Solar Energy
And Sustainable Development
Refereed, biannual scientific journal issued by:
The Libyan Center for Solar Energy Research and Studies

Solar Photovoltaic Power Prediction Using a Statistical Approach Based on Analysis of Variance

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ARTICALE INFO.

Article history:
Received 17 April 2024
Received in revised form 18 April 2024
Accepted 19 June 2024
Available online 27 June 2024

KEYWORDS

Solar PV system, Renewable energy forecasting, Statistical modeling, ANOVA, Fit summary.

ABSTRACT

With the increase in global demand for energy and the rise of environmental warnings supported by the United Nations and its sustainable development goals (SDGs) in 2015, transitioning from traditional energy systems to renewable ones, especially solar energy systems, has become necessary. However, this transition should be supported by prediction models that can help forecast these power outputs. This research aims to develop a data-driven model based on a statistical approach. Analysis of variance ANOVA and fit summary were the tools that were used in creating the model.

Three input variables, namely Global Radiation, Ambient Relative Humidity, and Ambient Temperature, were utilized alongside one output variable, output power. The model utilized 360 readings during six hours from 10:00 am to 4:00 pm. Stat-ease software was used to develop the model. The quadratic statistical model shows significant results with five statistical terms. The Model's F-value of 687.89 indicates that the model is highly significant, demonstrating only a small chance of 0.01% that such a large F-value could be caused by random variations. In addition, the P-values for the remaining model terms in the ANOVA table, all being less than 0.0500, confirm their significance. The developed model was validated by comparing the original experimental data with those obtained from the model. The validation showed an average percentage error of 7.35%.

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DOI: https://doi.org/10.51646/jsesd.v13i2.181

تنبؤ قدرة الطاقة الكهروضوئية الشمسية باستخدام نهج إحصائي قائم على تحليل التباين

معتز الهزاع، حسين عطية، خالد حسين.

ملخص: مع زيادة الطلب العالمي على الطاقة وارتفاع التحذيرات البيئية المدعومة من قبل الأمم المتحدة وأهداف التنمية المستدامة في عام 2015، أصبح من الضروري الانتقال من أنظمة الطاقة التقليدية إلى أنظمة الطاقة المتجددة، خاصة أنظمة الطاقة الشمسية. ومع ذلك، يجب أن يتم دعم هذا الانتقال بنماذج تنبؤية يمكن أن تساعد في توقع مقدار القدرة المتولدة من هذه المنظومات. يهدف هذه البحث إلى تطوير نموذج قائم على البيانات بناءً على نهج إحصائي. تم استخدام تحليل التباين ANOVA وملخص التناسب Fit summary كأدوات في إنشاء النموذج. تم استخدام ثلاثة متغيرات مدخلة، وهي الإشعاع الشمسي الكلي، والرطوبة النسبية، ودرجة الحرارة الجوية، جنبًا إلى جنب مع متغير الإخراج وهو مقدار القدرة المتولدة من نظام اللوح الشمسي. لتطوير النموذج تم استخدام 360 قراءة خلال ست ساعات متواصلة من الساعة 10:00 صباحًا إلى الساعة 4:00 مساءً. تم استخدام ايضا برنامج Stat-ease لتطوير النموذج. يظهر النموذج الإحصائي التربيعي نتائج مهمة مع خمسة حدود إحصائية. القيمة F للنموذج بلغت 687.89، مما يشير إلى أن النموذج ذو دلالة عالية، مع احتمالية 0.01٪ فقط بأن قيمة F الكبيرة تكون ناتجة عن التباين العشوائي. بالإضافة إلى ذلك، قيم القدرة لبقية عناصر النموذج في جدول ANOVA، حيث ان جميعها أقل من 0.0500، تؤكد أهميتها. تم التحقق من دقة النموذج المطور وذلك بمقارنة البيانات المعملية الحقيقية مع تلك التي تم حسابها بواسطة النموذج. أظهرت عملية التحقق اختلافًا متوسطًا بنسبة 7.35٪.

الكلمات المفتاحية – منظومة كهروضوئية، التنبؤ بالطاقات المتجددة، النمذجة الاحصائية، أنوفا، ملخص التناسب.

1. INTRODUCTION

Solar energy has become one of the most potential energy supply alternatives for the coming decades for many reasons, such as low fossil-fuel consumption, low noise, and not posing health and environmental hazards [1]. In 2022, the global installed capacity of solar photovoltaic energy reached 1,177 GW. This growth in the solar photovoltaic market underscores a global transition toward renewable and sustainable energy technologies. China and the USA are at the forefront of the global PV market in 2021, boasting 307 GW and 122 GW of installed solar PV capacity, respectively. Meanwhile, both Chile and Honduras had the largest proportion of photovoltaic energy in their total energy mix in 2022 [2].

Khatib et al. [3] claimed that solar energy is clean, free, and abundant in most world's locations throughout the year and is essential, especially during high fossil fuel costs and the atmosphere degradation caused by burning fossil fuels.

