

Forecasting photovoltaic power generation using the temperature-based model (A case study at Vuwani Science Resource Centre)

L. MASEVHE^a, N.E. MALUTA^{a,b}

^aDepartment of Physics, University of Venda, P/ Bag X 5050, Thohoyandou, 0950

^bNational Institute for Theoretical Physics (NITheP), Gauteng, South Africa

livhuw1m@gmail.com



University of Venda

INTRODUCTION

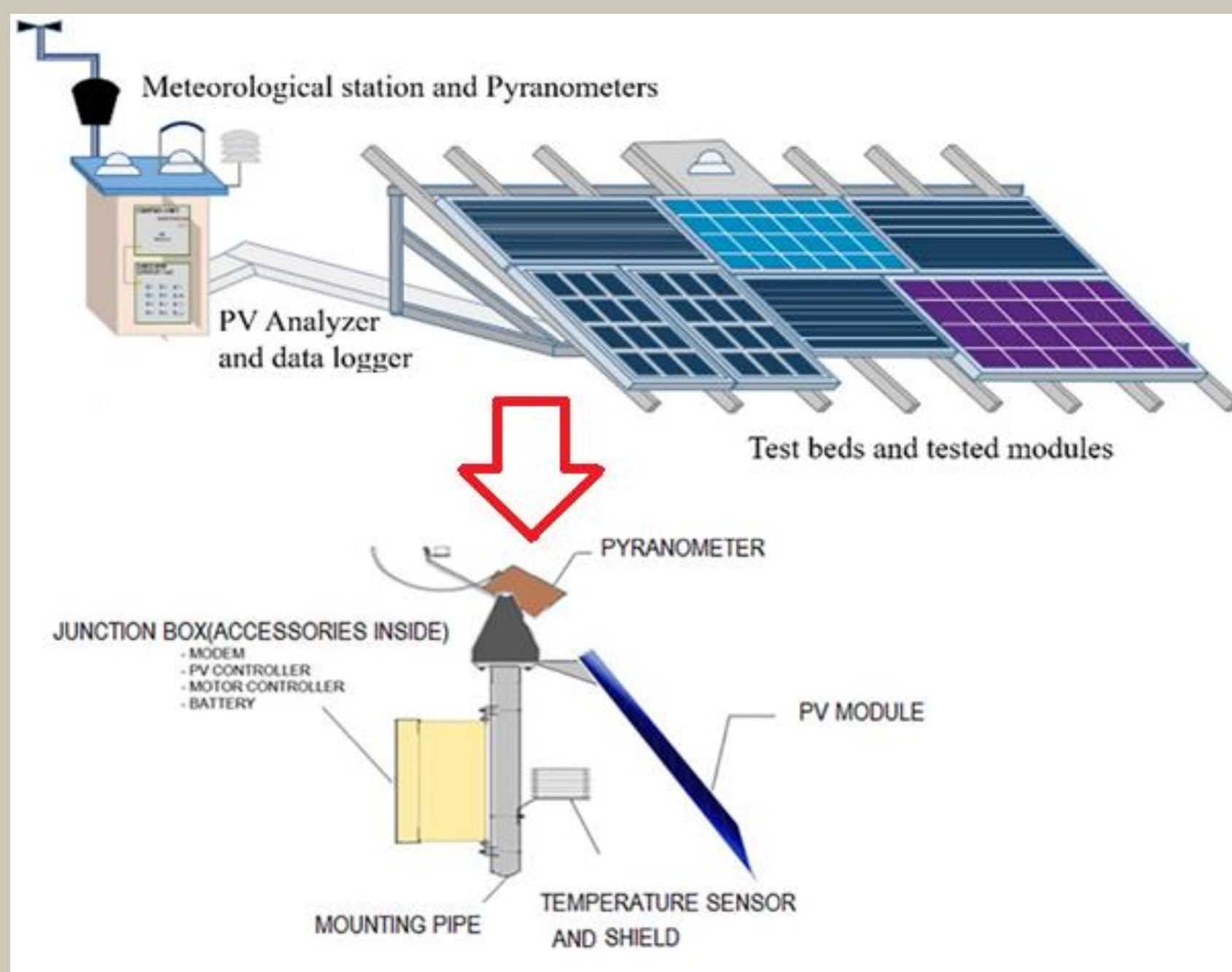


Figure 1: Meteorological station with pyranometer to measure solar radiation for PV generation [1].

