Ambient Factors Influencing Photovoltaic Module Temperature in Klang Valley

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***Abstract*—The study is conducted to evaluate the significance of solar irradiance, ambient temperature and relative humidity as predictors and to quantify the relative contribution of these ambient parameters as predictors for photovoltaic module temperature model. The module temperature model was developed from experimental data of mono-crystalline and poly-crystalline PV modules retrofitted on metal roof in Klang Valley. The model was developed and analyzed using Multiple Linear Regressions (MLR) and Principle Component Analysis (PCA) Techniques. Solar irradiance, ambient temperature and relative humidity have been proven to be the significant predictors for module temperature. For poly-crystalline PV module, the relative contribution of solar irradiance, ambient temperature and relative humidity are 64.28 %, 17.45 % and 12.64 % respectively. For mono-crystalline PV module, the relative contribution of solar irradiance, ambient temperature and relative humidity are 66.12 %, 17.46 % and 12.48 % respectively. Thus, there is no significant difference in terms of relative contribution of these ambient parameters towards photovoltaic module temperature between poly-crystalline and mono-crystalline PV module technologies.**

***Index Terms*—PV module temperature; ambient parameters; relative contribution**

I. INTRODUCTION

Photovoltaic is a technology that generates electricity from solar energy. The output from this technology depends on many factors such as the condition of the surroundings. The condition of the surroundings is referring to the ambient parameters where the PV system is installed. The ambient parameters may involve solar irradiance (SI), ambient temperature (AT), wind speed (WS) and also relative humidity (RH). These parameters will give significant effect to the PV module temperature(MT), which is one of the most influential factors that determine the PV output (S. Dubey, 2013). The main ambient parameters that effect the PV output are SI and AT (Koka, 2011).

Typical Meteorological year (TMY) is a representative of climate database for one year duration. In developing TMY, weighting factor (WF) is a compulsory input. WF is referring to the relative contribution of the independent variables towards the dependent variables. In this study, the dependent variable is MT, while the independent variables are the SI, AT and RH. WS is not included in this study due sensor failure.

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Many studies have been conducted in determining WF of these ambient variables towards MT(G. TamizhMani, L. Ji, Y. Tang, & L. Petacci, 2003). However, limited studies have been conducted in Malaysia. The current installed PV capacity in Malaysia is approximately 20 MW in year 2014 including free-standing (FS), building integrated photovoltaic (BIPV) and retrofitted mounting configuration (S. Mekhilef, et al., 2012) . Rooftop is an ideal place for placing PV module. Due to that, retrofitted mounting configuration is the most chosen mounting configuration in Malaysia and will be investigated in this study.

Thus, this study will evaluate the significance of SI, AT and RH as independent variables and determine the relative contribution of these independent variables towards MT model for retrofitted PV system in Malaysia.

II. METHODOLOGY

The study is conducted at the Green Energy Research Centre (GERC), UiTM Shah Alam, Selangor, Malaysia. Fig 1.0 show the setup of HOBO data logger and the two types of PV module investigated, which are monocrystalline and poly-crystalline. The PV modules are retrofitted on metal roof. The equipments and sensors involved are data logger, solar radiation sensor, temperature sensor and RH sensor. The data were collected started from 25th May 2016 until 8th June 2016 for every one minute. The amount of data collected was 9450.

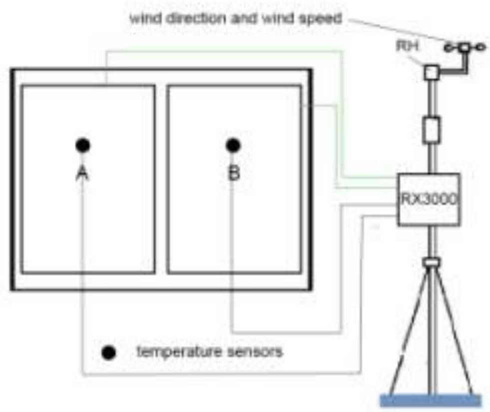

Fig. 1. Set up of Data Logger, polycrystalline PV module and monocrystalline PV module.

