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MODELING OF POWER GENERATION FOR A SOLAR POWER GENERATOR SYSTEM

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ABSTRACT

Solar power systems have evolved into a viable source of sustainable energy over the years and one of the key difficulties confronting researchers in the installation and operation of solar power generating systems is how to create a model for household power forecasting.

Multiple regression models were developed from experimental data to estimate rotational and static power as a function of time, current, and voltage, using Minitab 20.4 software. The model correlations were assessed using statistical metrics, Mean Absolute Bias Error (MABE), and Root Mean Square Error (RMSE).

The results showed that the rotational and static power models were built using the mathematical model as a function of time, current, and voltage, The coefficient of determination, R^2 for rotational and static power models were 99.64 % and 99.86 % respectively. MABE and RMSE for rotational model were 1.3030 and 0.7431 and MABE and RMSE for static power model were 1.3548 and 0.79405.

Statistical indicators revealed that regression models accurately predicted rotational and static power as a function of time, current, and voltage. The projected values of rotational and static power demonstrate that these quantities can be utilized to predict and compensate for energy deficit.

1. Introduction

The utilization of solar power systems has evolved into a practical and sustainable means of generating energy, finding application in various industrial and residential contexts (Dambhare et al., 2021). These systems are comprised of a solar collector which can store energy and convert it into either electrical power or thermal energy (Lee et al., 2009). According to Qazi (2019), the photoelectric mechanism's creation and the subsequent advancements in solar cell technology have enabled the conversion of perceived sunlight into direct current, hence facilitating the generation of practical electricity from solar energy. Solar panels are utilized to generate Direct Current (DC) by electrically connecting a sequence of solar cells, which may then be applied to a load (Basherand Shorowordi, 2015). The utilization of solar arrays or panels is becoming increasingly prevalent due to their increasing efficiency. It is well acknowledged that the installation of electricity lines in remote places is not economically viable (Li, 2014). According to the study conducted by Rizk and Chaiko in 2008, Solar energy is a cost-free and unbounded source of energy that does not generate any harmful byproducts or greenhouse gases.

According to Okhaifoh and Okene (2016), the rotation of the Earth around its axis causes a change in the direction of sunshine rays, necessitating the use of a tracking device to optimize solar energy capture and maximize its yield. The utilization of a monitoring system is employed to observe individuals or objects in motion and deliver a timely sequential arrangement of location data for further processing (Deb and Roy, 2012). According to Racharla and Rajan (2018), the fundamental elements of a solar tracking system consist of the tracking device, the tracking algorithm, the control unit, the positioning system, the propulsion mechanism, and the sensing devices. Adamo et al. (2011) developed the IP10P solar PV model by utilizing Matlab and Labview software to create PV panel evaluation tools. These tools were used to generate and monitor the modeling parameters and evaluate the model's performance in a summer outdoor environment.

Banu and Istrate (2012) conducted an analysis of solar photovoltaic (PV) module I-V and P-V characteristics. This analysis was based on empirical data and used a curve-fitting technique. One potential constraint of this methodology is its inability to collect sufficient data in the absence of a specified experimental configuration. Hence, the development and modeling of distinctive curves provide a challenging task. Rekioua and Matagne (2012) demonstrated the implementation of Matlab/Simulink to study several photovoltaic (PV) models. The models presented in this study provide a comprehensive analysis of the operational and behavioral properties of photovoltaic (PV) producers. Additionally, the experimental results were meticulously examined in conjunction with the simulation outputs. The circuit-based solar photovoltaic (PV) model was introduced by Patel and Sharma (2013) and Krismadinata et al. (2013). They implemented this model in Matlab and conducted simulations using various radiation and temperature values. The aforementioned publications solely described the ultimate model, nevertheless, they exhibit a deficiency in terms of providing an intricate modeling analysis of a subsystem within the end solar PV model.