Another driver that supports this argument is the rise of Sustainable Development Goals (SDGs) and the need for the nations to achieve their targets by 2023. Many researchers attempted to support this argument in their studies. Adenle [4] investigated the contribution of solar energy in implementing the 2030 agenda of SDGs in Africa. The benefits and challenges of applying solar energy technologies to meet SDGs in Africa were analyzed. In their research, Obaideen et al. [5] concluded that 72% of the research papers focused on SDG 7: Affordable and Clean Energy. Another study conducted by Obaideen et al. [6] claims that the initiatives of Mohammed bin Rashid Al Maktoum (MBR) Solar Park in the UAE help achieve the SDGs. Senthil [7] published a review paper discussing the latest innovations in solar energy in different sectors and their contribution in providing clean and affordable energy and clean water. The research focuses on SDG 7: Affordable and Clean Energy. Yousef et al. [8] analyzed the recent conducted research on hybrid concentrated solar power (CSP) over the last 10 years. Their results showed that hybrid CSP systems make important contributions to the SDGs directly and indirectly. Belgasim et al. [9] assessed the feasibility of CSP systems for electricity generation under Libyan climatic conditions. The outcomes demonstrate that Libya not only possesses suitability but also holds potential for economic competitiveness in the adoption of CSP technology. Cost is another driver for transforming traditional solar power systems. The results of increasing innovative trends in energy technology lead to cost reductions for renewable energy systems such as solar PV and onshore wind [10]. Another factor that supports this transmission is the country's location. For example, the location of the UAE with long hours of high solar intensity will increase and encourage this transmission.

Therefore, predicting and forecasting energy output, in general, is crucial for the power plant operations [11]. The development of models that can predict the power output in a specific area from solar energy stations depends upon many factors, such as global radiation, dust, humidity, ambient temperature, etc. Researchers have tried different approaches to developing models that can accurately predict power outputs. Al Hazza et al. [12] used fuzzy logic to forecast the harvested power from PV panels situated in a desert climate. While three input parameters including light intensity, ambient temperature, and dust intensity were considered, all other parameters were assumed to be constant. It was concluded that while ambient temperature and dust density negatively affect output power, light intensity exhibits a positive impact. Other researchers tried the artificial neural network approach. Perveen et al. [13] proposed a Radial-Basis-Function-Neural-Network (RBFNN) model that is able to significantly reduce the error compared to other methods. Barrera et al. [14] used open-source data, Internet of Things (IoT) sensors, and other installations across Europe to develop a tool using Artificial Neural Networks. It was reported that the model improves forecasting accuracy, achieving a smaller mean squared error (MSE) of 0.040 compared to 0.055 from the literature. Pang et al. [15] developed both an ANN model and a recurrent neural network (RNN) to examine the effectiveness of deep learning algorithms in solar radiation prediction. The results indicate that the RNN model outperforms the ANN model in solar radiation prediction, offering 47% and 26% enhancements in Normalized Mean Bias Error (NMBE) and Root-Mean-Squared Error (RMSE), respectively. Elsheikh et al. [16] carried out a theoretical study based on a comprehensive review to explore the applications of ANNs as an intelligent system-based method for predicting and optimizing the performance of various solar energy systems. Yaïci et al. [17] simulated the effect of different input factors on the robustness and accuracy of the ANN approach in predicting key performance parameters of a solar energy system. It was demonstrated that the degree of model accuracy decreases with reduced inputs. Ramedani et al. [18] utilized a daily meteorological dataset for a period of 15 years (1993–2008), collected via different types of ANN models. The results showed that ANN model outperformed utilizing empirical Hargreaves and Samani equation (HS) model and can be successfully used for prediction.

Some researchers tried the statistical approach in developing the predicted models. Thulasiram [19] used the Box-Behnken design matrix to develop forecasting models for exergy and pressure drop behaviors using experimental data. King et al. [20] used periodic regression equations in their prediction model. Parhizi et al. [21] implemented the central composite design (CCD) and the desirability function (DF) to minimize the energy use, energy use ratio and rate of exergy loss. Data obtained from experiments were used in modeling the key parameters of a water desalination process. These parameters were then applied in a Response Surface Model (RSM) [22]. Hossain et al. [23] utilized the Analysis of Variance (ANOVA) approach to investigate the application of solar energy in hydrogen production.

Samy et al. [24] attempted to develop an innovative statistical and ANN-based decision-making mechanism for evaluating green energy system optimization strategies. Al-Shamisi et al. [25] developed ANN models using historical data of the maximum daily temperature, mean daily wind speed, mean daily relative humidity, and mean daily sunshine hours in Abu Dhabi. The data between 1993 and 2003 were used to train the ANN, whereas data between 2004 and 2008 were utilized to test the estimated values. The results proved the ability of ANN approaches to generate precise estimation models. Rejeb et al. [26] used RSM to analyze a nanofluid PVT collector's efficiencies. The model correlates collector' thermal and electrical efficiencies to various operational parameters, including heat transfer coefficient, mass flow rate, Zinc oxide (ZnO) nanoparticle concentration, and tube number. Results highlight the significance of heat transfer coefficient and mass flow rate over nanoparticle concentration and tube number.