The accurate estimation of photovoltaic (PV) power output based on the weather information of the local area intended for the installation of PV system is crucial in many applications. PV converts the light into electricity using semiconducting materials that exhibit the photovoltaic effect [2]. The mathematical techniques to estimate global solar radiation (H_c) was used in this study to determine the potential power output (P_{PV}). Hargreaves-Samani ($H-S$) model (a temperature-based empirical model) was selected, taking the advantage of using available temperature data in areas where there is no weather stations and data [3]. The model is used to estimate the global solar radiation data which is then compared to the 2019 measured values collected from the South African Universities Radiometric Network (SAURAN) station at Vuwani Science Resource Centre, Thohoyandou.

The estimated H_c was used as input to the PV power output mathematical models to predict the power output of the 255 W solar panel that has been installed on site. The selected models for this study are Skoplaki ($P_{PV,model 1}$) and Rami ($P_{PV,model 2}$). The performances of the models were tested for the panel under standard testing conditions (STC) and outdoor weather conditions. The work presented in this paper lays a foundation for short to long term forecast of PV power output and the sizing of the system in the design phase which is adaptable to any location with limited weather data information as well as to determine the suitable panels for the site.

255 W PV PANEL



Figure 2: EnerSol255W PV poly-crystalline panels at VSRC.

Figure 2 shows a 255 W polycrystalline solar panel whose performance was assessed in this study under the weather conditions at Vuwani. The data set of the panel and its characteristics are shown in Table 1. The advantage of this PV technology is that it reduces the series resistance between cells due to back-to-back cell interconnectors. The panel key specifications are given in Table 1.

Table 1: Electric dataset of EnerSol255 PV characteristics.

P_{max} (W)	V_{oc} (V)	I_{sc} (A)	V_{mp} (V)	I_{mp} (A)	μ_{oc} (A/°C)	μ_{sc} (A/°C)
255	38.62	8.77	31.21	8.17	-0.11	0.04

METHODOLOGY

FLOW CHART PLAN:

Figure 3 represents the site assessment plan which was followed for the solar power output forecasting based on weather conditions on site.

