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Development of Photovoltaic Power Generation Prediction Model using ANFIS

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ABSTRACT

Prediction of photovoltaic (PV) performance is important for energy management practices. The power produced from renewable energy sources is uncertain in nature as it is subjected to continuous changing weather conditions. Hence accurate prediction of output power from these sources is difficult task. In this paper Adaptive Neuro-Fuzzy Inference System (ANFIS) based forecast model for predicting the PV power generation is developed. The proposed model is based on back propagation hybrid learning algorithm of ANFIS with four inputs and one output. Experimentally measured input data of 20 KW. PV system installed at Nashik, Maharashtra, India is used for developing prediction model. The inputs are solar radiation (Rad), ambient temperature (Temp), relative humidity (Hum) and day of year for measurement. Photovoltaic power generation is the output of the model. This data is utilized in the training and testing of the proposed model. Results obtained confirm the ability of the developed ANFIS model for assessing the power produced with reasonable accuracy. A comparative study has done between regression analysis and ANFIS. This shows that the ANFIS-model performs much better than regression. The advantage of the ANFIS model is that they do not need more parameters or complicate calculations unlike implicit models. The developed model could be used to forecast the profile of the produced power in uncertain whether conditions. The error due to ANFIS prediction model for energy produced from the given system considered in this research is 6.14 % which is much better when compared with regression analysis whose error is 16 %. The results indicate that this model can potentially be used to estimate and predict PV solar output power.

Keywords-- Photovoltaic, Regression, Forecast, Solar Radiation, Output Power

I. INTRODUCTION

To improve actual performance and condense possible adverse effects of photovoltaic (PV) systems, a perfect forecasting of PV productivity is important, which is a decisive task within the process of an energy management system for distributed energy resources. The forecast are keys to the reliable and integration of photovoltaic (PV) systems into electricity grids in price effective large scale manner. Additionally, estimation of photovoltaic electrical energy is essential to design and resizing of large scale PV plants, power grid stabilization, green power dealings and balancing control and power interruption warnings in independent power systems. The instant photovoltaic power estimating could be employed for numerous applications such as providing suitable for optimization, control of power, on demand power supply and supplementary generating stations. The following benefits can be achieved with exact forecasting of PV electrical power generation.

- To confirm efficient use of energy generation in PV systems from information reliability.
- To enhance the quality of service and better generation planning.
- To improve real-time performance and decrease possible adverse effects of photovoltaic (PV) systems.
- Power generation for subsequent day has to be scheduled on the day before need. Therefore, accurate projecting of PV power is a significant factor for system reliability and strength.

For consistent operation of PV solar plant, exact forecasting of power generation is important from the purpose of management of load to be connected just in case of off-grid system and if the system is associated to the grid then, the grid operator will be ready to do the effective planning of the facility management within the grid system. Many forecasting techniques have been introduced in past few decades. PV generation predicting methods are developed with different techniques. Those techniques are hybrid, artificial intelligence and statistical method. Due to the variability of solar radiation and environmental factors, the output power of PV system is a stochastic random process. However, due to the problem of uncertainty in the output power of the PV system, many attempts have been proposed in order to predict the output power of the PV system. These attempts in general can be classified as empirical mathematical models, regression based models, and statistical models based on time series of data and finally artificial intelligent neural network based models. The self-learning capability of ANFIS is considered as the main advantage of this model. Some of the researchers have utilized artificial neural network as a learning machine for this purpose. Prediction of the output power of a grid-connected photovoltaic system has done using Hybrid Multi-Layer Feedforward Neural Network (HMLFNN) technique [15].

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Artificial Immune System (AIS) was designated as an optimizer for the Multi-Layer Feedforword Neural Network (MLFNN) training process [2].The sensitivity analysis study of the uncertainty in the output due to different inputs for long term power prediction is studied [18]. Based on time-series models, different solar power prediction approaches such as autoregressive moving average (ARMA) [19], autoregressive integrated moving average [7], and ARMA with exogenous inputs [3] have been demonstrated in recent years. The time-series methods studied are typically linear prediction models. But PV power is a non-linear function of its inputs, which decrease the accuracy of these approaches [13].

To overcome this problem, some machine learning models have been proposed for solar radiation prediction and solar power prediction such as neural network (NN) approach [21], support vector machine (SVM) [4] and radial basis function (RBF) based SV regression [12]. However, these methods may trap in local optima for training the multi-modal input/output mapping function.

PV power generation forecasting method based on a combination of genetic algorithm (GA), particle swarm optimization (PSO) and adaptive neuro-fuzzy inference systems (ANFIS) is proposed [17]. Forecasting of output power is predicted for a PV system based on insolation at 24 hours ahead by using weather reported data, fuzzy theory, and neural network (NN) (1).In addition to this many researchers have successfully implemented ANFIS in different applications including engineering, medical and agriculture. The Sugeno-type adaptive-network-based fuzzy inference system (ANFIS) to predict the existence of mycobacterium tuberculosis leads to forecasting patients before the medical tests (16). The simulation study suggest that ANFIS is a the best controller compared to conventional PID controllers. The proposed technique can be used in the temperature water controller(20). An application of ANFIS (2)for maximum power delivery to the load based on maximum power point tracking offers an enormously fast dynamic response with high accuracy. Author projected technique is been tested for isolated load conditions. Simulation and experimental approaches are used to validate the proposed scheme [6]. Simulation models of PV system are developed for prediction of power output using Adaptive Neuro-Fuzzy Inference System (ANFIS) with hybrid learning algorithm [8]. The computing program is executed for every ANFIS model supported by MATLAB platform. The ANFIS is established to model the daily power generated with changing climatic conditions. The results gained from ANFIS can forecast and simulate the various supported experimental data like solar radiation, surrounding temperature and humidity. Daily average weather data measured at the selected site for one year is employed as an input for the planned forecast model.