Some studies focused on the UAE environmental conditions as one of the potential areas for solar energy. Tahir et al. [27] assessed key performance indicators for five case studies such as energy yield, capacity factor, internal rate of return, and net present value. It was highlighted the benefits of 2-axis tracking, bifacial modules, and battery storage, offering valuable insights for improving solar PV projects in the UAE. Experimental investigations were conducted by Hachicha et al. [28] to explore the characteristics of dust and its impact on the electric performance of PV systems under the climatic conditions of Sharjah, UAE. Indoor and outdoor experiment results revealed that the linear relationship between dust accumulation and performance degradation is reliable and can predict soiling losses in PV systems within the UAE and similar climatic regions. Salimi et al. [29] examined the UAE's solar energy production and consumption trends. They conducted a SWOT analysis on various types of regional solar energy and developed strategies based on the findings. The study identified promising strategies for the UAE's transition towards solar energy, aimed at reducing fossil fuel demand, mitigating GHG emissions by increasing solar energy share, and positioning the UAE as the carbon market center among the GCC countries.

This research aims to develop a data-driven model in a desert environment using three different inputs based on a statistical approach. This model can guide investors and support them in transitioning from traditional energy systems to renewable ones, especially the solar energy system.

2. RESEARCH METHODOLOGY

The current research used actual experimental data which were collected on September 24, 2023 under the weather conditions of Ras Al Khaimah, UAE. More details are found in [30]. However, the input data used in the proposed model were based on the period from 10:00 am to 4:00 pm, with 360 readings and one-minute intervals between each pair of readings, considering the most productive hours. These input data, which are expected to have a significant impact, include global radiation, relative humidity, and ambient temperature. Such data were collected via the weather station available at RAK Research and Innovation Center (RAKRIC), Ras Al Khaimah, as part of previous work conducted by the same authors. Fluke IRR1-SOL was also used to measure the solar radiation and ambient temperature for verification purposes of the collected readings (refer to [30] and [31]). The detailed steps of the current research are illustrated in Figure 1. As shown in the figure, the research was divided into three major parts: design and data collection, development of a forecasting model, and analysis of results.

2.1. Design of solar photovoltaic system

The photovoltaic module selected in the present study is Solar-module-100W-Mono-CL-100-WM (Figure 2a). This PV module is part of an experimental setup previously built at RAKRIC, Ras Al Khaimah, as shown in Figure 2b. A number of 36 solar cells are serially connected to the specified module. The solar cell produces electricity with a specific terminal voltage and load power directly proportional to the instantaneous global radiation. The ambient temperature inversely affects the generated electricity from the PV module.

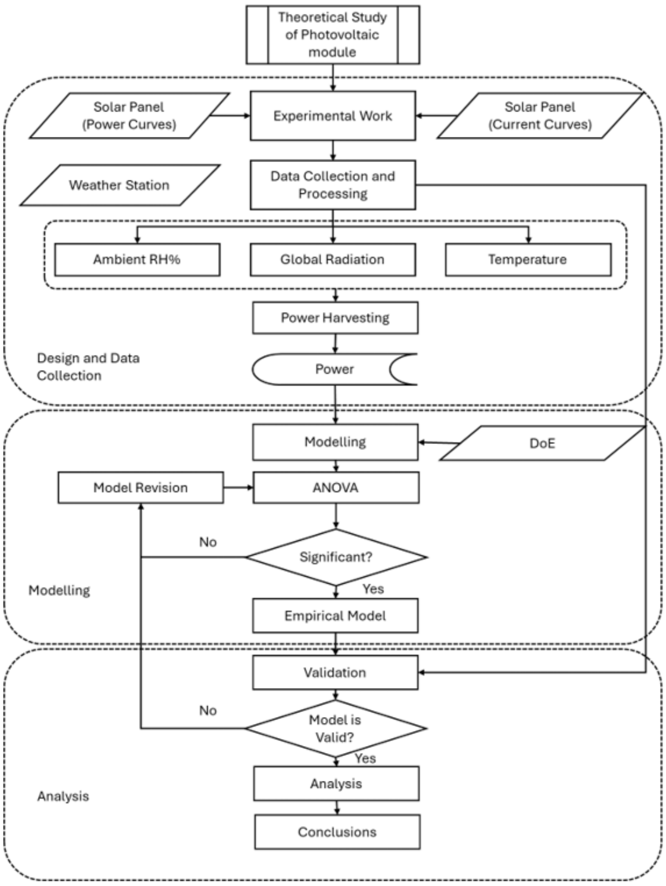


Figure 1. Research flow chart.

