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Development and Performance of Empirical Models for Solar Radiation Prediction

Aditi Chaturvedi[#], Manish Mishra[*]

[#]Electrical and Electronics Department, [*] Electronics Department, [#]University of Petroleum and Energy Studies, [*]Deen Dayal Upadhyay Gorakhpur University
[#]Energy Acres, Bidholi, Dehradun,Uttarakhand 248007, [*]Civil Lines,Gorakhpur, Uttar Pradesh 273009
[1]500087761@stu.upes.ac.in@gmail.com
[2]manish.ddu1976@gmail.com

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***Abstract*— Assessment of solar resources at a potential site is a primary step in investigating the feasibility of the site of a solar PV power plant. There are well-established empirical models in literature for determining global horizontal irradiation and direct normal irradiation of a site for pre-feasibility studies. These models, however, use data like maximum sunshine hours, extra-terrestrial radiation values etc. which are often unavailable due to lack of ground-monitored meteorological stations, especially at remote sites. This study develops models based on average temperature and relative humidity and compares them to well-established models using statistical tools for performance evaluation of solar data prediction for a case study location. The study concludes that two of the developed models are at par with the established ones and can be used alternatively for the case study location.**

***Keywords*—Global Horizontal Irradiation, Direct Normal Irradiation, Average Temperature, Relative Humidity, Solar Resource Assessment**

I. Introduction

Through the delivery of efficient and reliable illumination, cooling, cooking, mechanical work, transit, and communication networks, energy access provides a number of opportunities for progress and socio-economic growth, especially in the context of developing nations [1,2].

Furthermore, having access to energy has proven to be beneficial to businesses, as output increases, automated systems replace human labour, and a favorable circular growth phase ensues [3]. Sustainable Development (SD) is impossible without sustainable energy, as per the United Nations (UN), hence the subject has been emphasized by incorporating sustainable energy as Sustainable Goal Number Seven, which entails access to effective, dependable, and contemporary energy, universally [4].

According to the International Energy Agency (IEA), access to energy is defined as "households having reliable electricity and a relatively clean, safe means of cooking." [5].

Renewable off-grid technology is one possible approach for reaching the UN's Seventh Sustainable Development Goal in huge rural areas that still lack last mile connectivity. Photovoltaic (PV) systems in off-grid mode is a viable solution for Developing Nations to enable access of energy to such remote areas.

Decentralization of energy through standalones also aligns with the Ministry of New and Renewable Energy in the form of one of its earliest Off-Grid Solar PV Applications Program, aiming to provide solar Photovoltaic solutions in communities where grid power is inaccessible. The programme covers solar home lights, solar public utilities, solar farms, solar pumps, solar lamps etc.

With off-grid solar PV applications, the National Solar Mission has set a target of 2000 MWp. A goal of 200 MWp was set for Phase I of the Mission from 2010 to 2013, against which 253 MWp was sanctioned, and a target of 500 MWp was set for Phase II from 2013 to 2017, against which 713 MWp was sanctioned. A target of 118 MW has been set for Phase-III of the Off-grid and Decentralised Solar PV Applications Programme, excluding solar pumps that will be installed under the PM KUSUM Scheme and solar home lights that will be put under the Ministry of Power's 'Saubhagya' Scheme [6].

Assessment of solar resources at a potential site is a primary step in investigating the feasibility of the site for a solar PV power plant. The solar resource ultimately affects the Levelized Cost Of Electricity across all types of solar photovoltaic technologies and regions [7]. Interpolating observations from neighbouring ground-based measuring stations can yield long-term yearly average Global

Horizontal lrradiation and Direct Normal Irradiation values for a site. However, such a large amount of historical data is difficult to come by and it is not always accessible, especially from ground-based sources. [8] The protocol mentioned is complex and has time implications when adopted in a pre-feasibility study.

This is where the utility of empirical models in prefeasibility study of solar radiation resource prediction is seen. The well-established empirical models such as Angstrom-Prescott [9], Reitveld [10], Liu and Jordan [11], Gopinathan and Soler [12], Iqbal [13] used require data such as maximum number of sunshine hours, available sunshine hours, extraterrestrial radiation.

However, this data still needs to be recovered from meteorological stations which are mostly unavailable for remote sites where decentralized standalone are usually planned. This study proposes developing empirical models using simple measurable, recordable and widely available data such as relative humidity and average temperature of the region where the site is located. The radiation predicted from the proposed models are then evaluated against the established empirical models.