II. DEVELOPMENT OF FORECAST MODEL USING ANFIS

The measured data is used to train and test the ANFIS model. Three bell shaped membership functions are used to ANFIS model as fuzzy inputs. After training the model with suitable epochs, the network is tested to determine the forecast of energy generation. 80% of the data is used for training the model and 20% is used for testing purpose from the measured data.

2.1. Architecture of ANFIS

An ANFIS system is a multilayer feed-forward network composed of nodes associated by directed links. Fig.1 shows the structure of ANFIS model consisting of five layers, three inputs x,y and z and one output f.This structure is used to train the model with following two fuzzy rules (Olatomiwa et al., 2015)

Rule No.1: If x is E and y is F and z is I then

$f = j_1 x + k_1 y + l_1 z + s$

Rule No.2: If x is G and y is H and z is I then

$f = j_2 x + k_2 y + l_2 z + s$

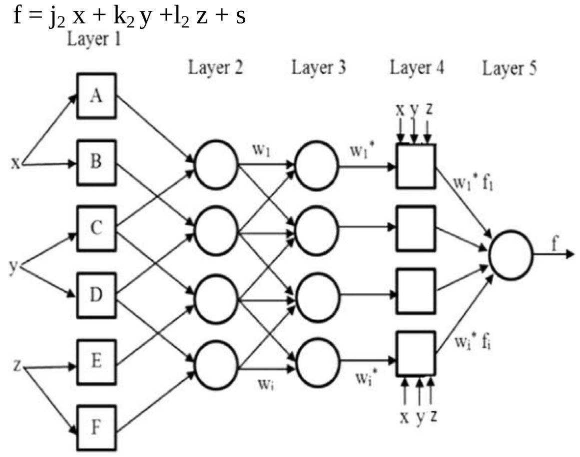

Figure 1: Adaptive Neuro–Fuzzy Inference System structure

2.2. ANFIS Layers

A summary of five layers of the ANFIS algorithm is summarized as follows.

- **Layer 1**

In this layer individually adaptive node may be a square node with square function represented using Eq. (1) and (2) as follows.

$$P_1,i = \mu v,i(v) \text{ for } i = 1, 2,3 \qquad (1)$$

$$P_1,j = \mu d,j(v) \text{ for } j = 1, 2,3 \qquad (2)$$

Where P_1,i and P_1,j denote output function and μv,i and μd,j denote membership function. If we select triangular membership function, μv,i(v) is given by Eq.(3).

$$\mu vi(v) = \text{Max. } [\text{Min. } (\frac{v-b_i}{c_i-b_i}, \frac{c_i-v}{d_i-ci}), 0] \qquad (3)$$

Where {bi,ci,,di} are the factors of triangular membership function. In other example, if we select μv,i(v) to be bell shaped is given by eq.(7).

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$\mu_{v,i}(v) = \frac{1}{1+\{(\frac{v-c_i}{a_i})2\}bi}$ (4)

- **Layer 2**

Weights of every membership function can be verify by using this layer. It can be calculated by using following equation.

$P_{2,i} = \mu_{v,i}(v).\mu_{Dj}(d)$, i=1,2,3 (5)

- **Layer 3**

This layer helps for matching the fuzzy rules and helps to calculate at the beginning of each rule. It is given by following equation.

$P_{3,i} = w_o \frac{w_o}{w_1+w_2}$,i = 1, 2 ,3 (6)

- **Layer 4**

The output of this layer can be calculated using following equation.

$P_{4,i} = \overline{w_i}\,(m_i v + n_i d + o_i)$, i = 1, 2 ,3 (7)

Where P4,i represents layer four output. During this layer, mi, ni and oi are linear parameters.

- **Layer 5**

This is a output layer which sums the outputs of previous four layers. This node calculates sum of all inward signals by using using Eq. (8).

$P_{5,i} = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{w1+w2}$,i =1, 2,3 (8)

Equation (9) shows the sum of all outputs due to n number of layers to be connected in ANFIS structure.

$$z = \frac{w_1}{w_1+w_2 f_1} + \frac{w_2}{w_1+w_2 f_2} + \cdots + \frac{w_n}{w_{n-1}+w_n f_n} \quad (9)$$

III. MEMBERSHIP FUNCTIONS OF INPUTS AND OUTPUT OF FUZZY INFERENCE SYSTEMS

Fuzzy inference technique uses the input vectors based on formation of fuzzy rules. The next step is to obtain output vector from the membership functions of input vector. The fuzzy inference systems are classified into two types those are Sugeno type and Mamdani type. They vary from each other in terms of the way outputs are obtained from them. In mamdani type a fuzzy set used for individual output variable.

The Sugeno process of fuzzy implication is similar to the Mamdani method in many ways. The first two portions of the fuzzy implication process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The key transformation between these two types is that the output membership functions are only linear or constant for the Sugeno-type fuzzy implication.

A typical fuzzy rule in a For first-order Sugeno fuzzy model the fuzzy rule is in the form of m

If x is P and y is Q, then

z = ax + by + c

Where P and Q are fuzzy sets in the antecedent, while a, b, and c are constants.

