AN EXTENSIVE ANALYSIS AND EVALUATION FOR THE POTENTIAL OF PHOTOVOLTAIC SYSTEMS

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***Abstract*—The decision to install a PV plant depends on three major factors: the climatic and environment conditions of the location, the viability of commercial operations, and the government policies. Economic feasibility of a PV system in the energy market depends on the cost of technology, the cost of installation, and the yield of the plant. Considering uncertain nature of climatic parameters, development of a reliable model to predict the energy output of a plant-to-be installed becomes essential. The presented study deals with PVGIS software method to estimate the total PV energy production of Odisha for a year. The proposed model considers only two meteorological variables collected from 1195 locations of Odisha: total annual incident global radiation on the surface of the module and annual average air temperature. The paper focuses on simplification at every stag of the development while analyzing the preciseness of the model. Solar radiation is waste when it falls on the earth in countries like India. India has a large agricultural industry that feeds the stomachs of the majority of the world's people, in addition to solar radiation. The Indian government has implemented measures to promote solar energy usage and reduce the use of non-renewable resources. The current research examines different advances in the use of solar energy in Indian agriculture, which may be utilized to reduce electricity consumption from non- conventional sources, which are both expensive and ecologically harmful. According to current study, further research is needed to improve the applicability and efficiency of solar power consumption for long-term use.**

Keywords—Solar PV production; Predictive Model; Geographical Parameters; PVGIS; Odisha

Nomenclature

Variables	Parameters name	Unit
g	Instantaneous incident global radiation	W/m^2
G,G'	Global irradiance incident on the surface	Wh/m^2, kWh/m^2
K_T	Temperature coefficient of the module	$^0C/(W/m^2)$
P	the power output of the module	kWh
P_K	Peak or nominal installed power of the module	kW
RMSE	Root mean square error	
T_a	Average annual air temperature	^0C
T_m	Temperature of the module	^0C
I'_m	Differential module temperature	^0C

I. Introduction

The generation using Photovoltaic (PV) system is a rapidly growing renewable technology option due to its decreasing per unit cost of electricity. By October 2013, the capacity of the total worldwide solar PV installation reached to 135 GW, out of which installation of 112 GW plant is in last four years alone[1]. India has installed 4.1 GW of utility-scale solar as of May 2015, and 60 GW is planned by 2022[2]. The reduction in LCOE (Levelized Cost of Electricity) of large scale solar PV in India at 5% and 10% of WACC (Weighted Average Cost of Capital) from the year of 2015 to 2050 is predicted as 3 EUR ct/kWh and 4.2 EUR ct/kWh respectively[3].The roadmap of the renewable energy production predicts the production of PV to provide 16% of global electricity and 10%-12% of India by 2050[1]. Interest for PV installations in last decade among all sectors (public sector,private sector, and common households) in Odisha is growing. In last five years alone the total installed capacity of the solar power plants in Odisha increased to 56.92 MW_p[4]. As per 'Odisha Solar Policy 2013', gross renewable energy potential stands at 53,820 MW for the state, out of which the possible potential for power generation using solar PV is about 8000 MW[5].

Various predictive models reported use different methods or algorithms to predict the energy production of a PV system. Huang C. et al.[6] proposed an EP algorithm to predict the power output of the PV array by adjusting the fill factor, with an acceptable R^2 parameter under sunny (99.79% and 99.08%) and cloudy (99.59% and 99.62%) conditions for two experimental stations considered. Another study by Steffen R.E. et al. examines six independent variables (installation capacity, shading, longitude, latitude, seasonal climatic.