Mohammedi et al. (2013) provided a mathematical description of photovoltaic (PV) models to accurately assess different model parameters. Additionally, the authors conducted a comprehensive comparison between experimental and simulated results obtained from these PV models. The authors also undertook the development and assessment of a water pumping system powered by photovoltaic technology. Rahman et al. (2014) constructed a model for a polycrystalline photovoltaic (PV) module provided by the National Institute of Standards and Technology. The purpose of this model was to assess the module's output power in comparison to the observed output power. Yatimi and Aroudam (2015) conducted a study wherein they employed mathematical modeling techniques to mimic the behavior of a solar photovoltaic (PV) module within the Matlab environment. The model was subsequently tested under real climatic circumstances in Tetouan, located in Northern Morocco. However, it is worth noting that the authors did not provide an extensive description of the PV model's intricate modeling process within the confines of this work.

Yıldıran and Tacer (2016) constructed a solar photovoltaic (PV) model by employing the fundamental governing equations in Matlab/Simulink. They successfully compared the simulated outcomes with the manufacturer data results. However, it is important to note that this research did not provide a comprehensive, step-by-step modeling approach for the PV module. One advantage of integrating solar tracking devices into the preexisting solar power system is the ability of the tracking mechanisms to maintain the alignment of the solar panel with the sun. Consequently, this alignment optimization leads to a notable enhancement in energy production (Onawumi et al., 2022). Ramya and Ananth (2016) have incorporated a tracking mechanism into the solar panel system to guarantee the alignment of the panel with the sun's position, hence optimizing the overall performance of the system. Hysa (2019) asserted that due to the perpetual movement of the sun with the Earth, it became imperative to employ a tracking system to ensure that solar panels remain oriented towards the sun.

Solar power trackers that exhibit optimal functionality are characterized by their ability to move along two axes, specifically azimuth and zenith (Deepthi,2013). According to Ferdaus (2014), the utilization of this particular solar tracking system has the potential to yield a substantial boost in energy acquisition when compared to the typical fixed solar panel. The development of these two-axis tracking systems involved the utilization of the two prevailing types of automatic control systems, namely open loop and closed loop (Juang and Radharamanan, 2014). The utilization of active sensors, such as the Light Dependent Resistor (LDR), in closed-loop tracking systems enhances their efficacy by facilitating the reception of solar radiation signals. Additionally, closed-loop tracking systems incorporate feedback mechanisms that enable continuous adjustment of the panel's orientation, thereby maximizing its efficiency (Mor, 2017). Sangotayo et al. (2023) developed operational characteristic models for air cooling system performance to meet future client needs. Local time inlet and output temperatures were recorded using the LSBLG 1200/MCF model central water chiller air conditioning system. The COP and EER curves were analyzed and MiniTAB 16.0 was used to create characteristic curves and models. The regression models are statistically significant at R^2 of 97.7% and a confidence limit of 95 percent for p-value < 0.05. Regression analysis explores the statistical link between operational parameters like input and output temperatures as a function of local time and response variables like COP and EER.

The global community is confronted with the task of addressing the growing need for energy production to meet both local consumption requirements and potentially facilitate exportation (Ezugwu, 2015). At now, the development of renewable energy sources, such as solar energy, for power generation remains incomplete (Onawumi et al., 2017). Hence, the challenges to the deployment of solar power generation systems encompass, primarily, the issue of power availability. This has emerged as a significant barrier for individuals and entities persistently in pursuit of a secure, reliable, and economically viable alternative energy solution to fuel their machinery and devices. Secondly, there exists a limitation in harnessing solar power to its full potential, irrespective of the abundance of sunlight hours. Additionally, there is a dearth of stored solar power data that may be utilized for analytical purposes (Oji et al., 2012). The present study aimed to examine the ability of mathematical models to forecast both spinning and static power, with a specific focus on the variables of time, current, and voltage. The model's performance was evaluated using statistical metrics.

2. Materials and methods

The energy utilized by the appliances was estimated by calculating the product of power consumption and the duration of intended usage, as seen in Table 1.

Determination of power required for solar panel (P_s)

The calculation of the power (P_s) necessary for the solar panel in Watts, as required for the system, was expressed by equation 1. (Saga, 2010)

$$P_s = \frac{T_{app}}{H_s} \quad (1)$$

$$= \frac{378}{6}$$

= 63 Watts assumed to use 80 Watts solar panel

where, T_{app} is Total appliance in Watts?

