



Analysis of Effects of Solar Irradiance, Cell Temperature and Wind Speed on Photovoltaic Systems Performance

Adnan Al-Bashir^{1,2*}, Mohammad Al-Dweri³, Ahmed Al-Ghandoor^{1,2}, Bashar Hammad⁴, Wael Al-Kouz⁴

¹Industrial Engineering, Abu Dhabi University, Abu Dhabi – UAE, ²Department of Industrial Engineering, the Hashemite University, Zarqa, Jordan, ³Department of Mechanical Engineering, the Hashemite University, Zarqa, Jordan, ⁴Department of Mechatronics Engineering, German-Jordanian University, Amman, Jordan. *Email: adnan.bashir@adu.ac.ae

Received: 19 August 2019

Accepted: 05 October 2019

DOI: <https://doi.org/10.32479/ijeeep.8591>

ABSTRACT

This paper proposes an analytical model to investigate the effects of solar irradiance, cell temperature and wind speed on performance of a photovoltaic system built at the Hashemite University, Jordan. The system is off-grid connected with the azimuth and tilt angles are being changed periodically and manually. The model has been developed employing Multivariate Linear Regression to estimate generated power based on experimental data. The methodology of building the model is demonstrated and validated for its accuracy using analysis of variance. The model indicated that a linear relationship among predicting parameters and generated power is valid agreeing with many other reported studies. In addition, the model emphasizes the independency of these predicted parameters; the model indicates that there is no correlation between the predictors themselves. The effect of each predicted parameter also found in agreement with the well-known relationship between each parameter and predicted power through algebraic signs. It is found that the model predicts generated power with R^2 values of 96.5% with the solar irradiance being the most effective parameter. Due to the low wind speed for the geographical location where the experiment carried out, its effect according to the model is not significant.

Keywords: Photovoltaic Systems, Irradiance, Cell Temperature, Wind Speed, Multivariate Linear Regression, Modeling, Simulation

JEL Classifications: C1, C3, C6, O3

1. INTRODUCTION

Solar Energy Systems, especially photovoltaic systems, became one of the main electricity providers in the last decade (Pillai, 2015). However, climatic, environmental and operative conditions, as well as geographical locations, play a crucial factor of energy yield for such systems. This fact triggered motivation for research of quantifying and modeling the output power/efficiency of those PV systems as a function of such conditions.

The energy generated from PV systems fluctuates depending on irradiance intensity. The solar irradiance changes the characteristics of the IV and PV curves. It increases the I_{sc} and the V_{oc} , in sequence the output generated power increases (Arjyadhara et al., 2013). However, the operating The dependency for the module

temperature is reversely proportional (Ye et al., 2013). Both the electrical efficiency and power output of a PV module depend linearly on the operating temperature; they decrease as it increases (Dubey et al., 2013). The output voltage is highly dependent on the temperature. It is found that, as the cell temperature increases, the I_{sc} increases slightly, the V_{oc} decreases and MPP decreases while the output power increases as the irradiance intensity increases (El-Khozondar et al., 2015). The amount of incident solar irradiance exposed on the array affects the energy generated. In the same time, the ambient temperature has a direct impact in reducing it while the energy generated is directly proportional to the irradiance intensity (Bhattacharya et al., 2014).

A study in Qatar stated that the performance of the PV system decreases when the temperature values increase higher than 40.4°C

(Touati et al., 2013). A case study was made in Tunisia to study the effect of both irradiance intensity and temperature. This study concluded that the PV efficiency increases with the irradiance intensity and decreases with operating temperature (Hamrouni et al., 2008). In Algeria, a study was made to examine the effect of the irradiance intensity and the temperature. The results stated that the conversion efficiency, and hence, output power, gradually decreases with cell temperature and directly proportional to the irradiance intensity (Bouزيد and Machich, 2010). Another case study that was made in Lithuania proved that the PV modules efficiency decreases due to the overheated situations (Pikutis et al., 2015). In Greece, it is found that a linear negative dependence exhibits the relation between the PV power and the temperature. However, the increase in the irradiance intensity leads to increase in the PV power (Panagea et al., 2014). In 2003 in Mexico City, a research was conducted to investigate the difference in PV conversion efficiency in urban and rural places. It was found that the conversion efficiency in the urban is higher because the temperature these areas is less than it would be found in the rural places (Tian et al., 2007). In Norway, a study was made to examine the effect of both the irradiance intensity and the temperature. It was found that the output power was reduced by 6 % when the irradiance decreased by 2 % and the performance of the PV decreased when the temperature increased (Fidje et al., 2006).

