasing linear relationship, and the values in between indicates the degree of linear relationship between for example model and observations. A correlation coefficient of 0 means the there is no linear relationship between the variables. From the Figure (10) it can be inferred 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 actual output.

There are several evaluation criteria for forecasting models, such as mean absolute error (MAE), root mean square error (RMSE), and others. In this work, the normalized root mean square error (NRMSE) was utilized because it can provide the comparative analysis for different installed-capacity cases. It is defined as follows:

$$\text{NRMSE} = 100 \cdot \sqrt{1/\text{N} \sum_{i=1}^{\text{N}} \left(\frac{\text{P}_a^i - \text{P}_f^i}{\text{P}_{\text{install}}} \right)^2} \ \% \tag{12}$$

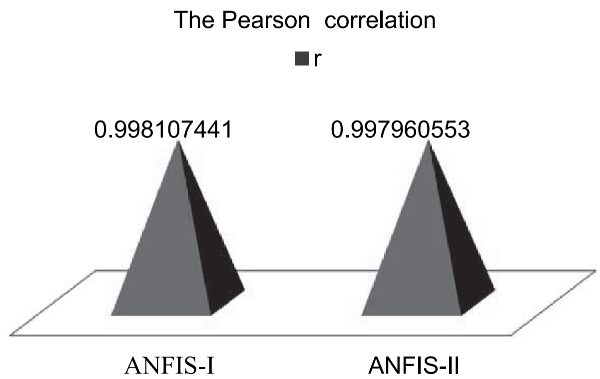

Figure 10: Pearson correlation for different approaches

Where $P_{install}$, P_a, P_f, indicate installed capacity, actual power output, and power forecast value, respectively, and N is the total number of samples.

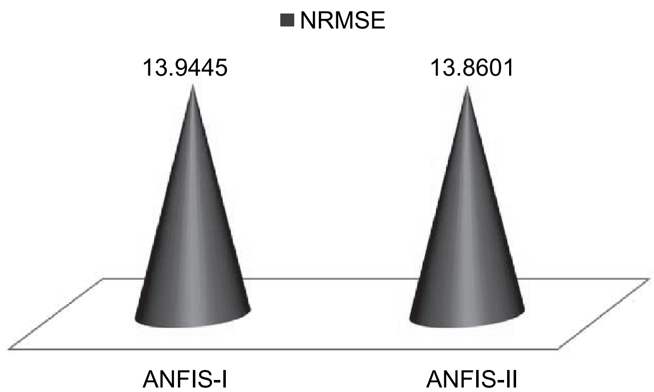

Figure 11: Plot of NRMSE for different forecast by ANFIS I and ANFIS II

7. CONCLUSION

In this research work an ANFIS based maximum power point prediction system has been successfully implemented and presented. It can be inferred from the results that the prediction accuracy is high at high insolation values and low at low insolation values. It is also interesting to note that the results delivered by the ANFIS system trained with the help of back propagation based trained delivers a slightly reduced error percentage when compared to the one trained using hybrid approach. Even the percentage of error at low insolation values are very high, the quantum of error in terms of actual generation is very less and acceptable. This fact is further supplemented through the results of the analysis using Pearson correlation. The Pearson correlation stands close to 1 for both the approaches, standing testimony to the accurate prediction by the proposed system.

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