H_s is Sunshine hour (an average of 6 hours)

Determination of Battery size (B_s)

The determination of battery size (B_s) in watt-hour for the DASPGS was given by equation 2.

$$B_s = \frac{T_{app}}{B_v} \quad (2)$$

$$= \frac{378}{12}$$

= 31.5 but 40 Ah was used

where, T_{app} is the total appliance of usage in Wh?

B_v Is battery voltage in Volts

Energy stored in the battery (E)

Equation 3 provides the mathematical representation of the assumption regarding the energy (E) that will be stored in a battery with a capacity of 40 Ah, expressed in hours.

$$E = B_s x B_v \quad (3)$$

= 40 x 12

= 480 Wh

where B_s is Battery size in AH, B_v = Battery voltage in Volts

Table *1: Appliances and the Power Usage*

Description of appliances	Power usage	Hours of usage	Total energy usage
Television	22 Watts	4 hours	88 Wh
Startime decoder	7.5 Watts	4 hours	30 Wh
1 Bulb	5 Watts	8 hours	40 Wh
Small standing fan	30 Watts	4 hours	120 Wh
Phone charger	10 Watts	1 hour	10 Wh
Portable laptop charger	45 Watts	2 hours	90 Wh
Overall Total Energy Usage			**378 Wh**

Output Energy of the battery (Eo)

The available energy of the battery is lower than the energy that is stored within the battery. In the case of a lithium-ion battery, the amount of energy that may be effectively utilized is approximately 80% of the total energy contained within the battery. Hence, the value of the output energy (E_o) was calculated using equation 4. (Saga, 2010)

$$E_o = 0.8\, E \quad (4)$$

$$= 0.8 \times 480$$
$$= 384\ Wh$$

where E is Energy stored in the battery

The energy that solar panels can generate (E_t)

The quantification of the energy produced by an 80 W solar panel at a specific period was conducted by employing Equation 5 as proposed by Saga (2010)

$$E_t = P_s \text{x} H_s \qquad (5)$$
$$= 80 \text{ x } 6$$
$$= 480 \text{ W}$$

where P_s Is solar panel in Watts?

H_s is Sunshine hour (an average of 6 hours)

Determination of inverter size (I_s)

The inverter was determined to have a size that is 25-30% larger than the total wattage of all appliances, to ensure safety. The calculation was performed with equation 6. (Abdar et al. 2012).

$$I_s = 27\%\ 0f T_{app} + T_{app} \qquad (6)$$
$$= (0.27 \times 378) + 378$$
$$= 480.06 \text{ W but } 500 \text{ W was used}$$

where I_s is the Inverter size in Watts, and T_{app} is Total appliance in Watts?

Determination of solar charge controller (Ch_C)

The utilization of a Maximum Power Point Tracking (MPPT) solar charge controller incorporates an additional 25% allowance to account for unanticipated surges in current, such as those resulting from light reflection. The calculation was performed with equation 7. (Hossain et al. 2012),

$$Ch_C = \frac{P_s}{B_v} + \left(25\ \%\ 0f \frac{P_s}{B_v}\right) \qquad (8)$$
$$= \frac{80}{12} + \left(0.25 \times \frac{80}{12}\right)$$

= 8.33 but 10 Amp was used

Where Ch_C = Charge comptroller in Amp, P_s = Solar panel in Watts

B_v = Battery voltage in Volts

Model development

The MiniTAB 20.4 software was employed to generate multiple regression models to examine the relationship between Rotational and Static powers concerning Time, Volts, and Amp. Subsequently, the statistical significance of the regression model and the parameters of the equation were assessed.