Wind speed plays an important role to improve the performance of the PV by cooling PV surfaces, this happened by decreasing the parallel resistance in the PV circuit model (Schwingshackl et al., 2013; Kaplani and Kaplanis, 2014). The humidity reduces the PV output by reducing the received amount of solar irradiance. However, humidity and wind speed together play a significant role in cooling PV surfaces that increases the efficiency of PV in hot climate (Zainuddin et al., 2010). Theoretical and experimental investigations are carried out to study the effect of temperature on PV modules under various environmental conditions. In addition, a parametric study in terms of module inclination, wind velocity and direction is conducted. The experimental study utilized the hourly PV temperature data collected and environmental parameters monitored for 1 year. The f coefficient that relates PV temperature with global solar irradiance intensity and the ambient temperature is assessed by angle of PV inclination, angle of incidence of wind stream and the wind velocity. The f coefficient is evaluated theoretically and experimentally based on energy balance equation. Finally, values of coefficient resulted from the simulation model are in good agreement with the experimental results (Kaplani and Kaplanis, 2014).

A review of the current available PV performance models in terms of their accuracy and compliance with data sheet specifications and guarantees is presented (de la Parra et al., 2017). Accuracy is assessed through experimental work conducted on PV arrays of four different technologies. They distinguished the models by either physical or empirical models. Physical models are based on full I-V curve, while the empirical models are based on the maximum power point (MPP). Results show empirical models are the best scenario of modeling PV performance (de la Parra et al., 2017). A novel mathematical model was proposed to determine cell temperature and solar intensity depending on PV

module parameters and thermodynamic efficiency figures (Cuce et al., 2017). The model was based on a simple one-diode with series resistance and shunt conductance. In addition, the results of model were compared with experimental test, and a very good agreement is found. Modeling, comparing and analyzing the performance of multiple PV array configurations under various partial shading and faulty PV conditions were the goal of the research conducted by Dhimish et al. (Dhimish et al., 2017). Many indicators such as short circuit current and voltage at MPP were used to compare the results. The software package MATLAB/Simulink was used to perform simulation and analysis for each PV configuration. LabVIEW real time interface system to characterize the performance of dynamic behavior of PV systems was utilized in (Chouder et al., 2012). Their results show a good agreement between the measured and simulation results. A full analysis of the primary energy and economic evaluation of solar thermal and PV cooling systems used for air conditioning in an office building is conducted (Eicker et al., 2014). Three different climates were used for comparison purposes. Simulations to determine the optimum work parameters in each climate are proposed in order to reduce energy demands. Moreover, sensitivity analysis is presented.

A multi linear adaptive regression spline model that considers the weather forecasts as an input in order to predict power production of a PV plant 1 day in advance is used (Massidda and Marrocu, 2016). Results show that the power obtained by the model correlates very well with the measured data. A regression model to predict the power loss at different levels of irradiances was developed (Pulipaka et al., 2016). An optimization model for PV/fuel cell/battery energy system was developed by Ren et al. (Ren et al., 2016). The proposed model can determine the optimal running strategies along with the annual running cost or annual CO₂ emissions. In order to validate the model a numerical example is implemental and analyzed.

Inspecting the published work discussed above, it is concluded intuitively that the effect of irradiance, cell temperature and wind speed on PV systems depends on geographical location and environmental and meteorological conditions. Researchers around the world strive to better comprehension of the impact of these parameters on PV systems. Understanding the effect of these parameter is realized by designing robust and reliable theoretical models and/or conducting experiments. By building simple and accurate mathematical models based on actual performance conditions to predict behavior of PV systems, this work aims to add a significant contribution to the PV literature. In this work, we have experimentally collected PV system parameters during 625 hourly data sets under real conditions. Based on the performance parameters, a model is developed to predict the system's output behavior employing multivariate linear regressions (MLR) (Alghandoor et al., 2008). The model considered the solar irradiance, cell temperature and wind speed as the independent variables, and PV output power as the dependent variable.

The aforementioned introduction discussed the effect of solar irradiance, cell temperature and wind speed on PV systems performance, with a focus on modeling techniques. The

remaining of the paper is divided as follows: Section 2 describes the experimental set-up and data collection for an experimental study in Zarqa, Jordan. Section 3 presents the model developed in this paper. This is followed by results and discussion of these models in Section 4. Finally, a summary of major findings and conclusions about the importance of this research is reported in Section 5.