Established models chosen for study are Angstrom-Prescott , Reitveld, Liu and Jordan , Gopinathan and Soler, Iqbal .

Gujarat has a renewable energy installed capacity of 7,645 MW, which accounts for only 28% of total capacity as of January 2019. Gujarat wants to increase it to 22,922 MW by 2022, accounting for 53% of the total.

The state has set a target of expanding overall energy generation from 15,000MW to 20,000MW over the next few years. By 2022, the state government plans to increase renewable energy's contribution to overall energy generation from 10% to 17 percent. In January 2019, the government announced that generation of solar power would be increased by 3,000MW per year. [15]

The progressive policy regarding the solar sector is expected to incentivize on-grid and off-grid solar PV plants. Hence, the city of Ahmedabad is chosen as a case study.

II. LITERATURE REVIEW

Various models have been created in the academia for predicting solar radiation, with sunlight hours as the primary parameter. However, there is still a lot of work to be done in terms of linking solar hours and other variables. [16] developed seven models for estimating mean global and mean diffuse radiation for the city of Amravati related with sunshine hours, average temperature, and relative humidity. In this case, it was shown that the developed models outperformed the established ones for this particular case study.

In [17], sunshine hours available for 14 years (2000 to 2014) were gathered from the World Radiation Data Centre (WRDC), Russia, to create generalised models to measure the monthly average global solar radiation of twelve places in India. To examine the accuracy of the model, statistical analysis is used. Additionally, the Global Performance Indicator (GPI) is used to rank models based on their overall performance as determined by scaling statistical indicators. The NREL estimated data and the WRDC data suggest that the satellite data overestimates the surface measured data by 10 to 15% for seven locations, while it is between 7 and 9.5 percent for the remaining four stations. The study finds that inaccurate representation of aerosols in satellite models, difficulty in obtaining cloud cover, snow, and dust storms from satellites, and atmospheric scattering led to inaccuracy in determining radiation levels.

[18] is a review and systematic arrangement of 732 empirical models and 65 functional forms for calculating global solar radiation in Africa found in the literature.

The goal of [19] was to assess the efficacy of seven empirical models in estimating daily solar radiation at 13 Peruvian meteorological stations from 1990 to 2004 (measurement) and 2004 to 2010 (testing). Multiple linear regression analysis was utilised to construct new models using the same factors used throughout estimation methods (temperature) as well as two additional parameters, precipitation and relative humidity (proposed models). At San Ramon station, the best performance of a developed framework (in percentage terms of error reduction) was 73 percent when compared to the average of all empirical models and 93 percent when compared to the worst empirical model result.

The goal of [20] was to determine the accuracy of fifteen empirical solar radiations models and their influence on ETo (evapotranspiration) estimates for three humid tropical locales (Abakaliki, Nsukka, and Awka). NASA's archived meteorological data (1983-2005) was utilised to derive empirical constants (calibration values) for the various models at each location, while data from 2006 to 2015 was used for testing the calibration. When comparing measured radiation with predicted radiation using original constants versus the revised constants, improvements were demonstrated.

III. METHODOLOGY

The four models developed on the basis of parameters like humidity and average temperature are obtained by linear curve fitting (Figures 1,2,3 and 4) on global horizontal irradiance (GHI), direct normal irradiance (DNI), relative humidity and average monthly temperature for 2017 and 2018. Data has been obtained from the NSDRB data viewer of NREL for the coordinates 23.0225° N, 72.5714° E, corresponding to the city of Ahmedabad. The data in 15-minute time series has been averaged to monthly values. The data is provided in Table 1. The models for evaluation are provided in Table 2.

A few parameters for calculating solar radiation are given as follows:

$$\delta = 23.45 \sin \frac{360}{365}(284+n) \qquad (1)$$

$$\omega_s = \cos^{-1}(-\tan\Phi . \tan\delta) \qquad (2)$$

$$H_0 = \frac{12}{\pi} I_{sc} \left(1+0.033 \cos \frac{360n}{365}\right) \bullet \left(\omega_s \sin\Phi \sin\delta + \cos\Phi \cos\delta \sin \omega_s\right) \quad (3)$$

$$S_{max} = \frac{2}{15}\omega_s \quad (4)$$

where,
δ= Angle of Declination
n= Day number of the year
Φ=Latitude in degrees
ω_s= Hour Angle
H_0= Extra-terrestrial radiation monthly average
H_g=Monthly average of daily global radiation on a horizontal surface
H_d= Monthly average of daily diffused radiation on a horizontal surface
I_{sc}= Solar Constant (approximately 1.366 kW/m^2)
S_{max}=Monthly average of maximum possible sunshine hours per day at the location
S= Monthly average of sunshine hours recorded per day at the location
H= Monthly average measured Relative Humidity for the location
T= Monthly average measured Temperature for the location

The established and developed models are applied for predicting 2019 solar data, the diffused and global irradiance.