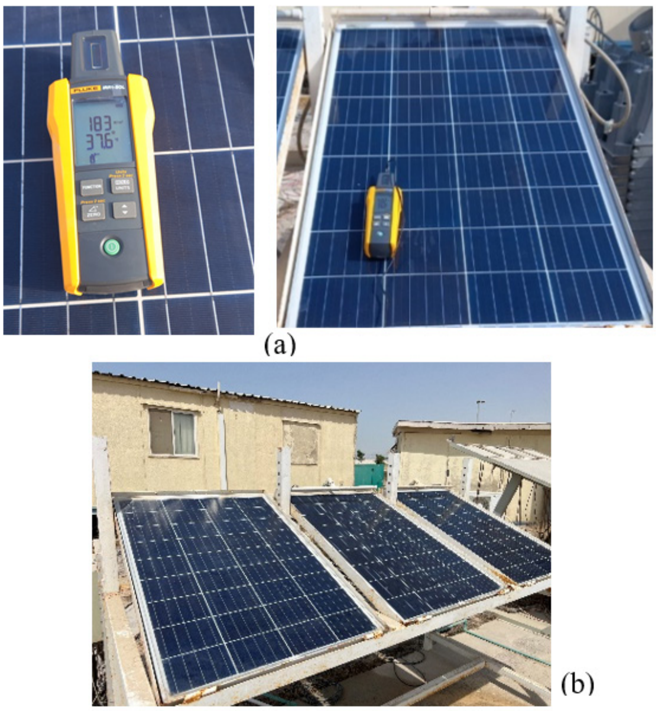


Figure 2. System setup.

The equivalent electrical circuit of a solar cell is illustrated in Figure 3, in which the representation of generated saturation current (I_{sc}), diode current (I_d), diode voltage (V_d), parallel resistor current

(I_p), serial resistor current ($I_{.R.s}$), and load voltage ($V_{.L.}$) all are shown. The equations from (1) to (7) below present the variation effects of the two parameters, namely: the insolation (G) and cell's temperature (T), on the produced current and voltage from a solar cell, as well as the total voltage of serially connected solar cells and the total current of parallel-connected cells. These equations determine the current and voltage and consequently the output power. The characteristic curves can be then obtained for the selected PV module. Equation (1) presents an expression of the output current from a solar cell with respect to the saturation, diode, and parallel resistor currents, respectively. How the saturation current is affected by the instantaneous values of insolation, reference insolation, and PV cell's temperature is given by Equation (2). Equation (3) shows the level of diode current and how it is affected by diode voltage and threshold voltage, whereas Equation (4) demonstrates the value of parallel current which depends on the diode voltage and the shunt resistor. Equation (5) shows the level of output voltage which equals to the diode voltage minus the drop voltage across the series resistor.

Equation (6) determines the total output voltage from serially connected PV cells. It is the summation of all voltages produced from each cell in the string. The total current from parallel-connected cells equals the summation of all cells' currents as given in Equation (7) [30].

$$I_L = I_{sc} - I_d - I_p \qquad ....(1)$$

$$I_{sc} = \frac{G}{G_{ref}}\left(I_{sc\_ref} + K_{SCT}\left(T_c - T_{c\_ref}\right)\right) \qquad .....(2)$$

$$I_d = I_{sat}\left[e^{\frac{V_d}{V_{th}}} - 1\right] \qquad ....(3)$$

$$I_p = \frac{V_d}{R_{sh}} \qquad ....(4)$$

$$V_L = V_d - R_s I_L \qquad ....(5)$$

$$V_{out} = N_s \times V_L \qquad ....(6)$$

$$I_{out} = N_p \times I_L \qquad ....(7)$$

Where I_{sc_ref} is the reference saturation current, G is the insolation, G_{ref} is the reference insolation, N_s is the number of serially connected cells, and N_p is the number of cells connected in parallel.

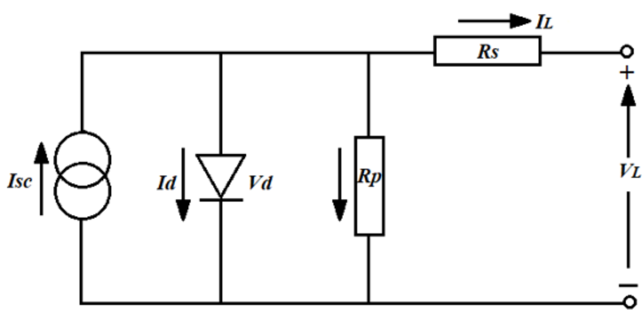


Figure 3. Equivalent electrical circuit of solar cell.

Table 1 lists the characteristics of the selected PV solar-module-100W-Mono-CL-100-WM [30, 32].

Table 1. Characteristics of the selected PV solar-module-100W-Mono-CL-100-WM.