The data was analysed using mathematical and statistical techniques. The fundamental mathematical model for MT applied in this study is Multiple Linear Regression (MLR) model. Hence, the statistical technique used is Principle Component Regression (PCR). PCR is used to filter data by using orthogonal transformation. It is a technique that is sensitive to outliers, missing data and poor linear correlation between variables (Nasir, et al., 2011).

III. RESULT AND DISCUSSION

The data obtained from the experiment was analyzed using SPSS software. The analysis was conducted using PCR mechanism. MT is the dependent variable, meanwhile the independent variables are SI, AT and RH. Table 1, shows the number of data (N), maximum value, minimum value, data range, mean value and standard deviation for the dependent and independent variables. The number of data is 9450. The minimum and maximum values of SI were 41 W/m^2 and 1056 W/m^2 respectively. The minimum and maximum values of AT were 25.38^{o}C and 36.34^{o}C respectively. The minimum and maximum values of RH were 45.3% and 93.7% respectively. Comparing for both poly-crystalline and mono-crystalline, the minimum and maximum temperature of MT showed not much difference between them. The mean for AT, RH, SI, MT (poly) and MT (mono) were 31.79, 65.6 %, 340 W/m^2, 38.9 and 38.6 respectively.

Table 1 Basic Descriptive Statistic for the Variables Investigated (AT, RH, SI and MT).

	N	Max	Min	Range	Mean	Std. Deviation
AT	9450	36.34	25.38	10.96	31.79	2.22
RH	9450	93.7	45.3	48.4	65.6	10.16
SI (W/m^2)	9450	1056	41	1015	340	258.52
MT_poly	9450	55.4	25.4	30.0	38.9	6.73
MT_mono	9450	55.3	25.5	29.8	38.6	6.43

Module temperature model has been developed using PCA and MLR method. Table 2, shows the total variance explained by PC1, PC2 and PC3. PC1 and PC2 contribute the largest eigenvalues that are 2.334 and 0.610 respectively. However, PC3 gives the lowest eigenvalue of 0.056. This indicates the presence of multicollinearity problem in PC3. Thus, PC3 is removed from the analysis as the function of PCA is to eliminate the multicollinearity problem (Ieong, Lou, Ung, & Mok, 2015). MLR is applied to PC1 and PC2. The percentage of variance for PC1, PC2 and PC3 are 77.805%, 20.337% and 1.859% respectively.

The values of coefficient were determined in the Table 3. This table indicates the component score coefficient matrix for PC1 and PC2. In MLR method, the score values were used as independent variables. The score coefficient value is important to determine the most significance PCs for MT prediction.

Table 2 Total Variance Explained By Each PC (PC1, PC2, and PC3)

Total Variance Explained

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
PC1	2.334	77.805	77.805
PC2	0.610	20.337	98.141
PC3	0.056	1.859	100.000

Table 3 Component Score Coefficient Matrix

	Component	
	PC1	PC2
AT	0.411	-0.373
RH	-0.403	0.489
SI	0.312	1.123

From the Component Score Coefficient Matrix, PC1 and PC2 are expressed by:

(1.1)

(1.2)

Table 4 shows the results and regression analysis for poly-crystalline, while Table 5 shows the results and regression analysis for mono-crystalline. From the standardized coefficient, for poly-crystalline, it shows that PC1 and PC2 gives positive impacts of 0.754 and 0.363 respectively. Furthermore, the standardized coefficient for mono-crystalline also shows positive impact of PC1 and PC2 with 0.766 and 0.376 respectively.

Table 4 Regression Analysis for Poly-crystalline

Model		Unstandardized Coefficients		Std. Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
2	(Constant)	38.853	0.038		1024.673	0.000	38.778	38.927
	PC1	5.071	0.038	0.754	133.722	0.000	4.996	5.145
	PC2	2.445	0.038	0.363	64.467	0.000	2.370	2.519

Table 5 Regression Analysis for Mono-crystalline

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Std. Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
2	Constant	38.640	0.035		1119.951	0.000	38.572	38.707
	PC1	4.919	0.035	0.766	142.575	0.000	4.852	4.987
	PC2	2.419	0.035	0.376	70.104	0.000	2.351	2.486

From the Table 4 and Table 5, PC1 and PC2 for both poly-crystalline and mono-crystalline give the zero significant values. Thus, each independent variable in PC1 and PC2 is significant. This has proved that SI, AT and RH are significant predictors for MT.