3. Results and Discussions

3.1 Regression Analysis for Rotational Power as a Function of Time, Volts, and Amp

The MiniTAB 20.4 software was employed to generate a multiple regression model that relates Rotational power to Time, Volts, and Amp, denoted as Eq. (1). The statistical significance of the regression model and the parameters of the equation were assessed and the results are presented in Table 1-3. Figure 2 depicts the graphical representation of the measured and expected rotational power concerning the observed values.

$$R\_Watt = -24.578 + 0.0153\ Time + 1.7876\ R\_Volts + 13.8204\ R\_Amp \qquad (1)$$

Table 1. Analysis of Variance of Regression Model for Rotational Power

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	208550	69517	288786	0
Time	1	0	0	0.07	0.793
R_Volts	1	2807	2807	11660.58	0
R_Amp	1	176552	176552	733430.3	0
Error	2228	536	0		
Lack-of-Fit	2086	536	0	*	*
Pure Error	142	0	0		
Total	2231	209087			

Table 2. Summary of Regression Model for Rotational Power

S	R-sq	R-sq(adj)	R-sq(pred)
0.490633	99.74%	99.74%	99.74%

Table 3. T-Value and P-Value of the Coefficients of the Regression Model for Rotational Power

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-24.578	0.227	-108.22	0	
Time	0.0153	0.0583	0.26	0.793	1.15
R_Volts	1.7876	0.0166	107.98	0	1.23
R_Amp	13.8204	0.0161	856.41	0	1.08

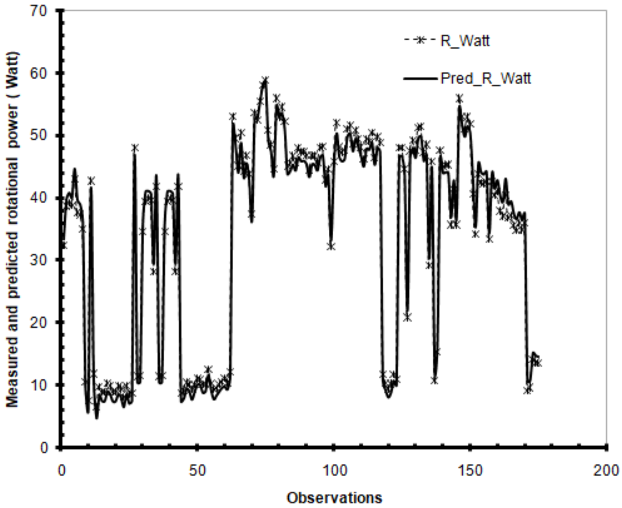

Figure 2 Plot measured and predicted rotational power against observations

The regression model was derived from the collected data using MiniTAB 20.4. The model comparisons were conducted using the aforementioned software, as depicted in Figure 2. Figure 2 illustrates a visual representation of the observed and estimated rotational power levels, allowing for a direct comparison. The concordance between the observed and estimated values is highly satisfactory. The accuracy of the projected data is evaluated by calculating the Mean Bias Error (MBE) and Root Mean Square Error (RMSE) using established methodologies. The standard deviation of Rotational Power, Time, Volts, and Amp is 0.9984. The coefficient of determination, which is 0.9974 in this case, suggests that about 99.74% of the rotational power can be explained by the variables of Time, Volts, and Amp.

Tables 2.0 and 3.0 present the statistical significance of the constant term and the regression model for the relationship between Rotational power and the independent variables Time, Volts, and amps. The regression model's P-values (0.00) for Voltage and Ampere are below the significance threshold of 0.05, suggesting that these variables are statistically significant. Conversely, the P-value (0.78) for time exceeds 0.05, showing that time is not a significant variable in the model. In the context of linear regression, the coefficient of determination, denoted as R2, serves as a metric for assessing the predictive or explanatory power of a model. The coefficient of determination, denoted as R-squared, quantifies the proportion of the variance seen in the dependent variable of rotational power that can be predicted or explained by the linear regression model and the predictor variables, namely Time, Volts, and Amp.

A high coefficient of determination (R^2) is frequently indicative of a strong fit between the model and the data. In the case of an R2 value of 0.9974, it signifies that the utilization of the model's variables for predicting the outcome may account for 99.74% of the observed variability in the outcome. To consider this influence, the adjusted R^2 incorporates the same dataset as the conventional R^2 but adjusts for the inclusion of predictor variables in the model. The standard deviation, denoted as 0.490633, is a measure of variability. Consequently, the adjusted R^2 of 99.74% will only increase if the improvement in R^2 exceeds what would be expected by random chance. The inclusion of additional components in a multivariate linear regression model leads to an increase in the coefficient of determination (R^2). The modified R^2 in this particular model provides the most accurate estimation of the proportion of variance that can be predicted by the variables included in the model.