The use of fossil fuels and other pollution-producing activities are contributing to climate change and global warming. These energy sources produce greenhouse gases, which have the ability to absorb solar radiation, resulting in a rise in global temperature. Developing nations, such as India, have a variety of difficulties when it comes to energy production. More than half of Indian households do not have access to power. As the world's population grows and the temperature rises, more people are becoming aware of the benefits of using solar energy to carry out their everyday tasks. Power demand is rising while electricity output is decreasing.

variation, and orientation) to calculate system output using a regression model (R^2 ~ 0.832) for grid-connected PV systems[7]. Cameron C.P. et.al propose and evaluates the system accuracy of SAM (Solar Advisor Model) which predicts the energy production precisely[8]. The SAM model comprises of the radiation model (< 2% error), inverter model (<1% error), and module performance models (within 5%, 10%, 4%, 11% absolute error). A short-term power forecasting model, developed byMonteiro C. et.al, for PV Plants named HistoricalSimilar Mining (HISIMI) provides a normalized RMSE of 10.14% during evaluation of the plant output[9].

A case-study shows the use of APROS simulation showing the error of 2% to 7% of the measured value[10]. Aste N. et.al presents a long-term prediction model by using TRANSYS and PVsyst software for Europe with R^2 value greater than 0.99[11].

Among various methods for the estimation of energy production,simulation software is the most traditionalway, where user simulates a PV module or plant and its environment. The examples of some free or commercially available software are PVGIS, SolarGIS, PVsysts, PVwatts, Tansysts[11, 12, 13]. Simulation software uses a solar radiation database to run embedded algorithms which predict the output for a particular location. The database includes solar radiation data measured by either geostationary meteorological satellites or by ground stations. Theworld coordinate system locates the installation site of the plant, and then the user selects different parameters, attributes, and orientation of the PV plant or module in the software for the chosen location.

PVGIS software estimates the annual PV energy production (response variable) from 1195 different locations in Odisha. PVGIS and SolarGISgivethe annual global radiation and air temperature[14] respectively. The prospective study deals with the development of a simplified model to predict the energy production and installationof the PV system for the state of Odisha. The first model takes only three input variables while predicting the output response of the PV system. Later the model is simplified to a second one which requires only two input values to estimate the expected output energy production. The aim of the paper is to analyze the preciseness of both the model's forecast for Odisha on simplification at every stage of the development.

II. METHODOLOGY AND DEVELOPMENT OF THE MODEL

The models presented in this section use the PV production data obtained for 1195 locations in Odisha using PVGIS method, after normalized to per kW_p, to predict the outcome of PV plant [15]. The regression analysis by a robustleast square method using MATLAB curve fitting tool provides the coefficients of the functions for the proposed models. The plotted 3D graphs show the distribution of the range of PV electricity production for all kinds of combination of the input parameters.

A. *Methodology to generate the model*

The initial phase of the modeldevelopment identifies and collects all the main influencing factors that affect the performance of PV module. The parameters affecting the performance of PV module are mostly the climatic and technical in nature. The climatic factors are stochastic in natur and have more influence on the performance of the PV module. Among all the climatic factors,the input parameters of the model areglobal radiation and ambient temperature. Similarly,the response parameter of the modelis temperature coefficient. By using different PV production, evaluation methods estimates the PV production output for the various selected location.

With these collected parameters and response, a simple model named simplified model (SFM) is created that takes three input parameters for the prediction of the annual PV production of the plant. Among the among the three parameters two are variables: annual incident global radiation and annual average air temperature, and one is a constant (temperature coefficient). The model converts the annual average air temperature into differential module temperature.And theactual input variable is the differential module temperature as shown in Fig. 1.Further simplified model (FSFM)is asimplification of SFM. The FSFM takes only two input variables (annual incident global radiation and annual average air temperature) for the prediction. The comparison of both the models is done simultaneously to analysis various cases and study the deviation inresults.

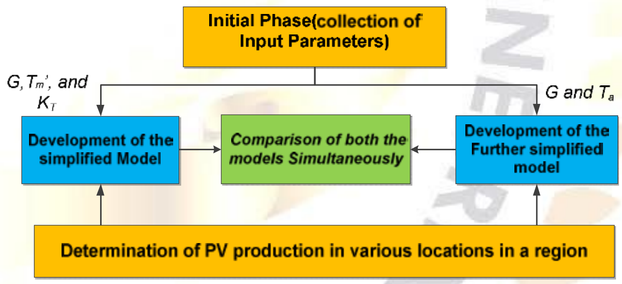

Fig. 1. Methodology to implement the SFM and FSFM

B. *Estimation of PV production using PVGIS*

The study deals with the PVGIS software to estimate the PV production in the region of Odisha. The method divides the total area of Odisha into 1195 equal parts. All the 1195 coordinates are the location input of the PVGIS, and the PV production is estimated. TABLE I provides the details of the input parameters set to the PVGIS for the region of Odisha [16].