For poly-crystalline, the relative contribution of SI, AT and RH were 0.6428, 0.1745 and 0.1264 respectively. While for mono-crystalline, the relative contribution of SI, AT and RH were 0.6612, 0.1746 and 0.1248 respectively. The PCR model for polycrystalline PV module is express by:

$$MT = 0.1745AT - 0.1264RH + 0.6428SI \quad (1.3)$$

On the other hand, PCR model for mono-crystalline PV module is express by:

$$MT = 0.1746AT - 0.1248RH + 0.6612SI \quad (1.4)$$

Table 6 and Table 7 show the standardized coefficient in determining the relative contribution of ambient parameters toward MT. The results show that there is not much difference in terms of relative contribution between poly-crystalline and mono-crystalline for retrofitted PV module technology. In comparison with the previous study (H. Zainuddin, 2014), the relative contribution for mono-crystalline for free standing PV system are 53.8% for SI, 37.2% for AT, 4.9% for RH, and 4.1% for WS. The total relative contribution of two main contributors of SI and AT towards MT is 82% for poly-crystalline technology. While for mono-crystalline, the total relative contribution is 84%. The differences of the total contribution relative contribution for SI and AT between free standing and retrofitted PV system is 7%. This shows that the total relative contribution of SI and AT for free standing is much higher than the retrofitted PV system which is 91%. This also suggesting that free standing PV mounting configuration is more affected by SI and AT, but retrofitted PV mounting configuration has other factors that affect its beside SI and AT.

Table 6 The Unstandardized and Standardized Regression Coefficient of the Original Variables for Poly-crystalline

Variables	Unstandardized	Standardized
AT	0.528	0.1745
RH	-0.0835	-0.1264
SI	0.0167	0.6428
CONSTANT	38.85	

Table 7 The Unstandardized and Standardized Regression Coefficient of the Original Variables for Mono-crystalline

Variables	Unstandardized	Standardized
AT	0.5378	0.1746
RH	-0.0787	-0.1248
SI	0.0164	0.6612
CONSTANT	38.640	

IV. CONCLUSION

In conclusion, SI, AT, and RH are proven to be the significant predictors for MT. The relative contribution of SI, AT and RH towards MT are quantified. For poly-crystalline, the relative contributions of SI, AT and RH are 64.28%, 17.45% and 12.64% respectively. For monocrystalline, the relative contributions of SI, AT and RH are 66.12%, 17.46% and 12.48 % respectively. Thus, there is not much different in terms of relative contribution between mono-crystalline and poly-crystalline PV modules technologies.

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REFERENCES

[1] G. TamizhMani, L. Ji, Y. Tang, & L. Petacci. (2003). *Photovoltaic module thermal-wind performance: Long term monitoring and model development for energy rating* (No. NREL/CD-520-33586): National Renewable Energy Laboratory.

[2] H. Zainuddin. (2014). Module Temperature Modelling for Free-Standing Photovoltaic System in Equatorial Climate. Universiti Teknologi MARA, Shah Alam, Malaysia.

[3] Ieong, I. I., Lou, I., Ung, W. K., & Mok, K. M. (2015). Using principle component regression, artificial neural network, and hybrid models for predicting phytoplankton abundance in Macau storage reservoir. *Environmental Modeling & Assessment, 20*(4), 355-365.

[4] Koka, K. (2011). Photovoltaic Module Performance and Thermal Characterizations: Data collection and Automation of Data Processing. Arizona State University.

[5] Nasir, M. F. M., Samsudin, M. S., Mohamad, I., Awaluddin, M. R. A., Mansor, M. A., Juahir, H., et al. (2011). River water quality modeling using combined principle component analysis (PCA) and multiple linear regressions (MLR): a case study at Klang River, Malaysia. *World Applied Sciences Journal, 14*, 73-82.

[6] S. Dubey, J. N. S., B. Seshadri. (2013). Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world - A review. Paper presented at the Energy Procedia.

[7] S. Mekhilef, A. Safari, W. E. S. Mustaffa, R. Saidur, R. Omar, & M. A. A. Younis. (2012). Solar energy in Malaysia: Current state and prospects. *Renewable and Sustainable Energy Reviews, 16*(1),