Parameter	Value
Voltage at max. power, V_{MPP}	18 V
Current at max. power, I_{MPP}	5.56 A
Open-circuit voltage	21.6 V
Short-circuit current	6 A
Power at MPP point	100 W
Power temperature coefficient	- 0.23%/°C
Voltage temperature coefficient	- 0.33%/°C
Current temperature coefficient	+ 0.05%/°C
Operating temperature	-40°C to +85°C
Efficiency	18.56%

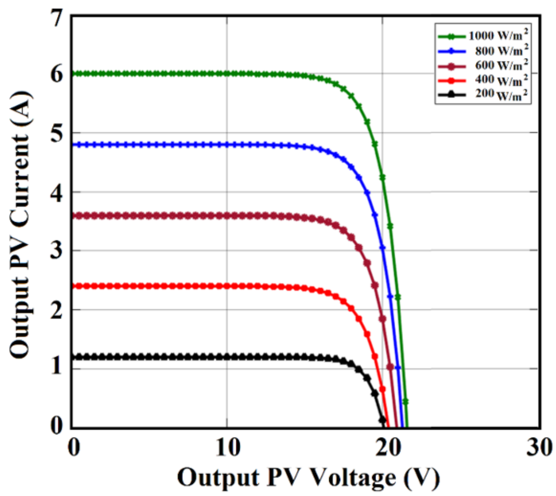


Figure 4. Current curves at different global radiations and fixed cell temperature of 25 °C.

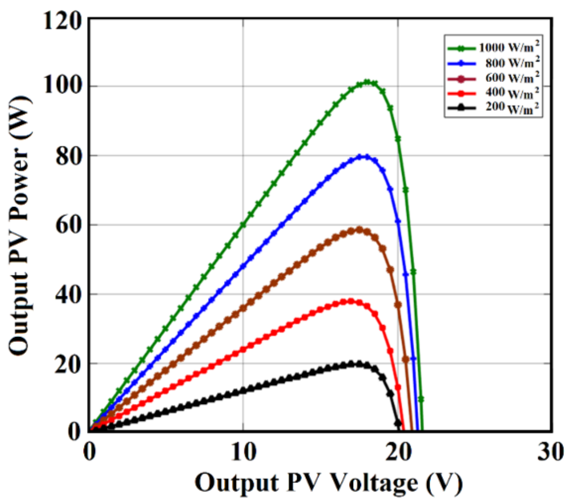


Figure 5. Power curves at different global radiations and fixed cell temperature of 25 °C.

The solar PV module is initially simulated to monitor the current and power curves. The current and power curves were generated at a fixed cell temperature of 25 °C and different global radiations (100 W/m^2, 500 W/m^2, and 1000 W/m^2). The curves were also plotted at a fixed global radiation of 1000 W/m^2 and different cell temperatures (5 °C, 25 °C, and 45 °C). Figures 4 and 5 show the direct relationship between both current and power, respectively, with solar radiation. Figures 6 and 7 show, respectively, an inverse relationship between current and power with the cell temperature.

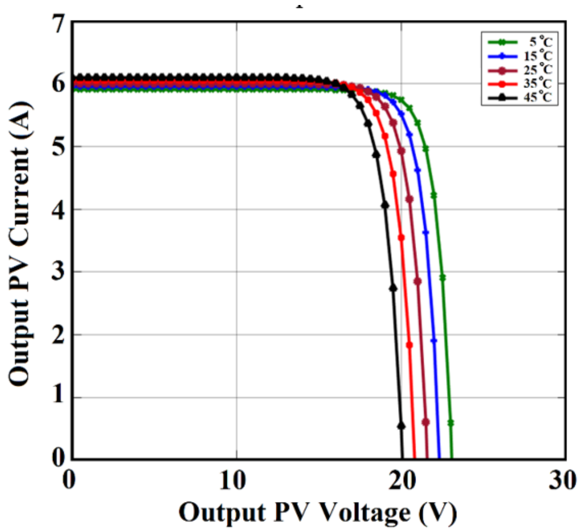


Figure 6. Current curves at different cell temperatures and fixed radiation of 1000 W/m^2.

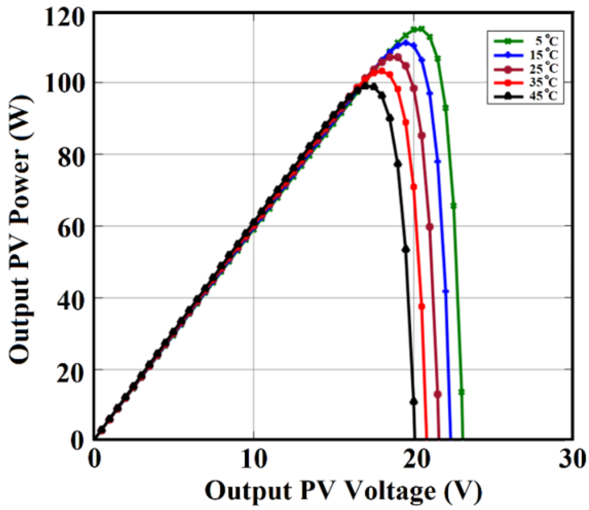


Figure 7. Power curves at different cell temperatures and fixed radiation of 1000 W/m^2.