In the system considered for power prediction based on three input functions and one output function. The input functions are solar radiation, ambient temperature and relative humidity at the selected location of system, whereas the output function is the electrical output power measured from the given system. Fig.2 shows the variation of temperature, radiation, humidity and output power over a one year of the measured data at the selected site. From this plot it has been observed that the PV system is always subjected to large variation of environmental conditions which make the system uncertain in terms of output power generation. Thus there is large variation in power generation from PV system and hence prediction of PV power becomes essential for proper management of power control. Fig. 3 shows 3D Scatterplot of temperature v/s output v/s radiation. Figure 4 shows contour plot of temperature v/s output keeping radiation constant. Fig. 5 gives contour plot of temperature v/s output keeping humidity constant. Fig.6 gives contour plot of radiation v/s output keeping humidity constant.

Fig.7 gives the variation of output power of system due to change in input variables. Radiation has major impact on power generation followed by ambient temperature of system. The output power generation is having the mean value of 80 KW. It has been observed that power generation fluctuates to very large extent between 35 KW to 100 KW. Fig.8 and 9 indicate the cumulative distribution function of temperature and radiation respectively. The mean value of temperature is about 26.25 ^{0}C with standard deviation of 4.731 ^{0}C. While for radiation, mean value is 5.126 Kw/m^2 and standard deviation is 1.664 Kw/m^2 and percentage standard deviation is 4.77 % and 1.57 % respectively. Also standard deviation for humidity is 18.53 %. It demonstrates that selected site temperature is favorable to system installation which is very close to standard temperature of 25 ^{0}C.

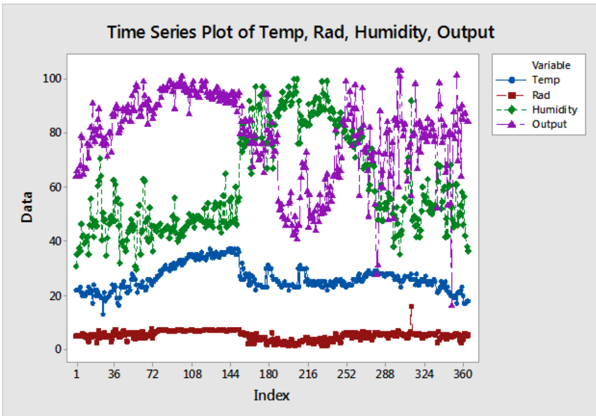

Figure 2: Variation of temperature, radiation, humidity and output over a one year of measured data

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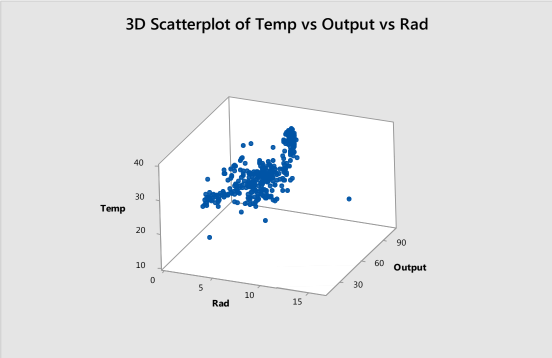