The following statistical tools are employed for performance evaluation against actual 2019 solar resource data obtained from NREL:

1. Mean Absolute Percentage Error

$$MAPE = \frac{1}{n} \sum_{1}^{n} \frac{|H_a - H_p|}{|H_a|} \times 100\%$$

2. Mean Square Error

$$MSE = \frac{1}{n} \sum_{1}^{n} \left(H_a - H_p\right)^2$$

3. Root Mean Square Error

$$RMSE = \left[\frac{1}{n} \sum_{1}^{n} \left(H_a - H_p\right)^2\right]^{1/2}$$

4. Linear Regression Coefficient

$$r = \frac{n \sum_{1}^{n} H_p \bullet H_a - \sum_{1}^{n} H_p \bullet \sum_{1}^{n} H_a}{\left[n\left(\sum_{1}^{n} H_p^{\,2}\right) - \left(\sum_{1}^{n} H_p\right)^2\right]^{1/2} \bullet \left[n\left(\sum_{1}^{n} H_a^{\,2}\right)\left(\sum_{1}^{n} H_a\right)^2\right]^{1/2}}$$

Where,
H_p= Predicted values from models
H_a=Actual measured solar resource data

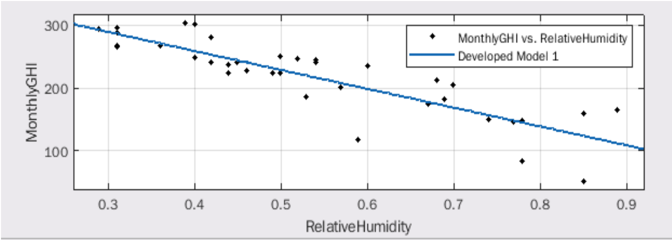

Fig 1. Developed model 1:Monthly GHI vs. Relative Humidity

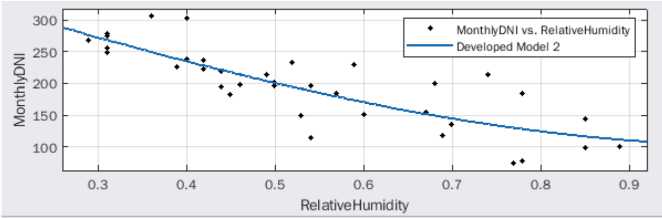

Fig 2. Developed model 1:Monthly DNII vs. Relative Humidity

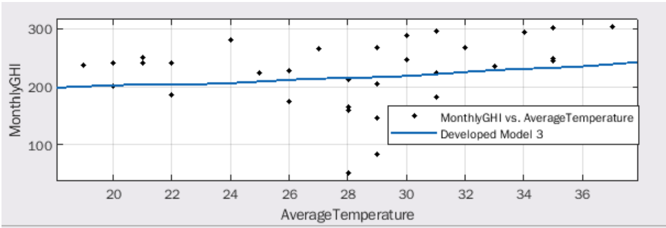

Fig 3. Developed model 3:Monthly GHI vs. Average Temperature

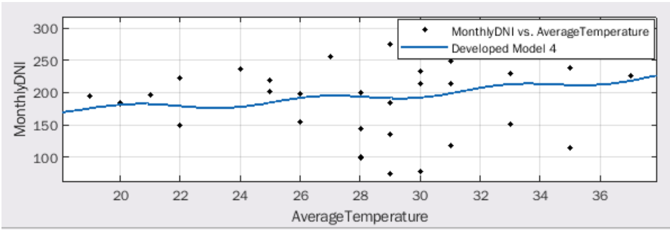

Fig 4. Developed model 4:Monthly DNI vs. Average Temperature

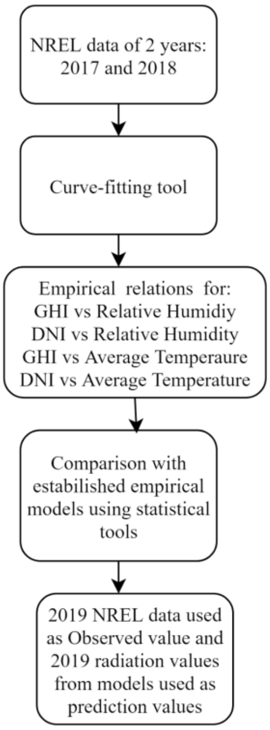

Fig.5 Flow chart of methodology used in performance evaluation

Table 3 shows the values obtained from different models. Table 4 depicts the statistical evaluation values.