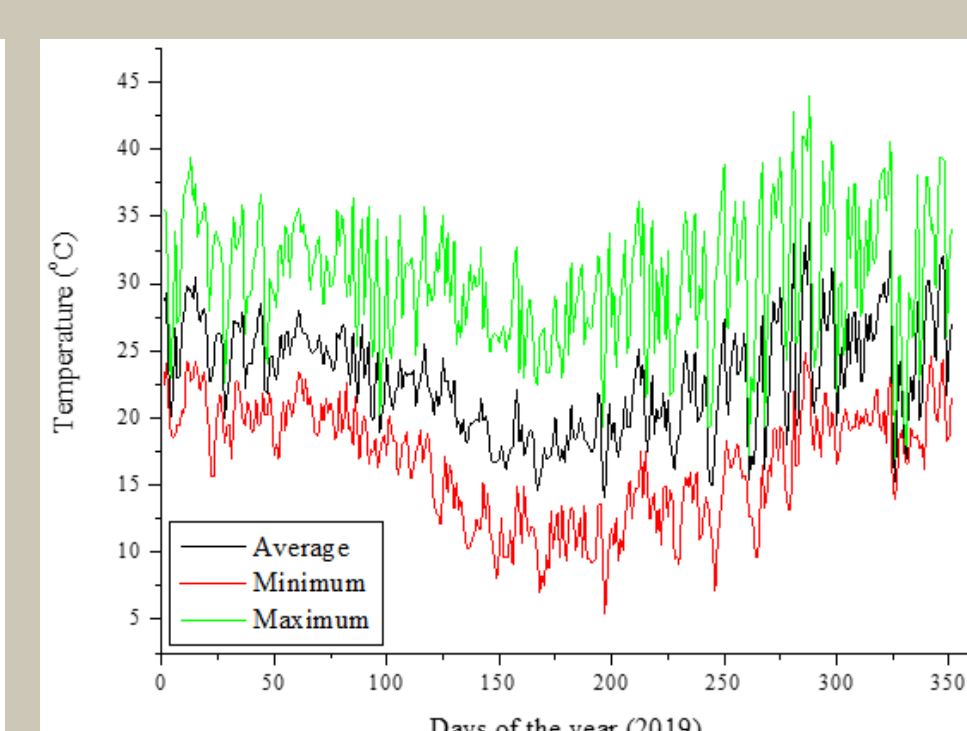
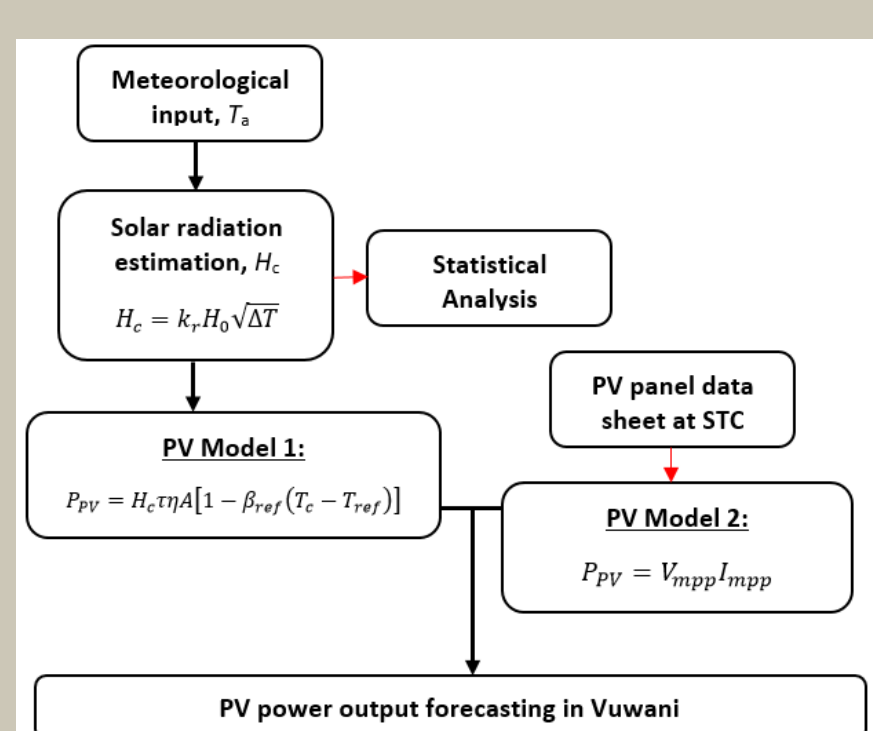


Figure 3: The flowchart presenting the inter-disciplinary model of the assessment. The average monthly temperature data measured at Vuwani's SAURAN station in 2019 in Figure 4 was used as input in Equation 1 to calculate H_c . Calculated H_c was used to forecast PV power output using a 255 W solar panel in Figure 2 installed at Vuwani.

TEMPERATURE-BASED SOLAR RADIATION ESTIMATION (Hargreaves-Samani Model):

The Hargreaves and Samani formulated a simple model to estimate H_c , which requires only maximum and minimum temperatures (T_{min} and T_{max}), the model is represented by Equation (1) [7]:

$$H_c = k_r H_0 \sqrt{\Delta T} \quad (1)$$

where k_r is an empirical constant equal to 0.16 for inland region [5]. The average daily extra-terrestrial irradiance H_0 ($W \cdot m^{-2}$) is estimated using Equation (2) [11]:

$$H_0 = \frac{1440}{\pi} H_{sc} D_f (\cos \varphi \cos \delta \sin \omega_s + \omega_s \sin \varphi \sin \delta)$$