Durbin-Watson Parameter for rotational power

The Durbin-Watson ratio is a statistical test used to assess the presence of autocorrelation in regression model outcomes. It is measured on a scale ranging from 0 to 4, where a value of 2.0 indicates the absence of autocorrelation. Values below 2.0 indicate positive autocorrelation, while values above 2.0 indicate negative autocorrelation. The Durbin-Watson index of the regression model is 0.738845. Positive autocorrelation indicates a positive level of similarity between two consecutive time intervals of a given variable.

Error Analysis for rotational power

The Statistical Analysis System (SAS) software was employed to compute the statistical metrics Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to evaluate and compare the model's performance. The Mean Absolute Error (MAE) was computed as 1.302958286 using the appropriate formula. This result signifies the average absolute discrepancy between the projected values generated by the model and the corresponding actual values. The root mean square error (RMSE) is computed using the appropriate formula, yielding a value of 1.354843375. This value signifies the square root of the mean of the squared discrepancies between the expected and actual points scored. Each metric offers insight into the average discrepancy between the predicted value of the model and the actual value in the dataset, although each statistic is subject to a slightly different interpretation.

3.2 Regression Analysis for Static Power as a Function of Time, Volts, and Amp

The MiniTAB 20.4 software was utilized to construct a multiple regression model that examines the relationship between Static power and its predictors, namely Time, Volts, and Amp. The resulting model is represented by Equation (2). Furthermore, the statistical significance of the regression model and the parameters of the equation were assessed, as detailed in Tables 4-6. Table 4 presents a study of the variance of the regression model for Static Power and Figure 3 presents the plot of measured and predicted static power against observations

$$S\_Watt = -16.072 + 0.0498\ Time + 1.23702\ S\_Volts + 13.0112\ S\_Amp \quad (2)$$

Table 4. Analysis of Variance of Regression Model for Static Power

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	110977	36992	536140.8	0
Time	1	0	0	2.82	0.093
S_Volts	1	1195	1195	17319.61	0
S_Amp	1	105729	105729	1532355	0
Error	2228	154	0		
Lack-of-Fit	2103	154	0	*	*
Pure Error	125	0	0		
Total	2231	111131			

Table 5. Summary of Regression Model for Static Power

S	R-sq	R-sq(adj)	R-sq(pred)
0.262674	99.86%	99.86%	99.86%

Table 6. T-Value and P-Value of the Coefficients of the Regression Model for Static Power

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-16.072	0.123	-130.47	0	
Time	0.0498	0.0297	1.68	0.093	1.04
S_Volts	1.23702	0.0094	131.6	0	1.05
S_Amp	13.0112	0.0105	1237.88	0	1.01

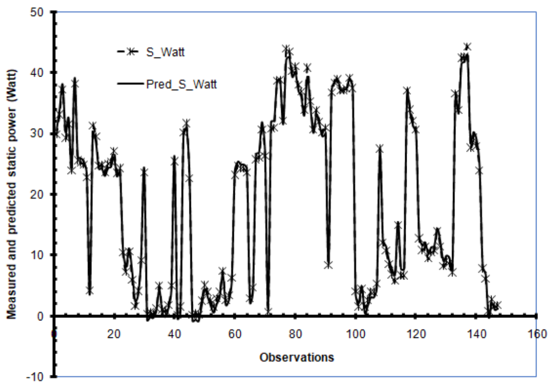

Figure 3 Plot measured and predicted static power against observations

The regression model was derived from the collected data using MiniTAB 20.4. The model comparisons were conducted, as depicted in Figure 3. Figure 3 displays a visual representation that compares the observed and estimated rotational power values. The concordance between the observed and estimated values is highly satisfactory. The accuracy of the anticipated data is evaluated by calculating the Mean Bias Error (MBE) and Root Mean Squared Error (RMSE) using established methodologies. The standard variation of rotational power, time, volts, and amps is 0.262674. The coefficient of determination, which is 0.9986 in this case, suggests that about 99.86% of the rotational power can be explained by the variables of Time, Volts, and Amp.