2.2. Development of statistical model

Analysis of variance (ANOVA) is a statistical method used for multiple data groups to gain information about the relationship between dependent and independent variables. This statistical approach was introduced by Ronald Fisher [33]. The assumptions of ANOVA include normality (data within each group should be normally distributed), homogeneity of variance (equal variances across groups), and independence (observations within each group should be independent). It serves as a critical tool for quality improvement and analysis.

It is one of the most effective approaches in testing prediction models. The Stat-Ese software (version 13) was utilized to develop the predicted model. In addition, it is a powerful parametric statistical approach for evaluating the significance of the means of various independent observation groups. ANOVA was created by, Sir Ronald Fisher, a founder of modern statistical theory, in the 1920s. It evaluates potential differences in a continuous-level (interval/ratio) dependent variable against a categorical-level (nominal/ordinal) independent variable that has two or more categories [34].

2.3. Analysis

Different tools were used to analyze the results: fit summary, coefficient of variance perturbation graph, standard residual plot, and 3D plot.

3. RESULTS

The data used in the proposed model was based on experimental measurements [30]. The data was utilized to develop a new statistical model for predicting the output power of the selected PV panel. The model suggested by the software was a quadratic model; however, it was modified manually by eliminating the significant factors for a better prediction capability. The final ANOVA table is shown in Table 2.

Table 2. ANOVA table.

Source	Sum of Squares	DF	Mean Square	F value	Prob > F	
Model	1.108E+05	5	22153.84	687.89	< 0.0001	significant
A- Global Radiation	31115.40	1	31115.40	966.15	< 0.0001	
B- Ambient R.H. %	1728.99	1	1728.99	53.69	< 0.0001	
C- Temperature	535.91	1	535.91	16.64	< 0.0001	
A^2	1970.52	1	1970.52	61.19	< 0.0001	
B^2	1212.41	1	1212.41	37.65	< 0.0001	
Residual	11400.74	354	32.21			
Cor Total	1.222E+05	359				

The ANOVA table clearly indicates the eliminated factors: AB, AC, BC, and C^2. The Model F-value of 687.89 shows that the model is significant, with only a 0.01% chance that an F-value of such a size could take place as a result of noise. Moreover, the P-values less than 0.0500 for the remaining model terms shown in the ANOVA table are significant. In this instance, A, B, C, A^2, and B^2 are significant model terms. Another test for the model's validity was conducted through the fit summary shown in Table 3. This table presents various metrics including standard deviation, mean, R^2, adjusted R^2, predicted R^2, adeq precision, and variance coefficient.

Table 3. Fit Summary.

Std. Dev.	5.67	**R^2**	0.9067
Mean	68.89	**Adjusted R^2**	0.9054
C.V. %	8.24	**Predicted R^2**	0.9044
		Adeq Precision	82.6519

The predicted R^2 value of 0.9044 shows a reasonable agreement with an adjusted R^2 of 0.9054, indicating that the deviation is less than 0.2. The signal-to-noise ratio is measured by Adeq precision. A ratio above 4 is desirable. The estimated ratio of 82.652 demonstrates an adequate signal. Therefore, this model can be confidently used to explore the design space. Moreover, the coefficient of variance value was 8.24, which is acceptable and reasonable. Based on the above results, the model showed significance with high agreement. Therefore, the statistical model was generated using the DoE software and given in Equation 8.

$$P = -79.4364 - 0.0754x_1 + 6.2722x_2 - 0.3728x_3 + 0.00016x_1^2 - 0.0634x_2^2 \quad ....(8)$$

where x_1, x_2 and x_3 are present global radiation in W/m², R.H. in % and ambient temperature in °C, respectively. P is the output power. The applicability of the developed model is limited to the range of input data. This implies that the model exhibits minimal error when the values fall within the ranges of 423-877 W/m² for global radiation, 24.5-46.5% for relative humidity, and 38-51 °C for the temperature.

The developed model is firstly validated against the actual results of the output power to verify its accuracy. The results obtained from the present model and those from actual experiments are presented in Figure 8. The validation was performed to include data between 10:00 am and 4:00 pm. As it can be seen, both results show a good agreement, with an average relative deviation of about 7.35%. This demonstrates a very reasonable accuracy of the developed model.