Figure 3: 3D Scatterplot of temperature v/s output v/s radiation

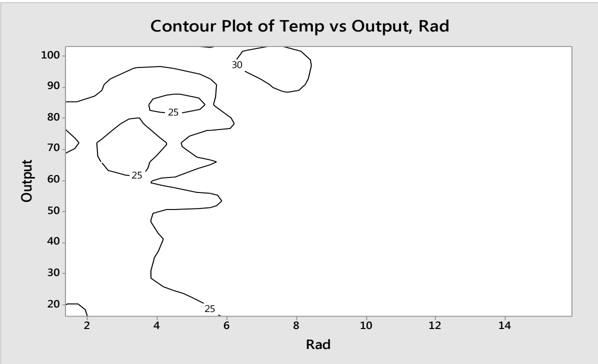

Figure 4: Contour plot of Temperature v/s Output keeping Radiation constant

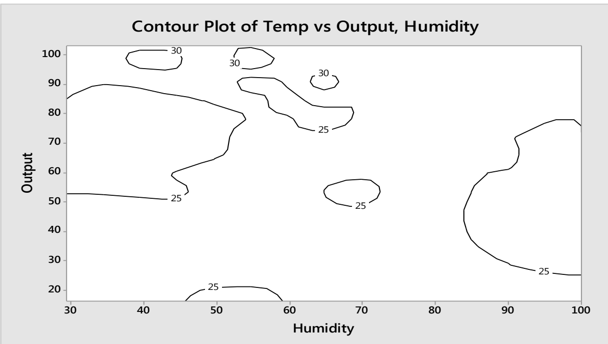

Figure 5: Contour plot of Temperature v/s Output keeping Humidity constant

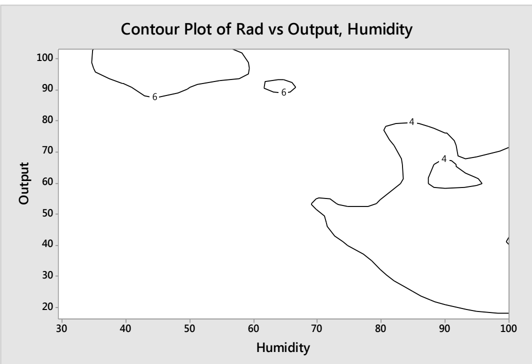

Figure 6: Contour plot of Radiation v/s Output keeping humidity constant

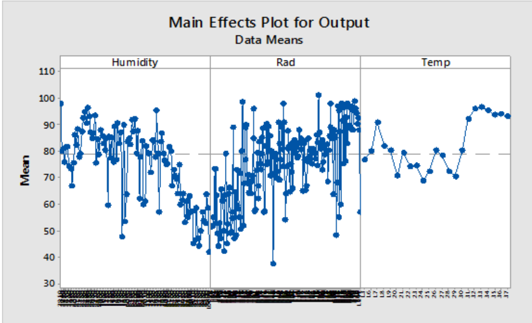

Figure 7: Variation of output power of system due to change in input variables

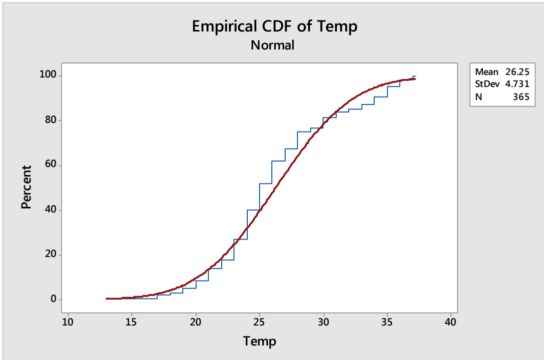

Figure 8: Cumulative distribution function of temperature

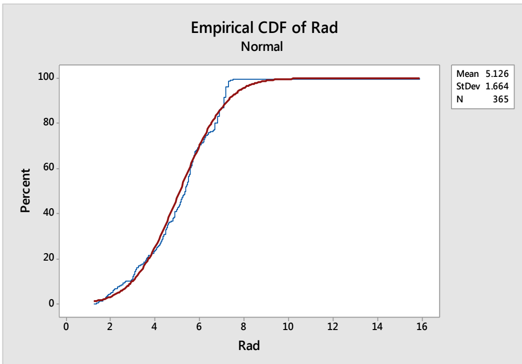

Figure 9: Cumulative distribution function of radiation

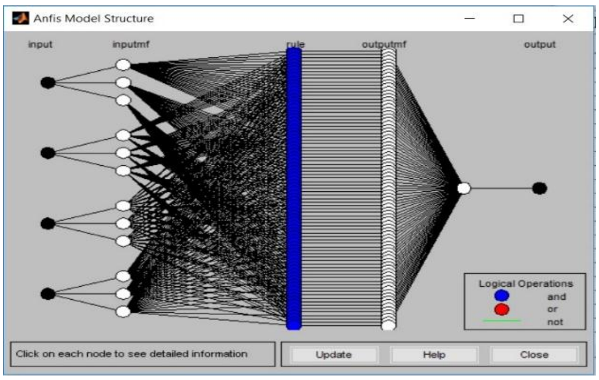

Figure 10: ANFIS Model structure

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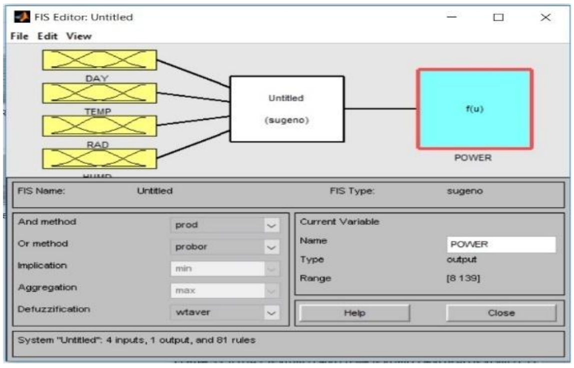

Figure 11: ANFIS Model with properties

IV. MEASURED DATA OF PV SYSTEM

In research, one years (1 Jan.2018 to 31 Dec.2018) experimental measured data of a 20 KWp photovoltaic solar systems installed in Nashik city, Maharashtra, India is used in developing the ANIS model. The installed solar system component specifications are given Table 1 and Table 2. The photovoltaic modules with tilt angle of 200 facing true south are mounted to obtain maximum power yield annually from the given system. The input data is recorded from morning 6 am to evening 7 pm. every 1 hour for one year and its average is taken on the daily basis. The data measurement system contains solar radiation transmitter of silicon photovoltaic detector model WP400 with precision of ± 2 %, temperature sensor model WP700 with precision of ± 0.25 ºC, air temperature sensor model WP700 with range of -60 °C to + 60 °C and precision of ± 0.2°C. This experimental data is used for training and testing the ANFIS model .

Table 1: Solar panel specifications

Model	ELDORA 325
Rated Power of panel (P_{mpp})(64 modules)	325 W
Open Circuit Voltage (V_{oc})	46.2V
Short Circuit Current (I_{sc})	9.13 A
Rated Current (I_{mpp})	8.6 A
Rated Voltage (V_{mpp})	37.8V
Fill Factor	77.07 %
NOCT	45 ^{0}C
Number of Panels	62
Efficiency	16.70 %

Table 2: Inverter specifications

Model	Delta 25000TL-30
Number of inverter	01 (20 KVA)
V_{dc} (Max.)	1000 V
I_{dc} (Max.)	33 A
I_{sc}	43A
V_{dc} (MPP)	360-800 V
Power Rating	20 KVA
I_{ac} (Max.)	36.2 A

V. REGRESSION ANALYSIS

It is a statistical method for building a relation among an descriptive variables and dependent variables. The aim is to forecast the dependent variable when you recognize the descriptive variable or found if there is an influence of one variable on another. It provides a degree of coefficient of relationship among the two variables which can be designed by taking the square root of the product of the two regression coefficients.The basic model for a deterministic set of n observations is given by following equation.

$P_i = d_0 + d_1 Q_i + e_i$ i = 1, 2,3 ------n. (10)

Where,
Pi= dependent variable,
Qi= Explanatory variable,
d_0= standard estimator,
d_1= explanatory variable estimator

Estimators d_0 and d_1 are calculated by the least squares method.