2. EXPERIMENTAL SETUP AND DATA COLLECTION

The system is installed at the Hashemite University (HU) in Zarqa, Jordan, at latitude of 32.1022° N, longitude of 36.1850° E and an altitude of 569 m. The system is off-grid connected, consisting of 5 modules of nominal power of 285 Wp (STP285-24/Vd) (Suntech) wired in series in one string as pictured in Figure 1. The azimuth and tilt angles of the system are changed periodically and manually using two actuators operated by two motors. The output power is absorbed completely by a rheostat. The system is monitored by a data acquisition system (Commission, 1998) for the period from the 4th of September 2016 to the 23rd of January 2017. The system outputs and climatic data are collected every minute, displayed in real-time, stored them and accessed by authorized persons. However, the data is manipulated on an hourly average base as shown later in the analysis section.

The acquired data and outputs are the following:

- Global incident irradiance: A pyranometer is fitted to the panels to measure the global irradiance incident directly on the PV system without any further calculations to consider azimuth and tilt angles.
- Cell temperature: A k-type thermocouple mounted at the bottom surface of a panel to measure cell temperatures.
- Wind speed: An anemometer installed in a location next to the PV system free of any obstacle is used to measure wind speed.
- Output DC voltage: A DC voltage transducer is used to measure the DC voltage of the PV string.
- Output DC current: A DC current transducer is used to measure the DC current flowing out of the PV string.

Figure 1: PV modules of nominal power of 285 Wp wired in series in one strings



A schematic diagram, shows the connection of PV system with a rheostat and measurement devices, is depicted in Figure 2. The output power is fed into a rheostat buried in the ground. The signals from anemometer, pyranometer, and DC voltage and current transducers are connected through a voltage-current converter for signal conditioning purposes before acquired by data logger. Signals from thermocouple is adapted by a temperature converter, then fed to the data logger.

A sample of data and outputs averaged on hourly basis (for further analysis) for 31 October, 2016 when azimuth angle is 0° and tilt angle = 50° is shown in Figure 3.

3. METHODOLOGY

3.1. MLR

This work aims at proposing a mathematical model utilizing a MLR to predict and estimate PV output power. The hourly output power is defined as the response variable, whereas the solar irradiance (I), cell temperature (T), and wind speed (V) are treated as predictors or causal variables. Therefore, the MLR model suggested in this work becomes as follows (Montgomery, 2013):

$$P_H = \mu_0 + \mu_1 I_H + \mu_2 T_H + \mu_3 V_H + \varepsilon_n \quad (1)$$

where P_H is the average hourly output power, I_H is the average hourly global solar irradiance, T_H is the average hourly cell temperature, V_H is the average hourly wind speed, μ_0 is the regression model intercept, μ_1 , μ_2 and μ_3 are the regression

Figure 2: A schematic diagram of PV system connected to rheostat and measurement devices

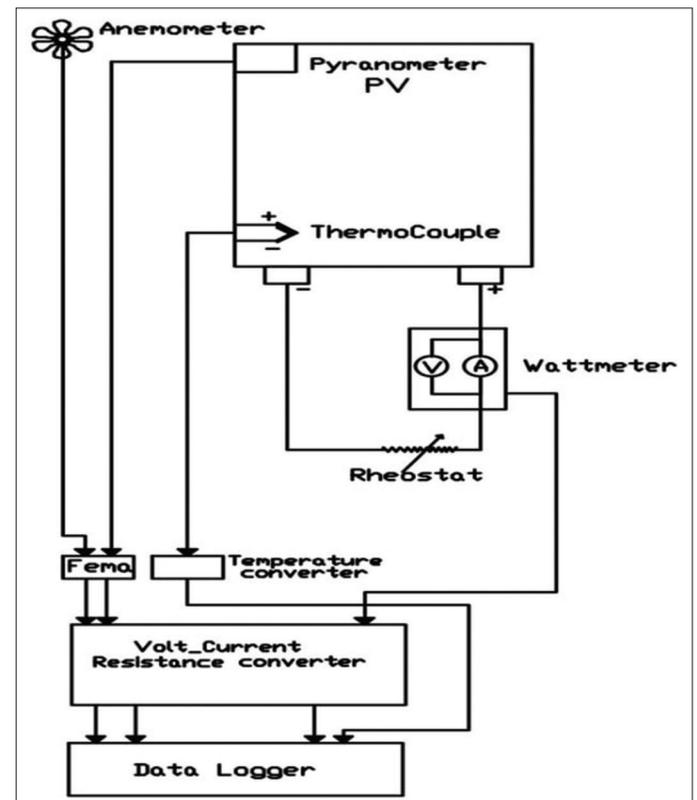


Figure 3: Average hourly (a) incident global irradiance on PV system; (b) wind speed; (c) cell temperature; (d) output power from rheostat for the PV system during the day of 31 October, 2016