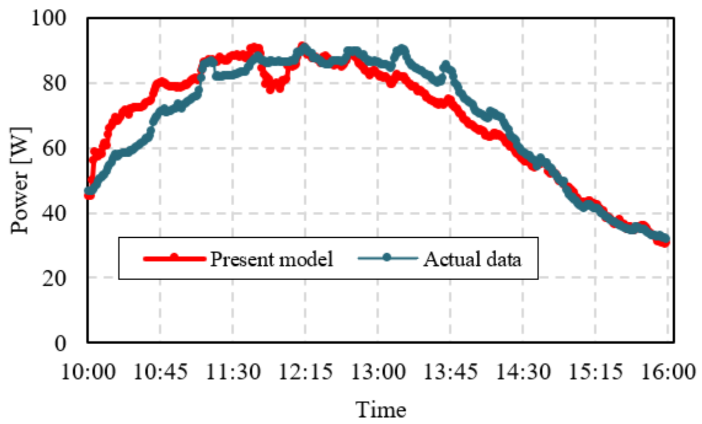
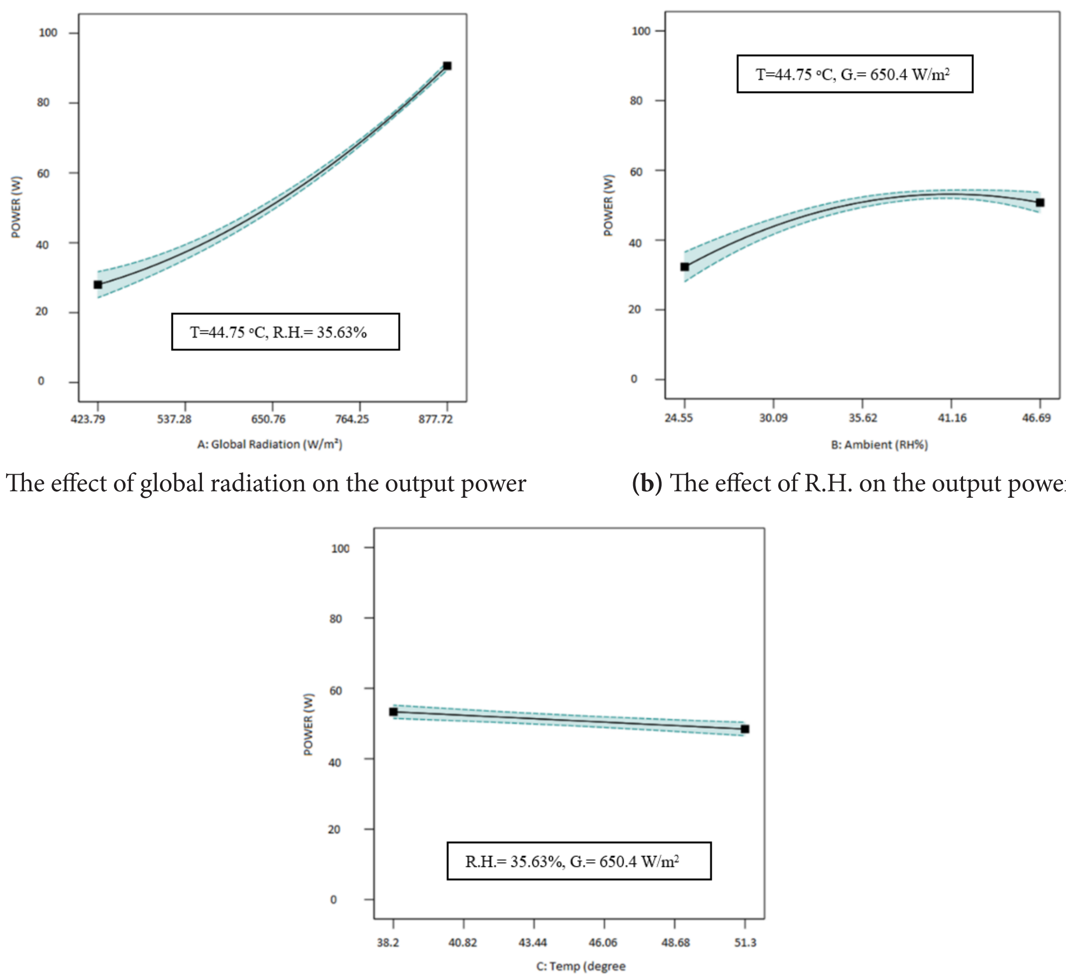


Figure 8. Comparison between present model and actual data.

Although several formulae that relate global radiation to the PV output power can be used, other climatic parameters such as ambient temperature, sunshine hours, and relative humidity are contributed [35]. Therefore, an equation from real data may better predict the power outputs. This is presented in one factor at a time graph (OFAT), which is generated by the software as shown in Figure 9. By default, the graph shows the change of only one factor while keeping other factors as constant with values in the middle point of the design space. Figure 9a shows that increasing the global radiation strongly and positively affects the output power within the range of the design space (423-877 W/m²) while maintaining the R.H. and ambient temperature constant at the 35.63% and 44.75 oC, respectively. Figure 9b presents the output power behavior when the relative humidity changes. In general, there is an increase in the output power when the relative humidity increases. The output power is about 32.2 W when the relative humidity is 24.5%, whereas it reaches approximately 51 W at relative humidity of 46.5%. However, the figure indicates that the model predicts a peak output power of 53 W achieved at relative humidity of 41.1%. In contrast, figure 9c indicates that the ambient temperature negatively affects the output power. As shown in the figure, the power output decreases with increasing the ambient temperature. At constant global radiation and humidity, the output power declines from around 53.4 W to nearly 48.6 W as the ambient temperature increases from 38 °C to 51°C.