TABLE I

MONTHLY DATA FROM NREL

2017			
Global Horizontal Irradiation (W/m^2)	**Direct Normal Irradiation (W/m^2)**	**Relative Humidity**	**Average Temperature (in degree Celsius)**
241.65	196.36	0.54	21
280.45	236.32	0.42	24
267.51	274.47	0.31	29
266.73	306.02	0.36	32
249.32	303.43	0.4	35
117.22	229.38	0.59	33
51.88	143.91	0.85	28
84.45	184.56	0.78	29
150.15	214.42	0.74	30
247.51	233.24	0.52	30
224.24	200.86	0.5	25
186.64	150	0.53	22
2018			
Global Horizontal Irradiation (W/m^2)	**Direct Normal Irradiation (W/m^2)**	**Relative Humidity**	**Average Temperature (in degree Celsius)**
249.8	196.45	0.5	21
223.11	219.23	0.44	25
288.81	278.47	0.31	30
295.21	249.25	0.31	31
303.13	226.51	0.39	37
245.02	114.67	0.54	35
147.95	77.61	0.78	30
145.35	74.71	0.77	29
205.34	135.19	0.7	29
223.6	213.67	0.49	31
228.35	197.6	0.46	26
240.87	182.51	0.45	20
2019			
Global Horizontal Irradiation (W/m^2)	**Direct Normal Irradiation (W/m^2)**	**Relative Humidity**	**Average Temperature (in degree Celsius)**
237.25	195.33	0.44	19
241.5	223.03	0.42	22
265.53	255.02	0.31	27
293.12	268.45	0.29	34
300.61	238.63	0.4	35
183.16	150.96	0.6	33
183.16	117.89	0.69	31
159.36	98.89	0.85	28
164.38	100.25	0.89	28
213.23	199.75	0.68	28
173.96	153.96	0.67	26
201.04	184.33	0.57	20

TABLE III

DEVELOPED AND ESTABLISHED MODELS

Angstrom-Prescott	$\frac{H_g}{H_0} = a+b\left(\frac{S}{S_{max}}\right)$ a= 0.1212 b=0.5822
Reitveld	$\frac{H_g}{H_0} = 0.18+0.62\left(\frac{S}{S_{max}}\right)$
Liu and Jordan	$\frac{H_d}{H_0}=1.390-4.027\left(\frac{H_g}{H_0}\right)+5.531\left(\frac{H_g}{H_0}\right)^2-3.108\left(\frac{H_g}{H_0}\right)^3$
Gopinathan	$\frac{H_g}{H_0} = a_1+b_1\left(\frac{S}{S_{max}}\right)$

	$a_1 = -0.309+0.539\cos\Phi - 0.0693E_L + 0.290\left(\frac{S}{S_{max}}\right)$ $b_1 = 1.527-1.027\cos\Phi + 0.0926E_L + 0.359\left(\frac{S}{S_{max}}\right)$
Gopinathan and Soler	$\frac{H_d}{H_0} = 0.87813-0.33280\left(\frac{H_g}{H_0}\right) -0.53039\left(\frac{S}{S_{max}}\right)$
Iqbal	$\frac{H_d}{H_0} = 1.2547- 1.2055\left(\frac{S}{S_{max}}\right)$
GHI vs. Relative Humidity	$p_1 \sin(H-\pi) + q_1 (H-10)^2 + r_1$ $p_1 = -49.12$ $q_1 = 18.1$ $r_1 = -1427$
DNI vs. Relative Humidity	$p_2 \sin(H-\pi) + q_2 (H-10)^2 + r_2$ $p_2 = 767.8$ $q_2 = -18.39$ $r_2 = 2229$
GHI vs. Average Temperature	$p_3 \sin(H-\pi) + q_3 (H-10)^2 + r_3$ $p_3 = -1.113$ $q_3 = 0.6038$ $r_3 = 196.4$
DNI vs. Average Temperature	$p_4 \sin(H-\pi) + q_4 (H-10)^2 + r_4$ $p_4 = -2.682$ $q_4 = 0.07175$ $r_4 = 168.2$