$$D_f = 1 + 0.033 \cos \left[2\pi + \frac{n}{365} \right]$$

$$\delta = \frac{23.45\pi}{180} \sin \left[2\pi \left(284 + \frac{n}{365} \right) \right]$$

$$\omega_s = \cos^{-1}(-\tan \varphi \tan \delta)$$

where H_{sc} is the solar constant ($1367 W \cdot m^{-2}$), φ is latitude (deg), δ is the solar declination for the month (deg), and ω_s is the mean sun-rise hour angle for a given month (deg). D_f is eccentricity correction factor of the earth's orbit on day n of the year (Julian days from 1 January to 31 December) [8].

SOLAR FORECASTING:

The physical model of PV power forecasting is the most common one and is based on the data measurement from both PV systems and weather stations [14]. The PV power produced by solar PV panels can be predicted by using mathematical equations [15]. The following two PV power output models have been used in this study:

PV Generation model 1 [10]:

$$P_{PV,model 1} = H_c \tau \eta A [1 - \beta_{ref} (T_c - T_{ref})] \quad (2)$$

where $T_c = T_a \left[\frac{NOCT-20}{80} \right] H_T$, $A: 0.16 m^2$, $\tau: 0.16$, $\beta_{ref}: 0.0045 \% / ^\circ C$, $T_{ref}: 25^\circ C$, $H_T: 1000 W \cdot m^{-2}$

PV Generation model 2 [12]:

$$P_{PV,model 2} = V_{mpp} I_{mpp} \quad (3)$$

$$V_{mpp}: V_{mpp,ref} + \mu_{voc} (T_c - T_{ref}),$$

$$I_{mpp}: I_{mpp,ref} + I_{sc,ref} \left(\frac{H_c}{H_T} \right) + \mu_{isc} (T_c - T_{ref})$$

STATISTICAL ANALYSIS:

The estimated solar radiation values using H-S model were compared with the observed values [13]. The coefficient of determination R^2 , root mean square error (RMSE), mean bias error (MBE) and mean percentage error (MPE) in Equations (4) – (7) were used to analyse the accuracy of the estimated values obtained [16].

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (H_{c,i} - H_{m,i})^2}{n}} \quad (4)$$

$$MBE = \frac{1}{n} \sum_{i=1}^n (H_{c,i} - H_{m,i}) \quad (5)$$

$$MPE = \frac{1}{n} \sum_{i=1}^n \frac{|H_{c,i} - H_{m,i}|}{H_{m,i}} \times 100 \quad (6)$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (7)$$

In the above relations, the subscript i refers to the i th value of the solar irradiation and n is the number of the solar irradiation data values. The subscripts "c" and "m" refer to the calculated and measured global solar irradiation values, respectively.

RESULTS AND DISCUSSION

ESTIMATED GLOBAL SOLAR RADIATION:

The performance of a widely used empirical model (Table 2) for estimating daily H_c at SAURAN Vuwani stations was evaluated.

Table 2: Observed and estimated solar radiation for Vuwani in 2019.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
H_o (W/m^2)	248	247	218	170	184	160	185	187	224	213	240	260
H_c (W/m^2)	264	245	221	185	185	162	179	195	236	264	263	262