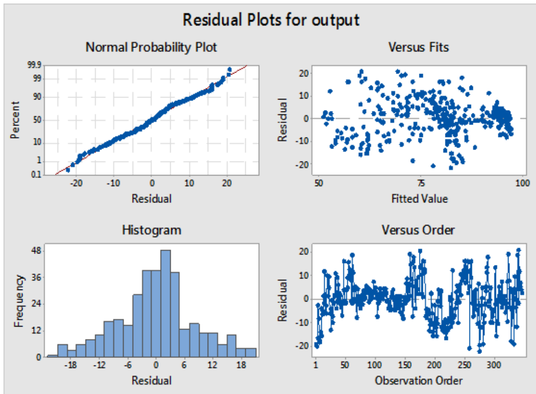

Figure 12: Residual plots for output

A regression analysis is carried out for output versus inputs day, temperature, radiation and humidity. The data used is for a year to forecast the performance of solar PV output of the selected site. The analysis is reported in tables from 3 to 5.

Table 3: Regression Analysis for Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	51017.3	12754.3	186.04	0.000
day	1	252.2	252.2	3.68	0.056
Temp	1	482.7	482.7	7.04	0.008
Rad	1	8060.8	8060.8	117.58	0.000
Hum	1	3117.7	7 3117.7	45.48	0.000
Error	343	23446.7	68.6		
Total	346	74464.1			

Table 4: Regression model summary

S	R-sq	R-sq(adj)	R-sq(pred)
8.27996	68.51%	68.14%	67.49%

Table 5: Coefficients of regression

Term	Coef	SE Coef	T-Value	P-Value	VIF
constant	61.93	3.72	16.64	0.000	
day	-0.00868	0.00453	-1.92	0.056	1.13
Temp	0.304	0.115	2.65	0.008	1.51
Rad	4.950	0.456	10.84	0.000	2.62
Hum	-0.2343	0.0347	-6.74	0.000	2.09

Output equation of regression analysis is given below.

$$Output = 61.93 - 0.00868\ day + 0.304\ Temp + 4.950\ Rad - 0.2343\ Hum \quad (11)$$

Where,

Temp = Ambient temperature

Rad = Solar radiation

Hum = Surrounding relative humidity

Fig.12 illustrates the residual plots for output for different values of residuals with respect to fitted values. It also indicates the observation order of residuals for a year of sampled data measurement. The frequency of occurrence of residuals indicates the samples of data. The plot of residual against the fitted values indicate that the residuals get smaller ie.near to reference line because the fitted values increase , which can indicate the residuals have non-constant variance. The regression analysis is useful as it offers the measure of coefficient of correlation among two variables, it possesses few drawbacks also which are listed below.

- In this analysis it is assumed that the reason and outcome correlation among the variables unaffected. This assumption leads to wrong results.
- It includes very extensive and complex practice of evaluations and analysis.
- It does not withstand the qualitative analysis but gives only quantitative analysis.

Session Window Output

1. The P-value within the regression model within the investigation of difference table demonstrates that model assessed by this method is critical at the α–level of 0.05.This shows that a minimum of one co-efficient is unlike from zero.

2. The P-values of projected coefficient of radiation and humidity both are 0.0000, indicating they are significant associated with output power. The P-value of day is 0.056 and temperature is 0.008, indicating it is not associated with output power at a α- level of 0.05. Moreover the consecutive sum of squares specifies that the forecaster east doesn't explain the considerable amount of unique difference. This means that a model with only North and South could also be more suitable.

3. The R^2 value specifies that the forecasters describe 68.51% of difference in output power. The familiar R2is 68.14 %, which responds for the amount of forecasters within the model become fit.

4. The anticipated R^2 value is 67.49%. As the anticipated R^2 value is on the brink of the R^2 and attuned R^2 values, the model doesn't seem to be over fit and has suitable predictive ability.

Graph Window Output

1. The histogram specifies that outliers may exist within the data, demonstrated by the 2 bars right hand side of plot which is far away.

2. The traditional possibility plot displays an nearly linear outline according to Gaussian distribution.

Thus predicted and experimental results show an average agreement with regression coefficient of 0.78. However data is much more scattered along the linear curve fit. Moreover probability plots did not provide information on regression agreement.

VI. ERROR ANALYSIS

The two error coefficients which are Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) can be to accomplish a effective evaluation between regression analysis and ANFIS analysis [21]. These two errors are given by following equations.

$$MAE = \frac{\sum_{i=1}^{N}[P_m - P_e]}{Pt * N} \quad (12)$$

$$MAPE\ (\%) = \frac{\sum_{i=1}^{N}\frac{P_m - P_e}{Max(P_m) - Min(P_m)}}{N} \quad (13)$$

Where P_m is forecast value, P_e is true value, P_t is the PV capacity and N is number of data (365).

Fig. 21 shows that actual temperature of selected site is deviated by 4.773 to standard from the mean temperature of 26.28 ^{0}C. It demonstrate that selected site temperature is favorable to system installation which is extremely on the brink of degree centigrade of 25 ^{0}C.From figures 5.21 to 5.24 , it is clear that P-value of all variables day , temperature, radiation, humidity and PV output is a less than 0.005.