TABLE IIIII

PREDICTED VALUES FOR 2019

Angstrom-Prescott	148.4424 158.3959 188.6775 208.5568 234.4852 200.4865 156.6133 143.975 162.2546 178.3435 151.9 49 142.3612	**Reitveld**	153.4428 164.1194 191.1649 211.8884 239.4642 196.2867 138.0349 124.6389 155.8963 182.8854 157.5126 147.4464
Gopinathan	251.08718 270.60278 291.04981 326.0897 375.76334 254.85567 61.468052 34.87913 181.20196 291.28551 260.11255 242.80391	**GHI vs. Relative Humidity**	248.2170597 254.25344 287.5783733 293.66313 260.2962603 200.11577 173.1644122 125.3317279 113.3759654 176.1565445 179.1492022 209.1132455
GHI vs. Average Temperature	201.4593 205.0831 214.9137 231.7662 233.6593 229.4539 222.5795 216.2629 216.2629 216.2629 212.7072 203.4548	**H_a - Liu and Jordan**	180.6715 197.6795 190.9124 215.9131 253.8932 158.2575 54.12918 40.84097 113.0027 200.5714 190.6376 176.9072
H_a - Gopinathan and Soler	153.0264 165.6101 168.3828 190.0118 221.2264 141.3934 53.98947 43.51666 100.7979 173.1764 159.3329 148.4899	**H_a - Iqbal**	149.4179 163.6158 152.1643 173.4476 206.5352 108.9417 18.29227 11.44933 70.09176 164.439 157.7968 146.4118
DNI vs. Relative Humidity	220.1294 227.0374 266.8624 274.3898 234.0563 169.5184 145.3508 111.7038 105.3707 147.8629 150.4198 178.3126	**DNI vs. Average Temperature**	174.349 180.562 190.917 205.414 207.485 203.343 199.201 192.988 192.988 192.988 188.846 176.42

TABLE IVV
PERFORMANCE EVALUATION

Model	MAPE %	MSE	RMSE	r

Angstrom-Prescott	20.86	3298.144	57.42947	0.6397
Reitveld	21.85	3153.055	56.15207	0.8264
Gopinathan	27.78	4552.108	67.46931	0.6194
GHI vs.Relative Humidity	10.77	750.9078	27.4027	0.8265
DNI vs. Average Temperature	17.4	1871.507	43.26207	0.169
H_a - Liu and Jordan	19.05035	1417.927	37.65537	0.7111
H_a - Gopinathan and Soler	22.60141	2359.539	48.57509	0.7336
H_a - Iqbal	34.2409	4101.494	64.04291	0.715
DNI vs. Relative Humidity	9.03693	404.7849	20.11927	0.8773
DNI vs. Average Temperature	34.42897	3286.444	57.32751	0.0024

IV. RESULTS AND DISCUSSION

Lower value of MAPE, RMSE and MSE indicate better performance. The closer the value of r to one, the better the performance of the model. While RMSE indicates the short-term performance of the model, MAPE represents the long-term and r shows the linearity of predicted values to the actual, measured values. The following observations are made in Table 4:

- Models using Relative Humidity as the principle parameter are seen to perform better than established models, according to their given MAPE, r and RMSE values.
- Although the models using temperature as a principle parameter perform better than established ones according to the MAPE and RMSE value, the r value suggests that temperature is not linearly correlated to solar radiation data. This rules out temperature to be used as the only reliable parameter in developing such an empirical model.
- Among the established GHI predictive models, Reitveld performs better than Angststrom-Prescott followed by Gopinathan.
- Among the established (Diffused Horizontal Irradiation) DHI predictive models, Liu and Jordan performs better than Gopinathan and Soler followed by Iqbal.

Temperature depends on various factors such as wind-speed, pressure conditions, CO_2 levels, topography an elevation of a location and cannot linearly be correlated with solar radiation levels of a location. Although humidity depends on several factors other than irradiation as well, it is largely a causation of irradiation.

V. CONCLUSION

Empirical models are cost-effective and less complex alternative to assess the solar potential of a site in a prefeasibility study. They are a useful tool in planning decentralized PV plants. Temperature needs to be correlated with several other factors to make a reliable model out of the parameter. This work evaluates the performance of various empirical models for the case study location of Ahmedabad and it is found that the models developed on the basis of relative humidity outperform the established models. The success of relative humidity, for the case study of Ahmedabad, to be used as a parameter needs to be verified for more locations for solar resource assessment.

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