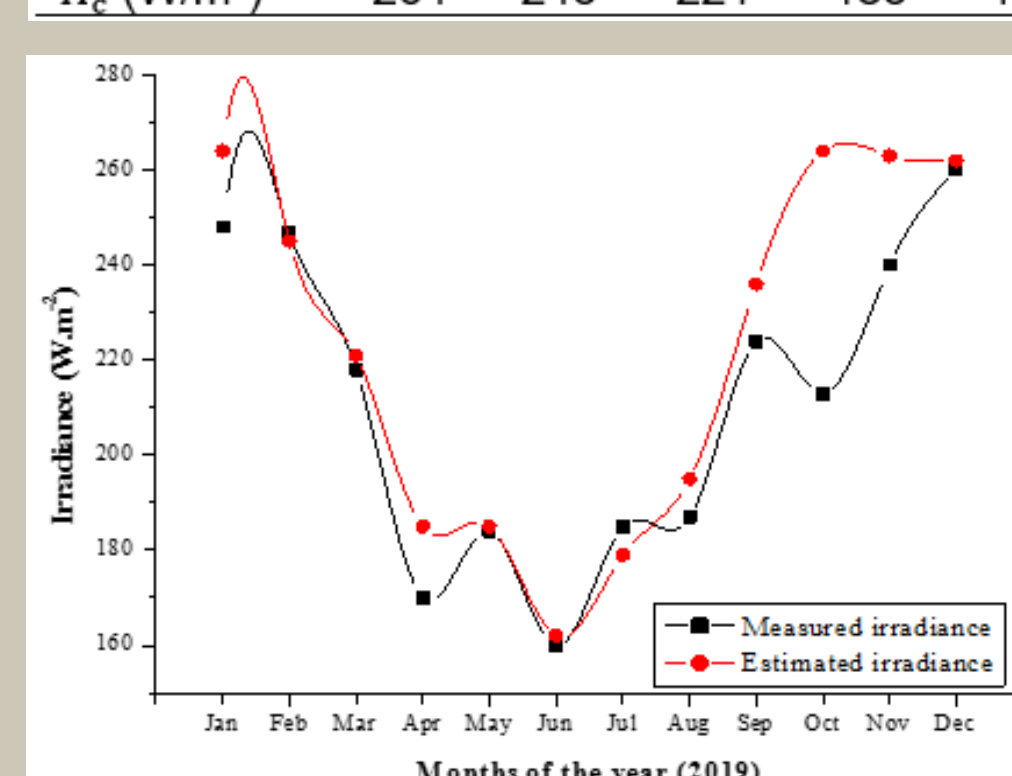


Figure 5: Estimated and observed inter-monthly global solar radiation.

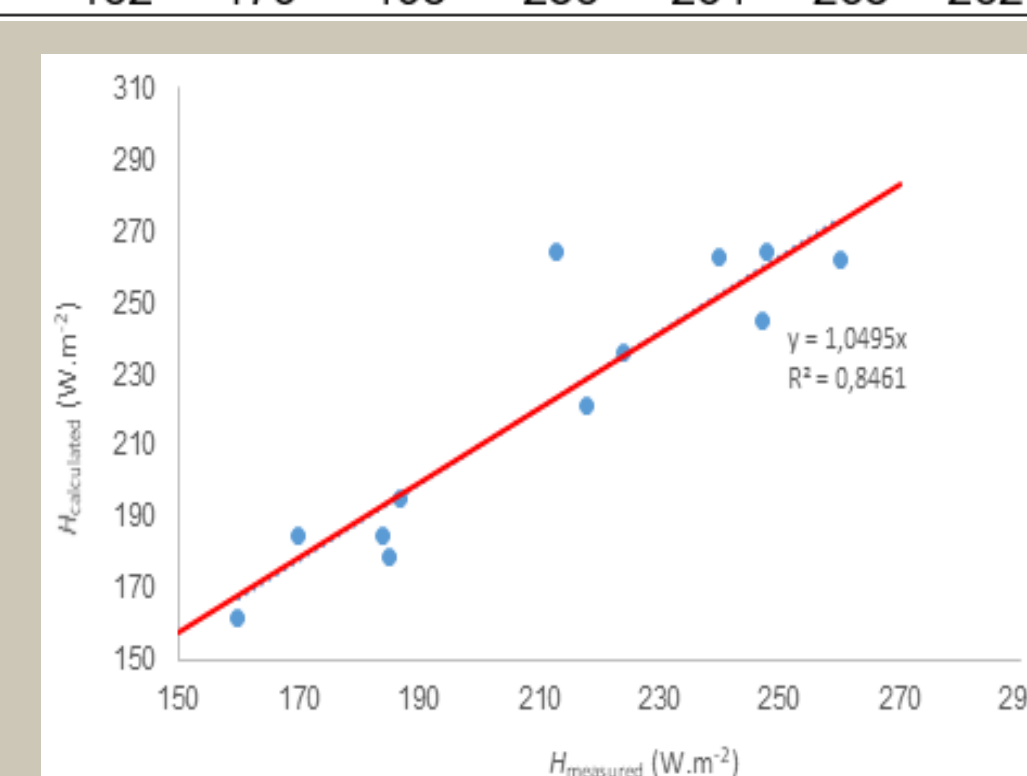


Figure 6: Correlation between the measured and calculated solar radiation.