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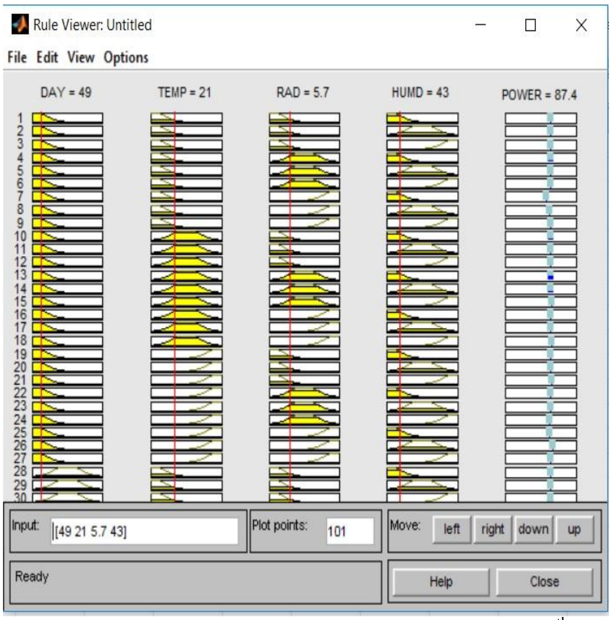

Figure 13: ANFIS prediction of output power on 49th day (February 2018)

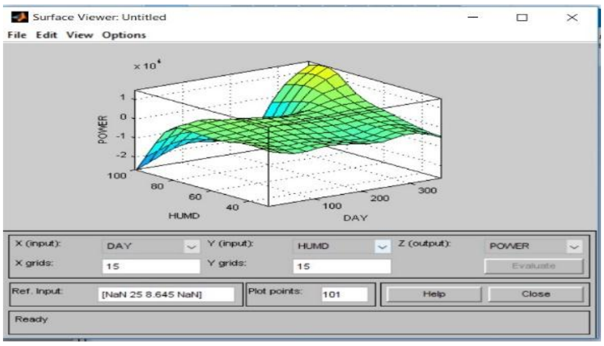

Figure 14: Influence of day and humidity on power generation

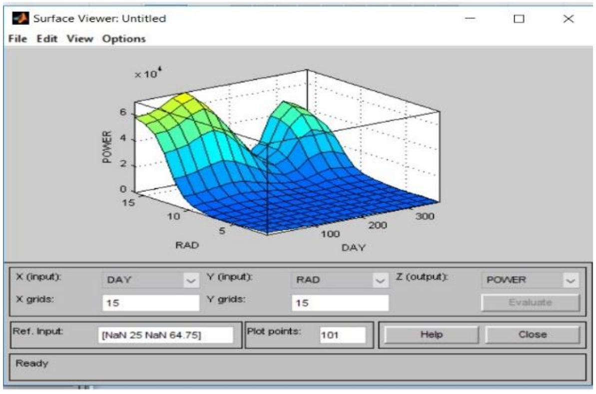

Figure 15: Influence of day and radiation on power generation

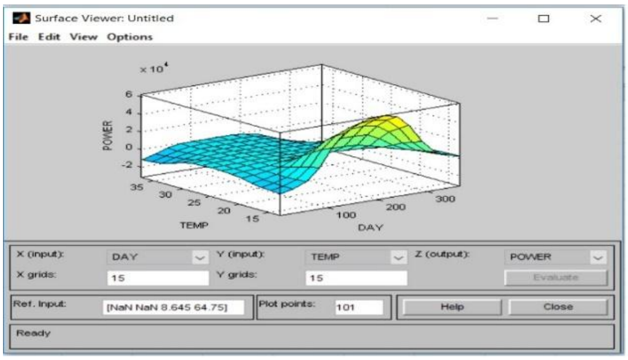

Figure 16: Influence of day and temperature on power generation

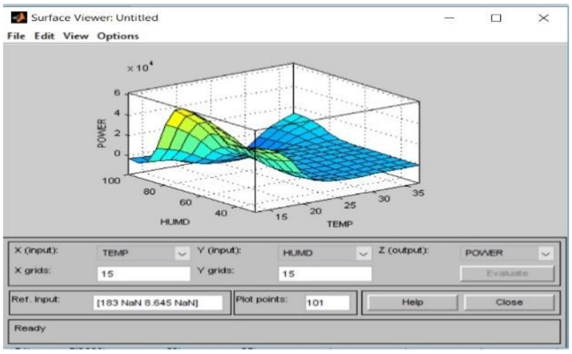

Figure 17: Influence of temperature and humidity on power generation

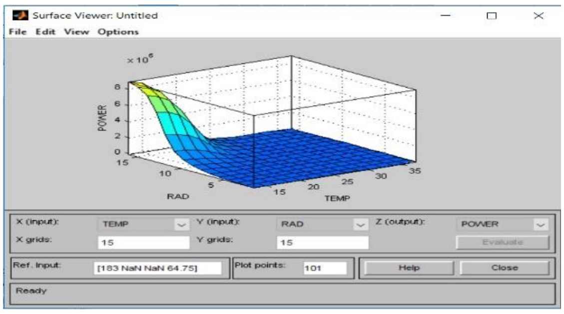

Figure 18: Influence of temperature and radiation on output Power

VII. ANFIS MODEL ANALYSIS

The PV solar power output prediction by ANFIS is obtained by using MATLAB software using ANFIS structure as shown in Fig. 10.From Fig.13 it is found that ANFIS predicted power on 19th February 2018 at temperature of 21 ^{0}C, radiation 5.7 KWh/m^2 and humidity 43 is 83.4 KWh . On the same day measured output power is 90 KWh. The error among the expected power and measured power is 6.60 KWh. The percentage error is equal to 8%. Thus, ANFIS prediction model fits the results.