Fig. 2represents the comparison of the estimated results for both tracking and non-tracking options of PV system for Odisha. The four-trend line of the plot between PV production and variation of global radiation incident on the surface of the module exhibits linear characteristics. As the temperature coefficient of the building integrated is higher than the freestanding mounting its module temperature raises more easily. The rise in temperature provides additional losses to the system, and the production decreasescomparatively.

TABLE I. SELECTED INPUTS IN THE PVGIS ESTIMATION TOOL

Parameters/attributes	Value Setting
PV technology	Crystalline silicon
Installed peak power	10 kW_p
System losses	14% (losses incables, inverter, soiling)
Mounting option	Freestanding or building integrated
Inclination	25^0(non-tracking)
Azimuth	0^0 (for Southwards orientation of module)
Tracking	Two-axis tracking (when opted for)

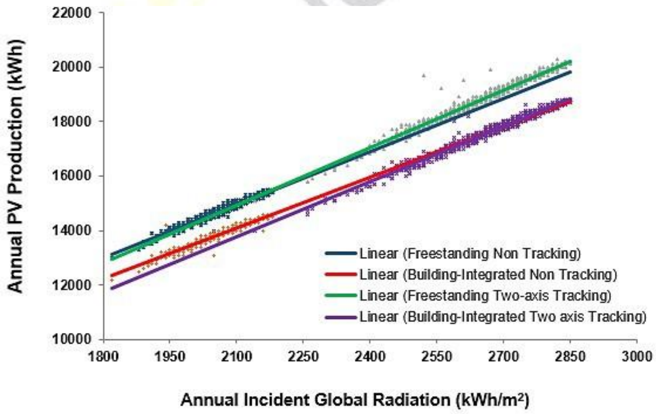

Fig. 2. Estimation of PV production of Odisha with PVGIS

C. Simplified Model (SFM)

The SFM is the modified Output function of PVGIS energy rating method. The estimated output of the model is independent of any other influencing factors except for three input parameters: global radiation, air temperature, and temperature coefficient. Model converts air temperature to differential module temperature defined as the function of the average air temperature and incident global radiation. Equation (1) and (2) describes the proposed model equation for SFM, based on PVGIS power estimation information [16].

$$\frac{P}{P_k}(G', T'_m) = G' + k_1 G' \ln(G') + k_2 G' \ln(G')^2 + k_3 G' T'_m + k_4 G' T'_m \ln(G') + k_5 G' T'_m \ln(G')^2 + k_6 G' T'^2_m \quad (1)$$

$$T'_m = T_a + K_T g - 25 \quad (2)$$

Where, $G'(= G/1000)$ is the total incident global radiation for the year in kWh/m^2, $T'_m(= T_m - 25)$ is the differential module temperature in ^{0}C, and g is the average incident global radiation per hour in kWh/m^2. TABLE IIgives the range of value of input and output parameters of SFM. The ranges of annual-incident-global-radiation are equal for both the mounting option, however, different for both the tracking methods.

After studying thefitting response of the developed SFM,as the temperature coefficient of the building-integrated mounting is higher compared to freestanding, the module gets heated more quickly. The increase in cell temperature in the building-integrated structure accumulates furthertemperature losses that reduce the production. The production of the freestanding structure is higher (indicated by comparing blue or higher color region in both the graphs) than the building- integrated structure.