The annual measured and estimated average solar radiation at Vuwani SAURAN in 2019 of 211 and 222 $W \cdot m^{-2}$, respectively, are very close. Results show good correlation H_c with $RMSE: 1.84$, $MAE: 1.39$, $MBE: 1.29$ and $R^2: 0.84$, which agreed with other researchers [14]: $MBE \leq MAE \leq RMSE$. Therefore, the high performance of H-S model is reliable for the potential solar power output assessment [9].

PERFORMANCES OF FORECASTING MODELS:

Table 3 shows that PV model 2 performed much better than that of PV model 1 with regard to maximum power output provided in the datasheet of the reference PV panel of 255 W at STC.

Table 3: Performance of two PV generation models.

	PV panel	$P_{PV,model 1}$	$P_{PV,model 2}$
P_{PV} (W)	255	177	231
Deviation (%)	0	30	9

FORECASTING PV POWER OUTPUT:

The values of P_{PV} calculated using the power output models are shown in Table 4 and Figure 7. PV model 2 estimated just about 10 % more than that of PV model 1. Results show the lowest and highest forecasted PV power that can be generated by the reference solar panel to be 38 and 60 W ($P_{PV,model 1}$), and 42 and 67 W ($P_{PV,model 2}$) in June and January, respectively. Therefore, a system should be designed to meet the available demand even in June with the lowest potential generated power. Figure 8 shows a strong correlation between the two power output models which indicates some high level of confidence in the two-step process followed in the current study to predict the solar power output in areas with limited weather data.

Table 4: Inter-monthly P_{PV} power output values estimated by the two models.

Models (W)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
$P_{PV,model 1}$	60	56	50	43	43	38	42	45	55	60	60	59
$P_{PV,model 2}$	67	62	57	48	48	42	46	50	60	67	67	67

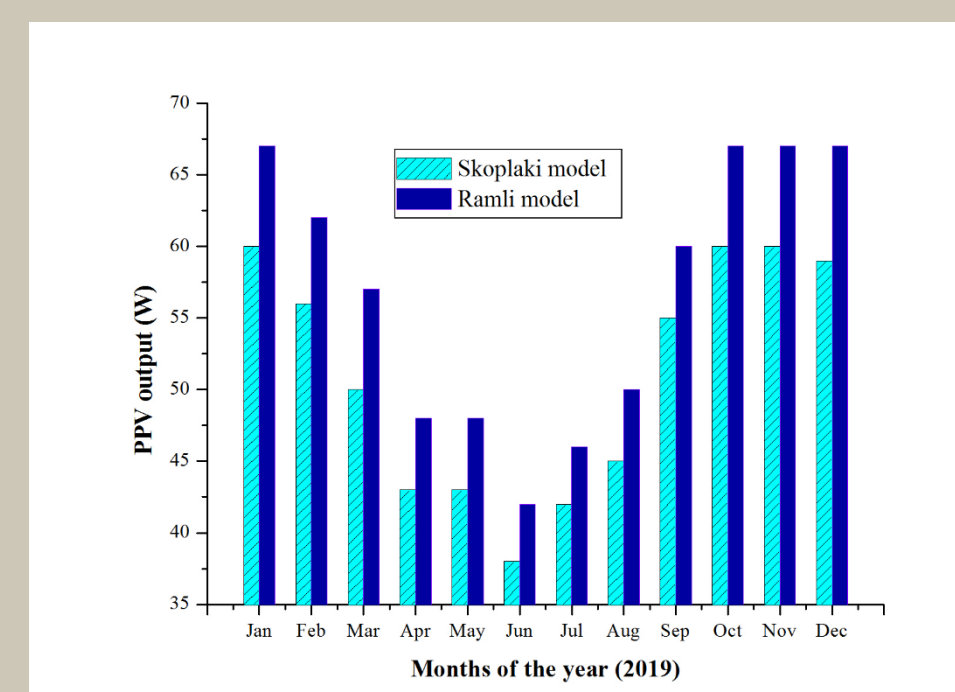


Figure 5: Estimated and observed inter monthly global solar radiation.