Tables 2.0 and 3.0 present the statistical significance of the constant term and the regression model for the relationship between Rotational power and the independent variables Time, Volts, and amps. The regression model's P-values for Voltage and Ampere (0.00) are below the significance level of 0.05, suggesting that these variables have a significant impact. Conversely, the P-value for time (0.093) is above the significance level, indicating that time is not a relevant component in the model. In the context of linear regression, the coefficient of determination denoted as R^2, serves as an evaluative metric for assessing the predictive or explanatory power of a given model. The coefficient of determination, denoted as R-squared, quantifies the proportion of the total variation seen in the dependent variable, rotational power, that can be accounted for or explained by the linear regression model and the predictor variables, namely Volts, and Amp.

A high coefficient of determination (R^2) is typically indicative of a strong fit between the model and the data. In the case of an R^2 value of 0.9986, it signifies that the model's covariates are capable of accounting for 99.86% of the variability observed in the outcome variable when used for prediction purposes. To incorporate this influence, the adjusted R^2 incorporates the same dataset as the conventional R^2 but adjusts for the inclusion of predictor variables in the model. The standard deviation is determined to be 0.490633. Consequently, the adjusted R2 of 99.86% will only increase if the improvement in R^2 exceeds what would be expected by random chance. The inclusion of additional components in a multivariate linear regression model leads to an increase in the coefficient of determination (R^2). The modified R^2 value in this particular model provides a more accurate estimation of the proportion of variation that can be explained by the variables included in the model.

Durbin-Watson Parameter for Static Power

The Durbin-Watson ratio is a statistical test used to assess the degree of autocorrelation in the outcomes of a static power regression model. In this particular case, the Durbin-Watson index for the static power regression model is determined to be 0.845881. Positive autocorrelation indicates a strong positive correlation between two consecutive time intervals of a given variable.

Error Analysis for Static Power

The model's performance was evaluated and compared by calculating the statistical measures of MABE, MSE, and RMSE using Statistical Analysis System (SAS) software. The Mean Absolute Error (MAE) was computed as 0.743077551, employing the MAE algorithm. This result signifies the average absolute deviation between the predicted values of the model and the corresponding actual values. The mean squared error (MSE) is computed as 0.630502303 utilizing the MSE formula. The root mean square error (RMSE) is computed using the appropriate formula and yields a value of 0.794041751. This value signifies the square root of the average of the squared differences between the expected and actual points scored. Each metric offers insight into the average discrepancy between the anticipated value generated by the model and the actual value present in the dataset. However, each metric possesses a distinct interpretation.

4. Conclusions

The investigation produced the following findings; the mathematical model was utilized to represent the relationship between time, current, voltage, and rotational and static power. The statistical criteria employed to assess the performance of the model were Mean Bias Error (MBE) and Root Mean Square Error (RMSE). The coefficient of determination, R^2 for rotational and static power models were 99.64 % and 99.86 % respectively. MABE and RMSE for rotational model were 1.3030 and 0.7431 and MABE and RMSE for static power model were 1.3548 and 0.79405.

Statistical indicators revealed that regression models accurately predicted rotational and static power as a function of time, current, and voltage. The projected values of rotational and static power demonstrate that these quantities can be utilized to predict and compensate for energy deficit. The regression models are reliable for forecasting rotational and static power in the surrounding environment.

The statistical indicators provided evidence that the regression models accurately predicted the rotational and static power by considering variables such as time, current, and voltage, exhibiting a notable level of precision. The anticipated values of rotational and static power indicate that these quantities can be used to foresee and compensate for energy deficits. The current correlation generated accurate estimates of rotational and static power, and the regression models are trustworthy for predicting rotational and static power in the surrounding environment.

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Conflict of interests

The authors declare no conflict of interest.