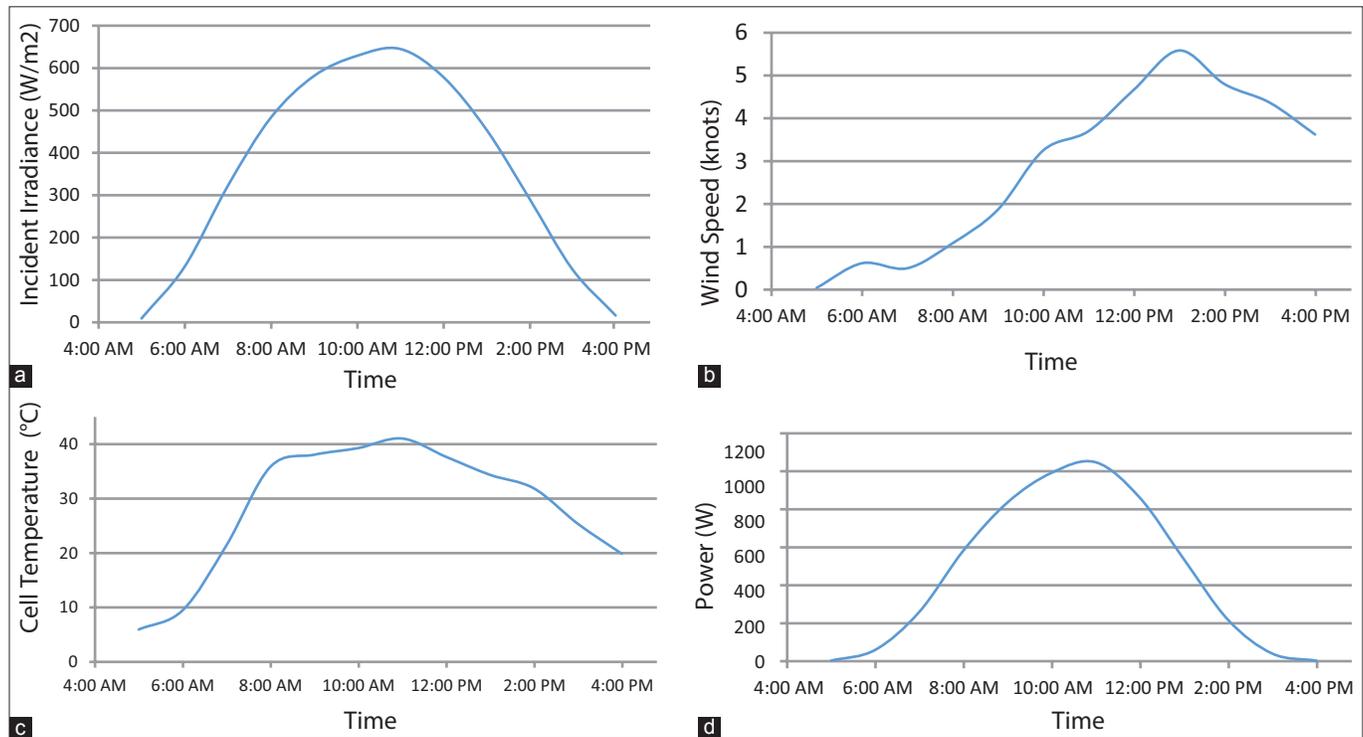


Table 1: Best subset regression models

Variable	R^2	R^2 (adj)	Mallows C_p	S	Global irradiance	Cell temperature	Wind speed
1	94.5	94.5	356.0	98.205	X		
1	18.4	18.2	13827.4	377.66		X	
2	96.3	96.3	29.0	80.042	X	X	
2	95.5	95.5	180.0	88.881	X		X
3	96.5	96.5	4.0	78.421	X	X	X

coefficients and ϵ_n is the difference between the actual and predicted hourly power of the PV system.