TABLE II. INPUT PARAMETERS FOR SFM AND PLANT OUTPUT

Input parameters range for SFM	Non-Tracking PV system		Tracking PV system	
	Free standing	*Building Integrated*	*Free standing*	*Building Integrated*
Annual Incident Global radiation (kWh/m^2)	1820-2180		2140-2850	
Differential module temperature (^{0}C)	22.44-33.93	33.69-47.41	27.06-43.59	40.28-61.21
Temperature Coefficient (^{0}C/ (W/m^2))	0.035	0.05	0.035	0.05
Plant production kWh	1220-1550		1400-2030	

Fitting of the non-tracking model uses Least Absolute Residuals (LAR) with Trust-Region[17], a type of robust least squares method. The Robust least squares method used for the fitting of the Two-axis tracking model is Bisquare method with Levenberg-Marquardtalgorithm[18].TABLE IIIgives the fitted model coefficients presented for four types of model. These six coefficients can be used in the SFM equation to estimate the predictive response of the model. The RMSE value is around 1.2 kWh for non-tracking and 7.1 kWh for tracking model. The R^2 parameter is around 0.99 for all the system that indicates a very close to the response parameter estimated in PVGIS method. The closeness of the predictive response of the non-tracking model is better than tracking model.

Fitting parameters	Non-Tracking PV system		Tracking PV system	
	Free standing	Building Integrated	Free standing	Building Integrated
K_1	-1.784	-2.989	-2.828	-3.879
K_2	0.2405	0.4067	0.3759	0.5192
K_3	2.452	2.564	2.482	2.322
K_4	-0.5927	-0.6123	-0.5689	-0.5311
K_5	0.03481	0.03526	0.03111	0.02884
K_6	0.0007039	0.0006302	0.00089	0.00065
RMSE	1.179	1.242	6.977	7.257
R^2	0.9989	0.9987	0.9918	0.9902

TABLE III. RESULTS OF FITTING OF DATA FOR SFM

D. *Further Simplified Model (FSFM)*

FMSM use only two inputs: annual incident global radiation and annual average air temperature by decreasing the dependents to three fitting parameters. Unlike the previous model,FSFM fromequation (3) uses the annual average air temperature value directly instead of modular differential temperature. TABLE IV gives the values for various input and output parameters.

$$\frac{P}{P_k}(G_a', T_a) = aG_a' + bT_a + c \qquad (3)$$

The 3D graphs provided inFig. 3 shows a comparison of the fitting response of the developedTwo-axis tracking FSFM for various tracking and mounting options. As the proposed model is a linear model, the decrease in PV production for the building-integrated mounting can be indicated by comparing the range of the Z-axis data of the plot. Here the change in the range of the productiondoes not affect the color pattern of the plot. Implementation of tracking raises the production of the PV significantly.

TABLE IV. RANGE OF INPUT VALUES FOR ANNUAL INCIDENT GLOBAL RADIATION AND PLANT PRODUCTION REMAINS SAME FOR BOTH THE MODEL

Annual Input parameters range	Non-Tracking PV system		Tracking PV system	
	Freestanding	Building Integrated	Freestanding	Building Integrated
Global radiation (kWh/m)	1820-2180		2140-2850	
Avg. Air temperature (^{0}C)	21.2-27.5			
Production (kWh)	1220-1550		1400-2030	

Fitting of the FSFM uses Bisquare method with Levenberg-Marquardt algorithm for both the development tracking and on-tracking model. The graphs show the results of the fitting for four kinds of the model. The number of the model coefficient for the FSFM is half of the SFM. The RMSE value is around 5.5 kWh for non-tracking and 7.7 kWh for tracking model. The R^2 parameter for the tracking model is around 0.99 and for the non-tracking model is 0.98. The closeness of the predictive response of the tracking model is better compared to the non-trackingmodel.