References

Abdar, H. M., Chakraverty, A., Moore, D. H., Murray, J. M. and Loparo, K. A. (2012). Design and Implementation of a Specific Grid-tie Inverter for an Agent-based Microgrid. *IEEE Energytech, Energytech*. https://doi.org/10.1109/EnergyTech.2012.6304676

Adamo F., Attivissimo F., Di Nisio A., Spadavecchia M. (2011) Characterization and testing of a tool for photovoltaic panel modeling IEEE Trans. Instrum. Meas., 60 (5) (2011), pp. 1613-1622, 10.1109/TIM.2011.2105051

Ajayeoba, A.O., Fajobi, M.O., Raheem, W.A., Adebiyi, K.A and Olayinka, M. . (2021). Risk Factor Assessments and Development of Predictive Model for Volatile Organic Compounds Emission in Petrol Stations in Nigeria. Digital Innovation and Contemporary Research in Science, Engineering and Technology, 9 (1):57-74. https://doi.org/: dx.doi.org/10.22624/AIMS/DIGITAL/V9N1P5

Banu I.V., Istrate M. (2012) Modeling and simulation of photovoltaic arrays, Bul. AGIR, 3 (2012), pp. 161-166 http://www.buletinulagir.agir.ro/articol.php?id=1378

Barnston, A., (1992). "Correspondence among the Correlation [root mean square error] and Heidke Verification Measures; Refinement of the Heidke Score." Notes and Correspondence, Climate Analysis Center

Basher, M. K. and Shorowordi, K. M. (2015). Fabrication of Monocrystalline Silicon Solar Cell using Phosphorous Diffusion Technique. *International Journal of Scientific and Research*

Publications, 5 (3):1-7.

Dambhare, M. V., Butey, B. and Moharil, S. V. (2021). Solar photovoltaic technology: A review of different types of solar cells and its future trends. International Conference on Research Frontiers in Sciences (ICRFS), pp 1-16 doi:10.1088/1742-6596/1913/1/012053.

Deb, G. and Roy, A. B. (2012). Use of Solar Tracking System for Extracting Solar Energy. *International Journal of Computer and Electrical Engineering*, 4 (1):42-46. https://doi.org/10.7763/ijcee.2012.v4.449

Deepthi, S., Ponni, A., Ranjitha, R. and Dhanabal, R. (2013). Comparison of Efficiencies of Single-Axis Tracking System and Dual-Axis Tracking System with Fixed Mount. *International Journal of Engineering Science and Innovative Technology (IJESIT)*, 2(2):425-430.

Ezugwu, C. N. (2015). Renewable Energy Resources in Nigeria: Sources, Problems and Prospects. *Journal of Clean Energy Technologies*, 3 (1):68-71. https://doi.org/10.7763/jocet.2015.v3.171

Ferdaus, R. A., Mohammed, M. A., Rahman, S., Salehin, S. and Mannan, M. A. (2014). Energy Efficient Hybrid Dual Axis Solar Tracking System. *Journal of Renewable Energy*.35 (3):584-591. https://doi.org/doi.org/10.1155/2014/629717

Hossain, N., Routh, T. K., Hamid, A. and Yousuf, B. (2012). Design and Development of a Grid Tied Solar Inverter. *IEEE/OSA/IAPR International Conference on Informatics, Electronics and Vision*, 5, 1024-1038. https://doi.org/10.1109/ICIEV.2012.6317344

Hysa, A. (2019). Modeling and Simulation of the Photovoltaic Cells for Different Values of Physical and Environmental Parameters. *Emerging Science Journal*, 3 **(**6):395-406

Juang, J. and Radharamanan, R. (2014). Design of a Solar Tracking System for Renewable Energy.*Proceedings of Zone 1, Conference of the American Society for Engineering Education*,

Krismadinata S., Rahim N.A., Ping H.W., Selvaraj J. (2013), Photovoltaic module modeling using Simulink/Matlab Procedia Environ. Sci., 17 (2013), pp. 537-546, 10.1016/j.proenv.2013.02.069

Lee, C. Y., Chou, P. C., Chiang, C. M. and Lin, C. F. (2009). Sun tracking systems: A review. *Journal Open Access Sensors*, 9 (5):3875-3890. https://doi.org/10.3390/s90503875

Li, H., Zhao, C., Wang, H., Xie, S. and Luo, J. (2014). An Improved PV System Based on Dual Axis Solar Tracking and MPPT. *IEEE International Conference on Mechatronics and Automation,* 5, 204-209. https://doi.org/10.1109/ICMA.2014.6885696