A multivariate regression analysis software package, Minitab (Minitab, Ltd., Coventry, UK), is used to estimate the regression model intercept and coefficients (μ 's) associated with each variable shown in Eq. (1). This software package is also used to test the significance of the MLR model using the analysis of variance (ANOVA), which is based on the least-squares method. The number of data points that will be used later in the analysis is 625 data sets.

3.2. Verification of Adequacy and Performance of MLR Model

3.2.1. Best subsets regression

Best subsets regression is a procedure that inspects the list of potential predictors and check that all necessary variables are included in the model to predict the response. In other words, it establishes the subset models that produce the highest R^2 values from full set of the predictors and determines the regression coefficients and predicts responses with smaller variance than the full model using all predictors. The results of best subset regression analysis are shown in Table 1. Each line is a different model. The item Variable is the number of predictors utilized in the model and indicated by an X. In addition to R^2 and adjusted R^2 , Mallows' C_p

and S are used to identify the best model. The adjusted R^2 compares the explanatory power of regression models that contain different numbers of predictors. It is a modified version of R^2 that has been adjusted for the number of predictors in the model. The adjusted R^2 increases only if the new term improves the model more than would be expected by chance. The C_p estimates the size of the bias that is introduced into the predicted responses by having an underspecified model, and S is the square root of MSE. It is concluded from Table 1 that when one predictor is used, R^2 and adjusted R^2 are relatively low, C_p is very high, and S is relatively high. But when all the three predictors are used in the model, the model has a significant improvement in R^2 (96.5 %) and adjusted R^2 (96.5 %), a significant reduction in C_p , and the lowest S value (0.26044) among the other proposed models. This undoubtedly shows the importance of using simultaneously all the independent variables of global solar irradiance I , cell temperature T , and wind speed V in the MLR model. However, the effect of global solar irradiance I has a significant effect in the model compared to cell temperature T and wind speed V .

In addition, a correlation matrix is used as an indicator to check the dependency between variables. Figure 4 shows the relations among the 4 parameters using a matrix plot graph. It is clear that there is a good relationship, because there is a clear trend in the

correlation, between the power (response) and the irradiance which is expected. However, this matrix discloses that there is a random dependency among global solar irradiance, cell temperature, and wind speed. This indicates that there is no correlation between the predictors themselves implying that these input variables are independent. Moreover, there are no clear trends in the correlation between the power (response) and each of the cell temperature and wind speed irradiance which agree with the results of Best Subset Regression Models discussed earlier.

3.2.2. Assumptions validation

The ANOVA tool, used in MLR analysis to testify the validity and significance of the model, is based on some assumptions. In order to check the model adequacy, the following analysis is conducted

3.2.2.1. Analysis of residuals

The residual plots of this model are analyzed and shown in Figure 5. If the residuals are normally distributed, then the points in the corresponding plot should generally form a straight line. But if the points on the plot depart from a straight line, the normality assumption may not be valid. The analysis demonstrates satisfactory results because the cumulative normal distribution is approximately a straight line as clearly noticed in Figure 5a, i.e., the normality assumption is valid. In addition, no leverage and influence points were detected in the model. Therefore, the histogram of residuals, depicted in Figure 5b, indicates that the data is not skewed and there are no outliers. The plot for residuals versus predictor (the output power in this work) shows that these residuals are contained within a horizontal band, Figure 5c, i.e., the