TABLE V. RESULTS OF FITTING DATA FOR FSFM

Fitting System parameter	Non-Tracking PV system		Tracking PV system	
	Freestanding	Building Integrated	Freestanding	Building Integrated
a	0.7015	0.6655	0.7433	0.7049
b	-4.269	-3.664	-5.031	-4.503
c	129.3	103.4	34.06	-8.927
RMSE	5.519	5.413	7.612	7.774
R^2	0.9768	0.9756	0.9902	0.9887

III. ANALYSIS AND COMPARISION OF DEVELOPED METHOD

To understand the preciseness of both the model the comparison of results of both the models for tracking options and mounting options simultaneously is necessary. Initially, the input parameters of both the models are equal before proceeding with the comparison. The annual average air temperature replaces the differential module temperature in the SFM by using theequation (2). The user can set two input parameters: *G* and T_a (for both the models) with various tracking and the mounting option to estimate theoutputs. Within the climatic condition of Odisha, the prediction of both the model within the radiation and temperature range is close to each other.**Error! Reference source not found.** and Fig. 3 show the comparison of the generated output for a non- tracking and Two-axis tracking PV system on variation in radiationrespectively. By keeping the ambient temperature constant at 25^{0}C,both the models predict the PV production. The model equation for both the models becomes in theequation (4) and (5).

$$\frac{p}{p_k} = G_1'^{3} \left(k_1 \ln(G_1') + k_2 \ln(G_1')^2 + k_3\right) | k_{13} = k_{23} = 0 \text{ (SFM)} \qquad (4)$$

$$\frac{p}{p_k} = a G_1' + b_1 \text{ (FSFM)} \qquad (5)$$

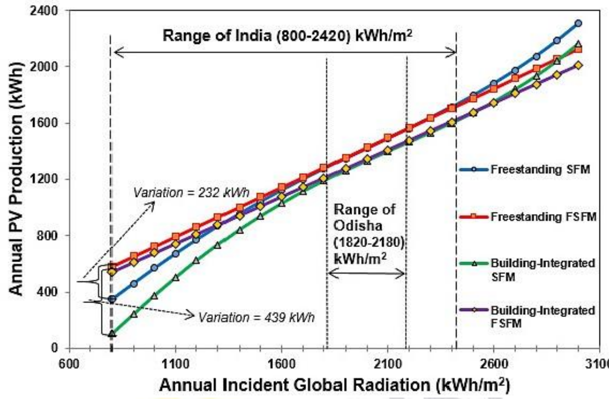

Fig. 3. Output for a Non-tracking PV system on variation in radiation

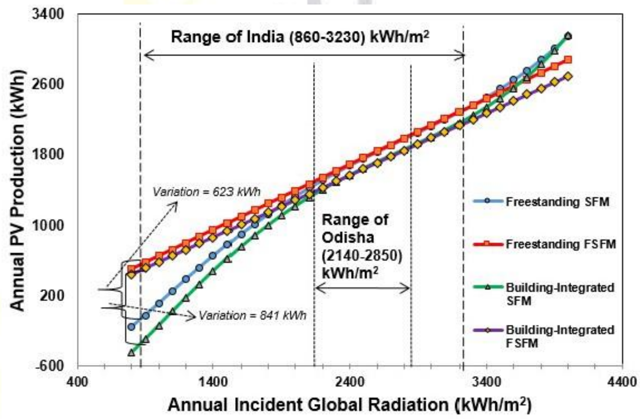

Fig. 4.Output for a Two-axis tracking PV system on variation in radiation

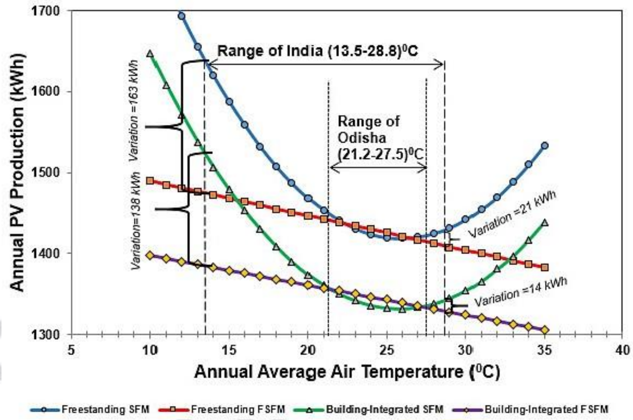

Fig. 5.Output for a Non-tracking PV system on variation (radiation constant at 2000 kWh/m^2)