Mohammedi A., Rekioua D., Mezzai N. (2013), Regular paper experimental study of a PV water pumping system J. Electr. Syst., 9 (2) (2013), pp. 212-222

Mor, C. (2017). New Prototype of Photovoltaic Solar Tracker Based on Arduino. pp 1-13. https://doi.org/10.3390/en10091298

Oji, J. O., Idusuyi, N., Aliu, T. O., Petinrin, M. O., Odejobi, O. A. and Adetunji, A. R. (2012). Utilization of Solar Energy for Power Generation in Nigeria. *International Journal of Energy Engineering* 2 (2):54-59. https://doi.org/10.5923/j.ijee.20120202.07

Okhaifoh, J. E. and Okene, D. E. (2016). Design and Implementation of a Microcontroller Based Dual Axis Solar Radiation Tracker. *Nigerian Journal of Technology (NIJOTECH), Faculty of Engineering, University of Nigeria, Nsukka*, 35(3):584-591. https://doi.org/10.4314/njt.v35i3.17

Onawumi, A. S., Akinrinade, N. A., Olojede, M. A and Ajayeoba A. O (2022). Development of a Solar

Power Generating System with Auto-Tracking and Data Logging Devices. *Journal of Engineering Research and Reports*. Vol 23, Issue 12, pp212-222. Article no.JERR 94670, ISSN 2582-9226. DOI:10.9734/JERR/2022/v23i12779

Onawumi, A. S., Okolie S. T. A., Mfon Udo, M. O., Raheem, W.A. and A. A. O. (2017). Noise Level Investigation and Control of Household Electric Power Generator. *Industrial Engineering Letters*, **7** (2):63-69.

Patel J., Sharma G. (2013) Modeling and simulation of solar photovoltaic module using Matlab/Simulink Int. J. Res. Eng. Technol., 2 (3) pp. 225-228

Qazi, A., Fayaz, H., Rahim, Abd. N., Hardeker, G., Alghazzawi, D., Shaban, K., and Haruna, K. (2019). Towards Sustainable Energy: A Systematic Review of Renewable Energy Sources, Technologies, And Public Opinions. IEEE Access, 7, 63837-63851.

Racharla, S. and Rajan, K. (2018). Solar Tracking System: A review. *International Journal of Sustainable Engineering*, pp 1-56. https://doi.org/10.1080/19397038.2016.1267816

Rahman S.A., Varma R.K., Vanderheide T. (2014), Generalised model of a photovoltaic panel IET Renew. Power Gener., 8 (3) (2014), pp. 217-229, 10.1049/it-rpg.2013.0094

Ramya, P. and Ananth, R. (2016). The Implementation of Solar Tracker Using Arduino With Servomotor. *International Research Journal of Engineering and Technology*, 3(8):969-972.

Rekioua D., Matagne E. (2012), Optimization of Photovoltaic Power Systems: Modelization, Simulation and Control Springer Science & Business Media (2012), 10.1007/978-1-4471-2403-0

Rizk, J. and Chaiko, Y. (2008). Solar Tracking System: More Efficient Use of Solar Panels. World Academy of Science, Engineering and Technology. *International Journal of Electrical and Computer Engineering*,2 (5):784-786

Saga, T. (2010). Crystalline and Polycrystalline Silicon PV Technology. *International Journal of Research and Analytical Review*, 6 (1):545-549.

Sangotayo E. O., Nnamchi S. N., Mundu M. M. and Kibogo I. (2023). Modeling of the Operational Parameters on the Performance of an Air Conditioning System. *IDOSR Journal of Experimental Sciences* 9(2) 135-148. https://doi.org/10.59298/IDOSR/JES/101.1.7011

Yatimi, H., Aroudam, E.H., 2015. A Detailed Study and Modeling of Photovoltaic Module under Real Climatic Conditions. http://dx.doi.org/10.12720/ijeee.3.3.171-176

Yıldıran N., Tacer E. (2016), Identification of photovoltaic cell single diode discrete model parameters based on datasheet values, Sol. Energy, 127 (2016), pp. 175-183, 10.1016/j.solener.2016.01.024