Figure 4: Matrix plot for the parameters investigated in this work

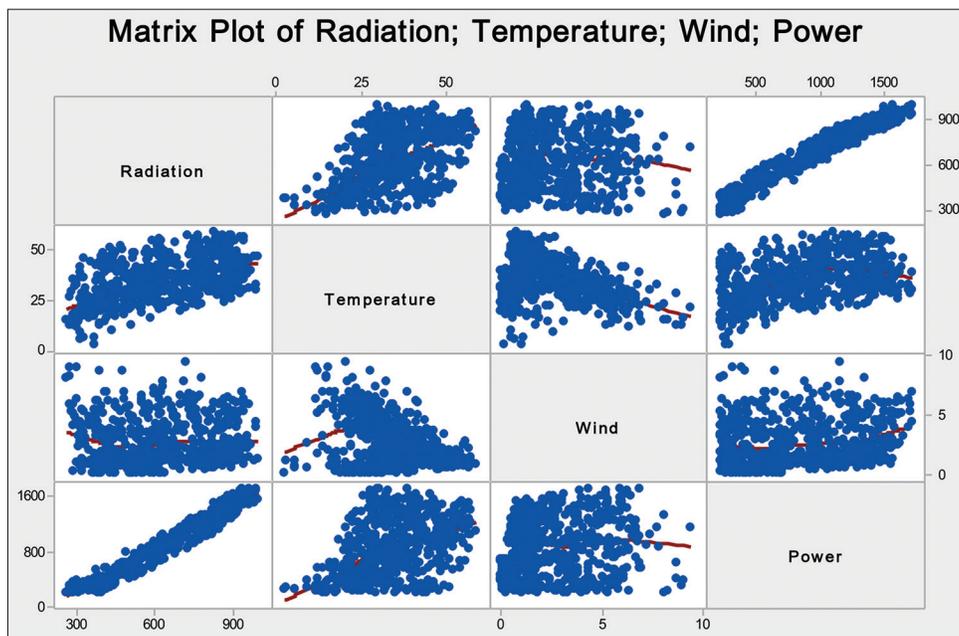


Figure 5: Residuals for multivariate linear regressions model: (a) Normal probability plot; (b) histogram of residuals; (c) residual versus fitted values; (d) residual versus order of data

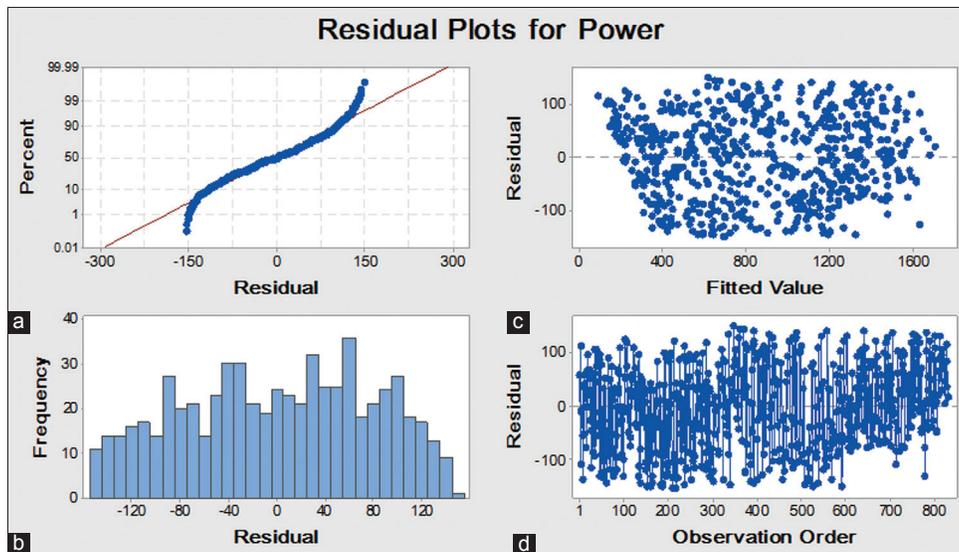


Table 2: Regression summary outputs of the full-period model

Variable*	Coefficient**	P value	VIF
Intercept	-509.5	0.000	
IQA	+2.1849	0.000	1.313
T	-2.007	0.000	1.313
V	+24.07	0.000	1.313

*: $R^2=96.5\%$, Adjusted $R^2=96.5\%$, **: Coefficients are significant at the 0.01 level

constant variance is satisfied. In other words, this plot shows a random pattern of residuals on both sides of 0. This indicates that a correct function form is used to model the curvature. Moreover, Figure 5d shows obviously that the residuals are random with order of the data indicating independency of variables where there is no trend pattern for the residuals to be distinguished in the plot.

3.2.2.2. Analysis of model coefficient signs

Increasing global solar irradiance increases output power due to increase of energy incident on PV system. But as cell temperature increases output power decreases due to significant decrease in output voltage compared to marginal increase in output current, and hence, decreasing output power. However, increasing wind speed results in cooling effect for cell temperature (i.e., decreasing its temperature) and, ultimately, increases output power. This implies that the coefficients in the model for the irradiance and wind speed should have positive signs whereas the coefficient for cell temperature should have negative sign. As noticed in Table 2, signs of the three coefficients in the model are as expected.