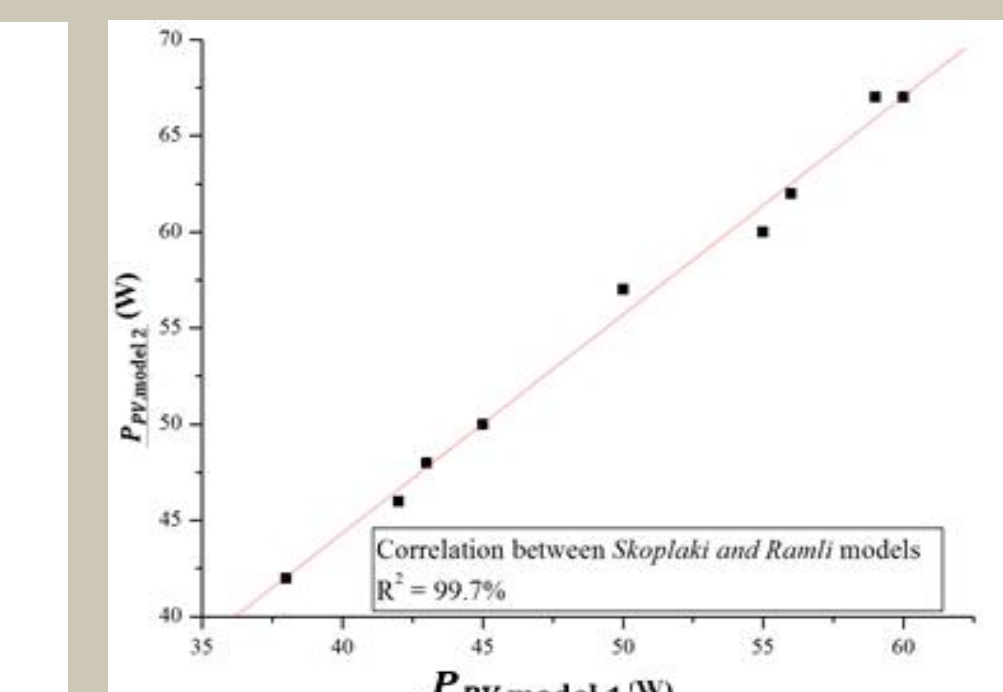


Figure 6: Correlation between the measured and calculated solar radiation.

CONCLUSION

The performance of H-S model for estimating H_c has been compared with observed data in Vuwani. Results suggest that the empirical model provides acceptable H_c estimation at any location. Accurate estimation of H_c is important for various applications including PV power forecasting during the design and sizing of power generation system. This work aimed at examining the capability of empirical models in forecasting PV power output in areas with no other weather data, but temperatures only. The average measured H_m , 211 $W \cdot m^{-2}$; ranging from 160 to 260 $W \cdot m^{-2}$ while empirical model gave an average H_c : 221 $W \cdot m^{-2}$ with values ranging from 162 to 264 $W \cdot m^{-2}$.

The two PV power models ($P_{PV,model 1}$ and $P_{PV,model 2}$) predicted average annual power outputs, respectively as follows: 51 and 57 W, hence about 22 % of the maximum power output of the panel at STC. This performance was found to be consistent with the local solar radiation that has been observed in Vuwani, which was about 21 % of the reference solar radiation of 1000 $W \cdot m^{-2}$. Vuwani has a 5 kW solar plant consisting of 20, 255 W PV panels. On the two models predicted an annual average power output of 1018 and 1135 W.

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