Fig. 14 to 18 shows the variation of effects of day, temperature, radiation and humidity on the output of PV solar system with combinations of any two inputs simultaneously. Throughout the year for humidity unto 80 , power is high. But as humidity increases above 80 , the power suddenly drops to large value , output is highly sensitive to radiation above 5 KWh/m^2 and for temperature from 20 ^{0}Cto 30 ^{0}C.

VIII. RESULT ANALYSIS

ANFIS model is run till the error is minimized. Fig.19shows the correlation between training and testing data.Fig.20 shows the variation of output power in a year. Power generated in months June to August is low due to lower value of solar irradiation. It also indicates that solar power output is highly variable in nature due to changing climatic conditions. Fig. 21 to 24 demonstrates the probability plots of temperature, humidity, radiation and power output respectively. From these plots, it is found out that the p-value of all the system variables is less than 0.05. The probability plot also indicates the values of measured variables are lie along the mean line of plot and which indicates the normal distribution of the variables. Hence, these variables are favorable at the selected site for power generation Anderson- Darling normality test is performed to obtain output at 95 % confidence interval for mean, median and standard deviation. The report of this test is shown in Fig.26. The 95 % confidence interval for mean is between 76.992 to 80.248 ie. 6 % and that for median is between 79.600 to 83.270 ie. 5 %. The confidence interval for standard deviation is between 14.745 to 17.054 ie. 9 %.These results gave the effectiveness of the proposed test wherein the deviations are within the prescribed levels. The output power generation prediction trend for a year of measurement is demonstrated in Fig.27. The mean average percentage error of this prediction error is 16.412 %. Also the mean average deviation is 11.351 % from a mean average value. This shows the suitability of model tested.

Fig.28 shows the actual (blue colour) and predicted (red colour) values of PV Solar power output. The experimental versus predicted output of the system is shown in Fig. 29. The red line indicates the predicted output whereas blue points shows the actual measured experimental results. The locus of experimental values is in the vicinity of predicted values. This gives the robustness of proposed method of prediction of power generation.

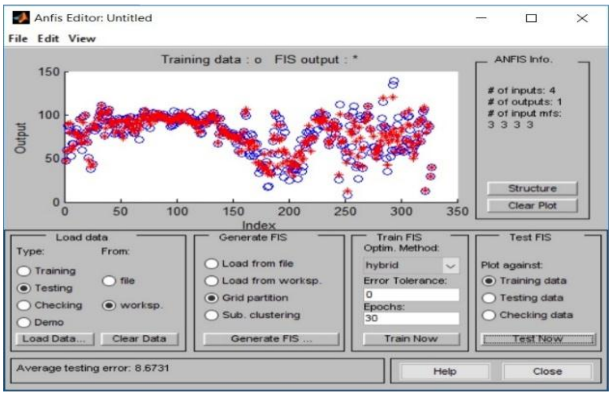

Figure 19: ANFIS training and testing data correlation

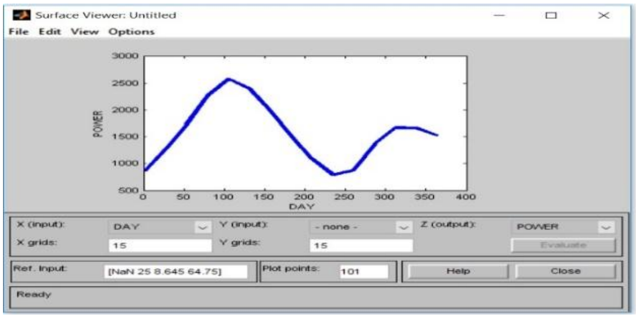

Figure 20: Plot of day v/s power for a year

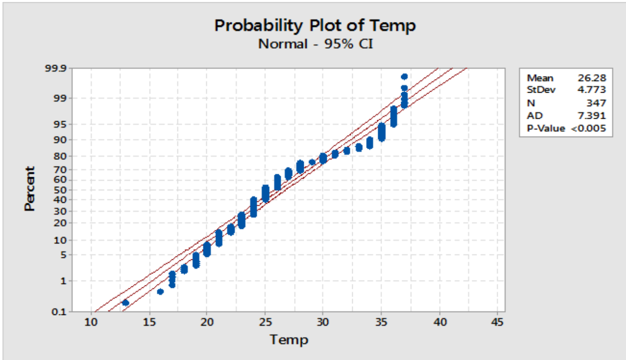

Figure 21: Probability plot for temperature

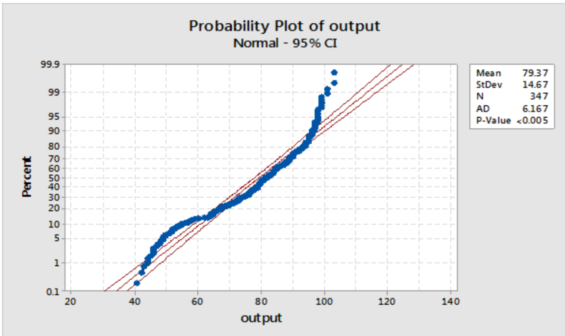

Figure 22: Probability plot of output

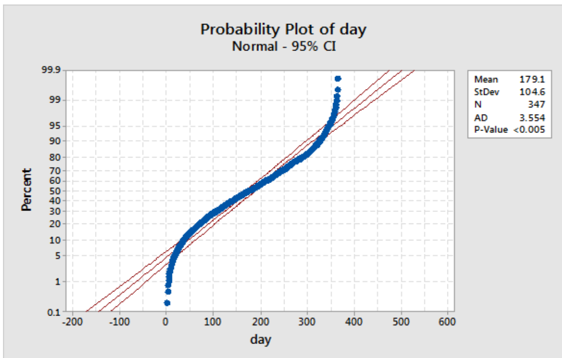

Figure 23: Probability plot of day

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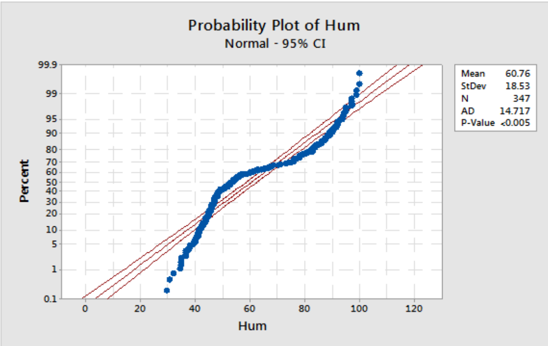