3.2.2.3. Goodness-of-fit

Coefficient of determination (R^2) value of a model describes the variability in the output (dependent variable) based on those independent variables only. A 100% R^2 -value means that all the variability of the data is explained by the input variables, and no other variables affect the output. An R^2 value <100% means that there are other unaccounted factors affecting the target data in addition to the input data. However, the adjusted R^2 compares the explanatory power of regression models that contain different numbers of predictors. The adjusted R^2 is a modified version of R^2 that has been adjusted for the number of predictors in the model. The adjusted R^2 increases only if the new term improves the model more than would be expected by chance. The model represents the behavior of data reasonably, because the values of R^2 and adjusted R^2 , used to measure goodness-of-fit, are 96.5% and 96.5%, respectively.

The predicted R^2 indicates how well a regression model predicts responses for new observations. This statistic helps determine when the model fits the original data but is less capable of providing valid predictions for new observations. A key benefit of predicted R^2 is that it can prevent from overfitting a model. An over-fit model contains too many predictors and it starts to model the random noise.

3.2.2.4. Multicollinearity

The correlation among predictors is examined through variation inflation factors (VIFs). VIFs measure how much the variance of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related. When VIFs

is equal to 1, this indicates that there is no correlation among variables. But if VIFs ranges between 5 and 10, the correlation among predictors would be high. VIFs larger than 10 indicate that the associated regression coefficients are poorly estimated because of multicollinearity. Multicollinearity indicates near-linear dependencies among the regression variables that can lead to misleading results. Table 2 shows that the VIFs for the three variables is close to 1; implying that the multicollinearity does not exist in the model.

ANOVA was also performed and it was found that all the predictors (input parameters) were significant with $P < 0.05$.

From the previous tests, we can conclude that the suggested model does not violate the main assumptions and can represent collected data accurately. The complete linear regression model is

$$\hat{P}_H = -509.5 + 2.1849 I_H - 2.007 T_H + 24.07 V_H \quad (2)$$

Where \hat{P}_H is the predicted hourly output power.

4. CONCLUSION

Regression statistical analysis is used to predict the PV system performance under different conditions of actual global incident irradiance, cell temperature and wind speed that was collected during this study. A data set of 625 reading was collected and analyzed. A model shows the relation between the predictors (inputs: Irradiance, cell temperature and wind speed) and the response (Power) considered being linear. The coefficient of determination for this model is 96.5% which statistically considered being an excellent value. R^2 adjusted is a percentage of how the variation of the response is explained with the change of the predictors adjusted for the number of the predictors in the regression model. This means that 96.5% of the variability can be explained and verified by the model above. The model shows the importance of using simultaneously all the independent variables of global solar irradiance I , cell temperature T , and wind speed V in the MLR model. However, the effect of global solar irradiance I has a significant effect in the model compared to cell temperature T and wind speed V .

5. ACKNOWLEDGEMENT

The authors would like to thank the Deanship of the Scientific Research at the HU for the financial support of procurement of the PV system.

REFERENCES

- Alghandoor, A., Phelan, P., Villalobos, R., Phelan, B. (2008), US manufacturing aggregate energy intensity decomposition: The application of multivariate regression analysis. *International Journal of Energy Research*, 32, 91-106.
- Arjyadhara, P., Ali, S., Chitrlekha, J. (2013), Analysis of solar PV cell performance with changing irradiance and temperature. *International Journal of Engineering and Computer Science*, 2(1), 214-220.