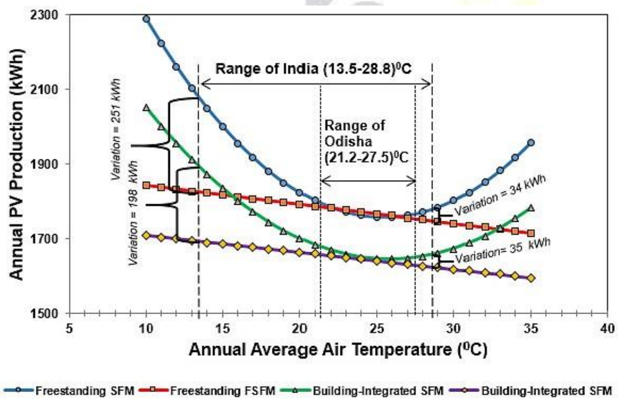

Fig. 6.Output for a Two-axis tracking PV system on variation, radiation constant at 2500 kWh/m^2

The estimated PV production is linear for a change in radiation while the temperature remains constant. Outside the region of Odisha, the difference between the predictions gradually increases. In the lower radiation boundary of India,a distinction between the prediction for the non-tracking and tracking setting of both the models are 232 kWh, 623 kWh (Free-standing) respectively and 439 kWh, 841 kWh (Building-Integrated) respectively. The difference in prediction for the building-Integrated system is more than the freestanding one. In the lower bounds of radiation, the sensitivity of the building-integrated system increases. As the prediction value for SFM becomes negative in the lower regions (refer Fig. 3), it justifies the inaccuracy of the SFM to be more beyond the operating area of Odisha.

Similarly,Fig. 4 and Fig. 5 show the comparison of the generated output for a non-tracking and two-axis tracking PV system on variation in ambient temperature in respectively.The radiation is kept constant at 2000 kWh/m^2 and 2500 kWh/m^2 for non-tracking and two-axis tracking model respectively as shown in Fig. 5 and Fig. 6. The respective mode equation is given byequation (6) and(7).

$$\frac{p}{p_k} = k_x T_a^2 + k_y T_a + k_z (\mathrm{SFM}) \qquad (6)$$

$$\frac{p}{p_k} = a_2 T_a + b_2 (\mathrm{FSFM}) \qquad (7)$$

Within the climatic condition of Odisha, the error in prediction of both the model reduces, whereas, outside the region of Odisha, the error between the predictions gradually increases. In the lower radiation boundary of India,a distinction between the prediction for the non-tracking and tracking setting of both the models are 163 kWh, 251 kWh (Free-standing) respectively and 138 kWh, 198 kWh (Building-Integrated) respectively. In those conditions, the error in prediction for the building-Integrated system is less than the freestanding one. Again, the error in prediction becomes more in the case of variation in the radiation rather than the variation in temperature. By refitting of the model with newly collected data, the accuracy of the response of the model extends to theoutside of the region of Odisha.

IV. CONCLUSION

In the study, SFM model is developed to take three input parameters and predict the output production of the plant if established in Odisha. FSFMis further simplification of the SFM, which takes only two input parameters to predict the output production.

Both models consider different predictive response for various combinations of the tracking and mounting options. The prediction of both the models does not depend on the other influencing parameters that affect the performance of PV systems. In SFM and FSFM, the differencein RMSE value for Non-Tracking and Tracking PV system is found to be 4.3 and 0.64 and that of R^2 is found to be 0.2 and 0.0016 in freestanding position respectively. Both the models show the fair value of the fitting parameter R^2 with RMSE value.The implementation of the proposed model is simple, and the user can build own model to estimate the PV output for any location desired.The preciseness in the response for studied model is within Odisha; however, it extends to any region under consideration with proper corrections. To do so, refitting of the model to estimate model coefficients with newly collected data from the areaunderconsideration.

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