

Solar Power Forecasting Using Artificial Intelligence

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Abstract: Analysing the Output Power of a Solar Photo-voltaic System at the design stage and at the same time predicting the performance of solar PV System under different weather condition is a primary work i.e. to be carried out before any installation. The level of solar Power that can be generated by a solar photovoltaic system depends upon the environment in which it is operated and two other important factors like the amount of solar insolation and temperature. As these two factors

$$\begin{aligned} & \left(\frac{G}{G_{stc}} \right)^{\frac{1}{n}} \\ &= \frac{I_{ph, stc}}{I_{ph, stc}} \\ &+ K_i \left(\frac{T - T_{stc}}{T_{stc}} \right)^{\frac{1}{n}} \end{aligned} \quad (1)$$

Apart from ongoing discussed forecasting methods, some other statistically used method usually start with mathematical function which describe the linear and nonlinear relationship between the datasets and their behaviour to the environmental parameter with an objective to minimize the variation of mathematical function. In this case the analyst takes long time to analyse the result and thereby making convergence of the system optimized parameters. This paper presents a comparative analysis of all the forecasting method mainly used by researchers over past decade. The paper describes about the artificial intelligence based extremum learning algorithm for forecasting the solar hidden network such as analysing some kind of weight to the hidden layer and arbitrary selection of hidden bias was selected by applying the genetic algorithm to the master real time data which are collected from open source data based on meteorological department. Different section of the paper includes the proposed idea is arranged in the following manner. 1st section describes about brief description of forecasting followed by 2nd section which mainly deals with the modelling of PV cells along with different MPPT technique with special focus on incremental conductance method. 3rd and 4th section describes about result analysis and comparison with new technique. 5th section describes about the conclusion along with future development.

2 PV Model

The main aim of solar PV forecasting is to forecast the weather conditions such as temperature, solar radiation. Where G represents the solar radiation, G_{stc} represents the standard solar radiation, $I_{ph, stc}$ represents photo generated current during standard temperature condition (STC), T and T_{stc} temperature and temperature at STC respectively. Similarly the maximum power generated by the solar PV cell is $P_{max} = A [0.05 (T - T_{stc})]$ (2) Where total conversion efficiency is represented by

This is for the entire solar PV array, total area covered by the solar PV array represented by $A (m^2)$. Solar insolation falling on the array is represented by $I (kW/m^2)$ and

represents the total ambient temperature of PV array in $(^{\circ}C)$. The real time model which was developed in MATLAB simulink model consist of 72 no of cells having total maximum output power of 300 Wp (P_{max}). Maximum short circuit current is,

(1) Intraday Forecasting

In the competitive energy market, availability of electrical energy at the point of demand is the most challenging job. Intraday forecasting which is usually from some few seconds to minute could be able to ensure the availability of energy.

$$\sum_{i=1}^n |e_i| \quad (5)$$

selectionfortheelectricity market.

tive function as shown below

$$y = 3.6169x^2 + 4077.3x - 25301 \quad (14)$$

The objective function as shown in equation 14 was derived from the Polynomialisation of Temperature and AC output (kWh), which is shown in Figure

Table1: Observed & Calculated value of Environmental Temperature and Solar PV Output

Month	Month	AC System Output (kWh)	AC System Output (kWh) - Calculated	Observed Temp.	Forecasted Temperature	Solar Radiation (kWh/m ² /day)
1	Jan	82257.875	81609.98438	26.53	26.77	4.2925396
2	Feb	100442.0313	99655.03125	30.97	30.91	5.67678547
3	Mar	135883.5938	134822.3594	34.81	37.95	6.68656969
4	Apr	142563.4375	141450.9688	39.92	40.28	6.84843159
5	May	145573.6094	144436.5625	39	40.23	6.48288298
6	Jun	125976.9844	124990.3047	32.34	37.9	5.53810167
7	Jul	119612.6172	118674.0938	31.28	32.85	4.99226809
8	Aug	114054.0469	113159.0781	32.68	35.56	4.94502401
9	Sep	113528.625	112638.5859	35.76	34.24	5.49704838
10	Oct	110454.2891	109588.3906	31.37	33.34	5.54661322
11	Nov	90045.02344	89337.64844	28.1	29.08	4.85409641
12	Dec	80529.05469	79894.44531	33.71	35.03	4.25716782

Table2: MSE and the Hidden layer details

Number of Neurons	Hidden Layer	Train	Mean Square Error	
First Hidden Layer Second			Validation	Test
10	10	0.0071	0.0198	0.0189
10	15	0.0082	0.0174	0.0192
10	20	0.0001	0.0146	0.0120
10	25	0.0009	0.0180	0.0173
10	30	0.0089	0.0191	0.0175
20	10	0.0023	0.0131	0.0117
20	15	0.0072	0.0171	0.0145
20	20	0.0018	0.0176	0.0169
20	25	0.0010	0.0195	0.0202
20	30	0.0017	0.0216	0.0185

Table3: Regression Statistics using ANOVA

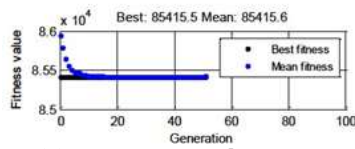
ANOVA						
	df	SS	MS	F	Significance F	
Regression	1	3198110075	3198110075	14.78798	0.003236	
Residual	10	2162641479	216264147.9			
Total	11	5360751554				
	Coefficients	Standard Error	t Stat	P-value	Lower 95.0%	Upper 95.0%
Intercept	29300.6	37352.97934	0.784425135	0.450973	112528	53927.01
X Variable 1	4319.441	1123.241284	3.845514379	0.003236	1816.703	6822.178

Figure 3 shows the Simulation and data validation of Forecasted value with Genetic Algorithm. It is found that the Forecasted result as shown in the Table 1 is under the Normalcy. Similar to the AC Output Forecast, statistical analysis of Temperature is shown in the 5.