- Bhattacharya, P., Dey, S., Mustaphi, B. (2014), Some analytical studies on the performance of grid connected solar photovoltaic system with different parameters. *Procedia Materials Science*, 6, 1942-1950.
- Bouzid, F., Machich, S.B. (2010), The effect of solar spectral irradiance and temperature on the electrical characteristics of a ZnO-SiO₂-Si (N) photovoltaic structure. *Revue des Energies Renouvelables*, 13(2), 283-294.
- Chouder, A., Silvestre, S., Taghezouit, B., Karatepe, E. (2012), Monitoring, modelling and simulation of PV systems using LabVIEW. *Solar Energy*, 91, 1-12.
- Commission I. (1998), International Standard IEC 61724: Photovoltaic System Performance Monitoring Guidelines for Measurements, Data Exchange and Analysis. IEC.
- Cuce, E., Cuce, P.M., Karakas, I.H., Bali, T. (2017), An accurate model for photovoltaic (PV) modules to determine electrical characteristics and thermodynamic performance parameters. *Energy Conversion and Management*, 146, 205-216.
- de la Parra, I., Muñoz, M., Lorenzo, E., García, M., Marcos, J., Martínez-Moreno, F. (2017), PV performance modelling: A review in the light of quality assurance for large PV plants. *Renewable and Sustainable Energy Reviews*, 78, 780-797.
- Dhimish, M., Holmes, V., Mehrdadi, B., Dales, M., Chong, B., Zhang, L. (2017), Seven indicators variations for multiple PV array configurations under partial shading and faulty PV conditions. *Renewable Energy*, 2017, 438-460.
- Dubey, S., Sarvaiya, J.N., Seshadri, B. (2013), Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world a review. *Energy Procedia*, 33, 311-321.
- Eicker, U., Colmenar-Santos, A., Teran, L., Cotrado, M., Borge-Diez, D. (2014), Economic evaluation of solar thermal and photovoltaic cooling systems through simulation in different climatic conditions: an analysis in three different cities in Europe. *Energy and Buildings*, 70, 207-223.
- El-Khozondar, H.J., El-Khozondar, R.J., Matter, K. (2015), Parameters influence on MPP value of the photo voltaic cell. *Energy Procedia*, 74, 1142-1149.
- Fidje, A., Martinsen, T. (2006), Effects of Climate Change on the Utilization of Solar Cells in the Nordic Region. Vol. 5. Extended Abstract for European Conference on Impacts of Climate Change on Renewable Energy Sources, Reykjavik, Iceland.
- Hamrouni, N., Jraidi, M., Chérif, A. (2008), Solar radiation and ambient temperature effects on the performances of a PV pumping system. *Revue des Energies Renouvelables*, 11(1), 95-106.
- Kaplani, E., Kaplanis, S. (2014), Thermal modelling and experimental assessment of the dependence of PV module temperature on wind velocity and direction, module orientation and inclination. *Solar Energy*, 107, 443-460.
- Massidda, L., Marrocu, M. (2017), Use of multilinear adaptive regression splines and numerical weather prediction to forecast the power output of a PV plant in Borkum, Germany. *Solar Energy*, 146, 141-149.
- Montgomery, D.C. (2013), *Applied Statistics and Probability for Engineers*. 6th ed. New York, USA: Wiley; 2013.
- Panagea, I.S., Tsanis, I.K., Koutroulis, A.G., Grillakis, M.G. (2014), Climate change impact on photovoltaic energy output: The case of Greece. *Advances in Meteorology*, 2014, 1-11.
- Pikutis, M., Vasarevičius, D., Martavičius, R. (2015), The influence of temperature of photovoltaic modules on performance of solar power plant. *IOSR Journal of Engineering*, 5, 2278-8719, 09-15.
- Pillai, U. (2015), Drivers of cost reduction in solar photovoltaics. *Energy Economics*, 50, 286-293.
- Pulipaka, S., Mani, F., Kumar, R. (2016), Modeling of soiled PV module with neural networks and regression using particle size composition. *Solar Energy*, 123, 116-126.
- Ren, H., Wu, Q., Gao, W., Zhou, W. (2016), Optimal operation of a grid-connected hybrid PV/fuel cell/battery energy system for residential applications. *Energy*, 113, 702e712.
- Schwingshackl, C., Petittaa, M., Wagnera, J.E., Belluardoc, G., Moserc, D., Castella, M., Zebischa, M., Tetzlaff, A. (2013), Wind effect on PV module temperature: Analysis of different techniques for an accurate estimation. *Energy Procedia*, 40, 77-86.
- Suntech. (2011), STP285-24/Vd. Polycrystalline Solar Module. EN-STD-Vd-NO1.01-Rev.China: Suntech.
- Tian, W., Wang, Y., Ren, J., Zhu, L. (2007), Effect of urban climate on building integrated photovoltaics performance. *Energy Conversion and Management*, 48(1), 1-8.
- Touati, F., Massoud, A., Hamad, J.A., Saeed, S.A. (2013), Effects of environmental and climatic conditions on PV efficiency in Qatar. *Renewable Energy and Power Quality Journal*, 11, 262-267.
- Ye, J.Y., Kun, D., Thomas, R., Armin, G.A. (2013), Outdoor PV module performance under fluctuating irradiance conditions in tropical climates. *Energy Procedia*, 33(1), 238-247.
- Zainuddin, H., Shaari, S., Omar, A.M., Zain, Z.M., Soumin, J., Surat, Z. (2010), Preliminary Investigations on the Effect of Humidity on the Reception of Visible Solar Radiation and the Effect of Humidity and Wind speed on PV module Output. In: Yahya, A.K., Alam, S., editors. *AIP Conference Proceedings*. Vol. 1250. AIP.