Figure 24: Probability plot of humidity

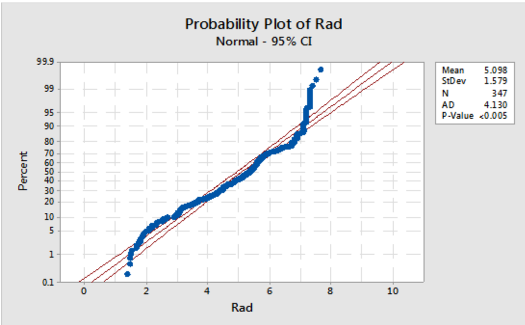

Figure 25: Probability plot of radiation

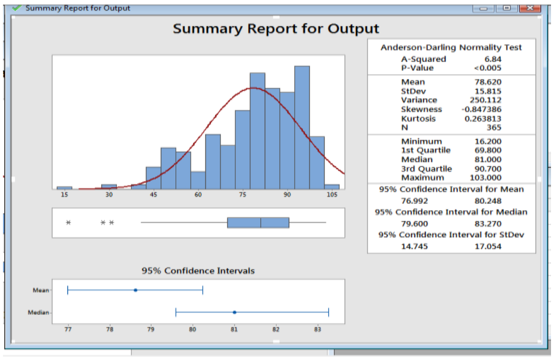

Figure 26: Summary report for output

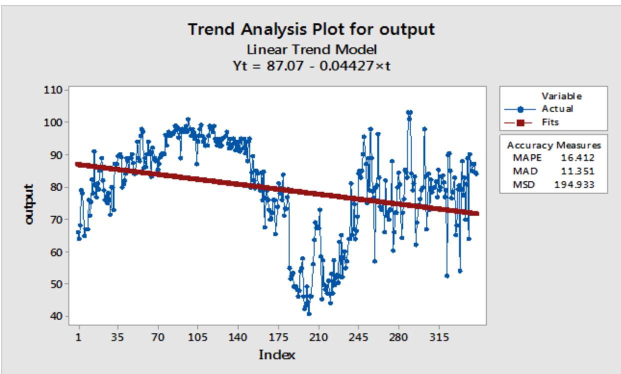

Figure 27: Output prediction trend for a year

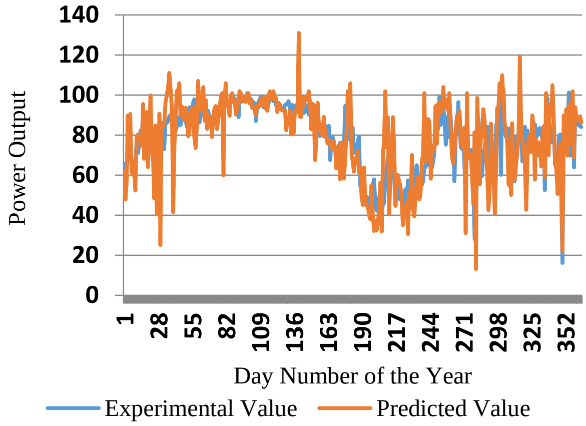

Figure 28: Forecasting of Solar PV Power output over a year

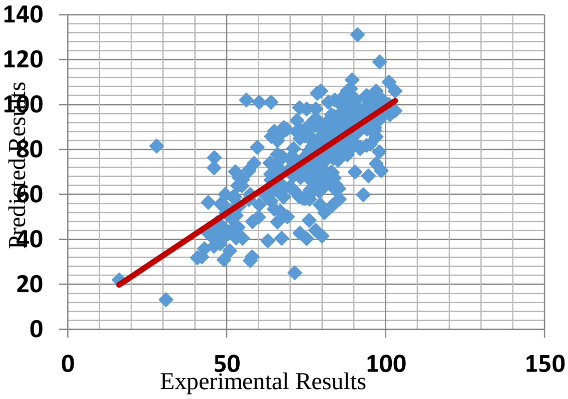

Figure 29: Experimental versus predicted output

IX. CONCLUSION

The solar photovoltaic power is much unstable in nature as it is subjected to continuously changing weather conditions. This leads in dissatisfaction where different solar power applications are to be used. So considering the above fact the ANFIS model is developed to forecast of electrical power produced from the given of PV system. This helps in better power management between the system and the utility grid. Results obtained from ANFIS model are compared with regression analysis to verify accuracy of ANFIS model. The ANFIS model gives the more accurate outcomes in evaluation with regression model. The comparative outcomes realize the projecting ability of ANFIS model and its feasibility at any site with dissimilar weather circumstances. The error due to ANFIS prediction model for energy produced from the given system considered for this research is 6.14 % which is much better when compared with regression analysis whose error is 16 %. Hence, ANFIS model provides the better forecast of electrical energy produced from solar photovoltaic system that could give the effective use of solar power in different applications.

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