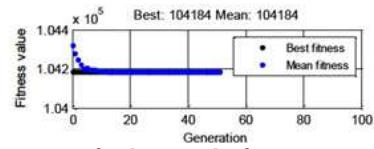
Table 5 and 6 shows the Statistical analysis of Temperature Histogram over 18 years and Regression analysis using ANOVA for Temperature respectively. The one-way analysis of variance (ANOVA) is used to determine whether there are any statistically significant differences between the means of two or more independent groups. Here df represents the degree of freedom which is 1 for Regression and 16 for Residual in this present study. Significance F represents the ratio of Mean Square Error to Sum Square Error, which is unity in the present case. This signifies that the forecasted result for solar PV is the best accurate one with respect to temperature. The F-test is used for comparing the factors of the total deviation. In the present analysis of ANOVA, F is found to be 22.1812 which is inside the prescribed limit of F.

Table4:ProbabilityOutputVs.PredictedOutput

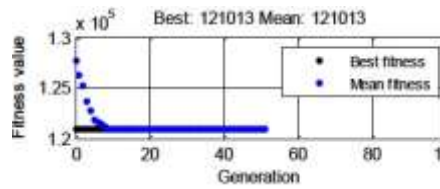
RESIDUALOUTPUT T Obse	PROBABILITYOUTPUT
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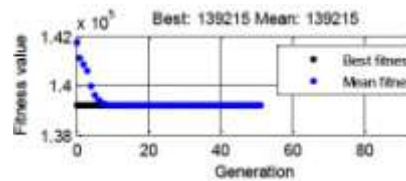
(a) Best Fitness Value of Forecasted Solar PV System for the Month of January



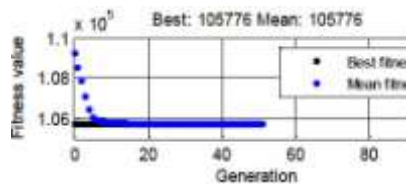
(b) Best Fitness Value of Forecasted Solar PV System for the Month of February



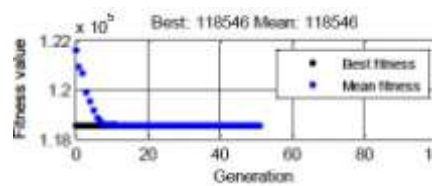
(c) Best Fitness Value of Forecasted Solar PV System for the Month of March



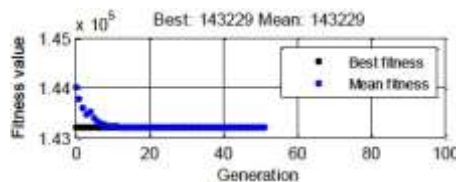
(d) Best Fitness Value of Forecasted Solar PV System for the Month of April



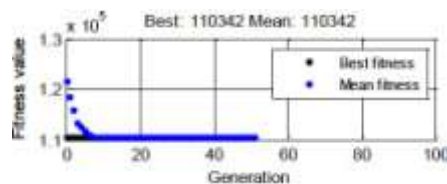
(e) Best Fitness Value of Forecasted Solar PV System for the Month of May



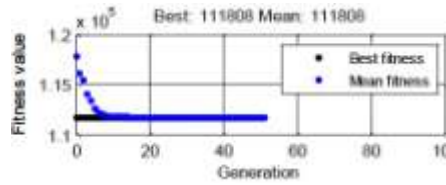
(f) Best Fitness Value of Forecasted Solar PV System for the Month of June



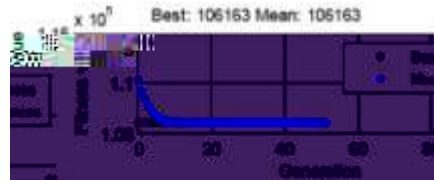
(g) Best Fitness Value of Forecasted Solar PV System for the Month of July



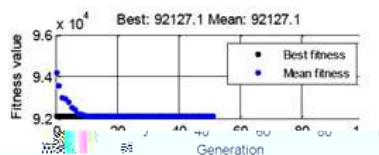
(h) Best Fitness Value of Forecasted Solar PV System for the Month of August



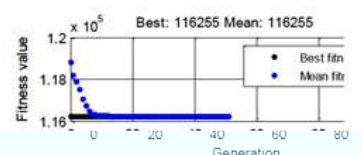
(h) Best Fitness Value of Forecasted Solar PV System for the Month of August



(l) Best Fitness Value of Forecasted Solar PV System for the Month of December



(j) Best Fitness Value of Forecasted Solar PV System for the Month of October



(k) Best Fitness Value of Forecasted Solar PV System for the Month of November

Figure 3: Shows the Best Fitness Value of Forecasted Solar PV System for the every month of Year

Conclusion

The level of solar Power that can be generated by a solar photovoltaic system depends upon the environment in which it is operated and two other important factors like the amount of solar insolation and temperature. Application of GA to Forecasting of the Solar AC Output system is discussed in this paper. It is found that the forecasting using GA is much more convenient and accurate as compared to statistical methods of analysis. In the next paper of this series, Optimization of Solar PV Output with respect to two variables such as Temperature as well as Solar Radiation will be presented. Grid-connected solar Photovoltaic issues based on the Forecasted result and their mitigation techniques will be discussed in future work.

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