(a) The effect of global radiation on the output power **(b)** The effect of R.H. on the output power

(c) The effect of ambient temperature on the output power

Figure 9. The relationship between input and output variables.

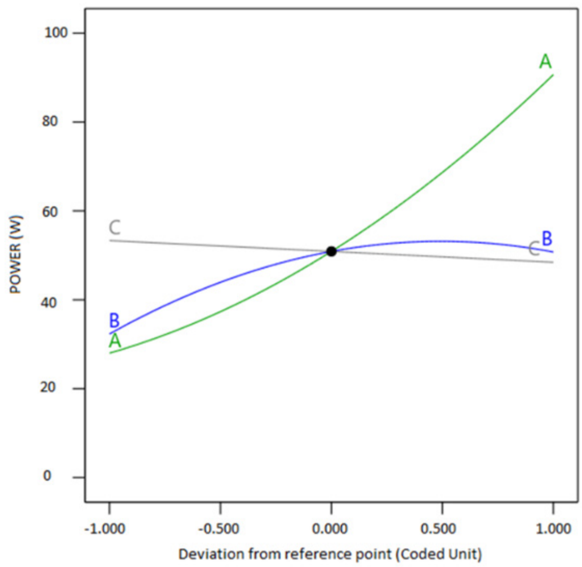
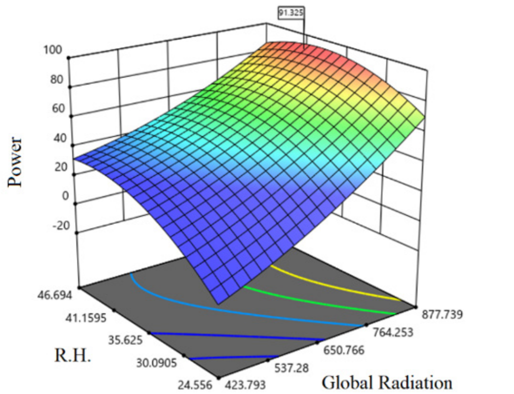


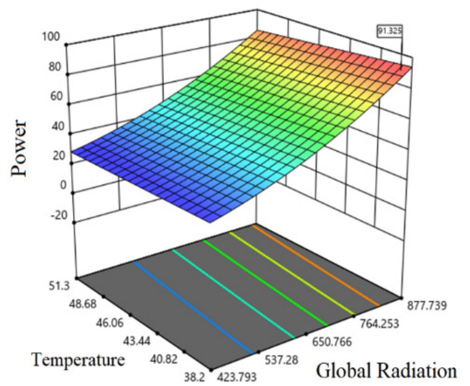
Figure 10. Perturbation Plot.

However, for a better understanding of the integration of the effect of the three inputs on the power output, a perturbation graph has been generated as shown in Figure 10. Such a plot assists in comparing the effects of all investigated variables at a particular point within the design space. Typically, the graph tested the middle level of all input factors. Figure 10 shows the three factors (global radiation of 650.4 W/m^2, R.H. of 35.63%, and ambient temperature of 44.75 ^{o}C). The graph shows clearly that global radiation is the most influential factor on the power that can be harvested from the PV panels, which is aligned with most of the previous research work. The response is plotted by changing only one factor across its examined range, while maintaining all remaining factors constant (State-Ese).

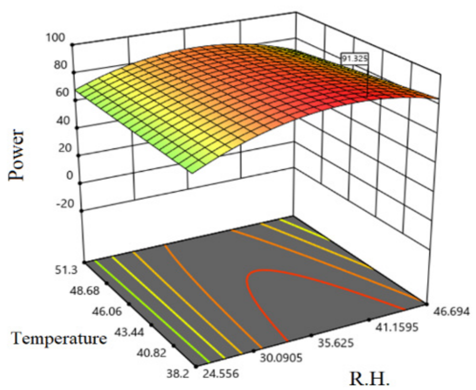
A 3D plot was generated for each two input variables together, providing an additional visual aid for better understanding the various relationships between the input variables and the response (power output), as depicted in Figure 11. This serves as a useful tool for comprehending the interrelation between the investigated variables.



(a) Relationship of global radiation and R.H. on the power.



(b) Relationship of global radiation and ambient temperature on the power.



(c) Relationship of R.H. and ambient temperature on the power.

Figure 11. 3D Plots.

In Figure 11a, the relationships between both the global radiation and relative humidity (R.H.) with the power output are presented. This visualization clearly reveals that the power output increases significantly with increasing the global radiation. The power also increases with increasing the R.H. This indicates a direct relationship of the output power with both the global radiation and R.H., highlighting the impact of these factors on the generated power. Figure 11b demonstrates that the power output increases as the global radiation increases while it decreases as the ambient temperature rises. This indicates a direct proportionality between global radiation and power and an inverse proportionality between ambient temperature and power, emphasizing the impact of these factors on the power production rate. Finally, the impacts of both ambient temperature and the R.H. on the power output are presented in Figure 11c.

This figure illustrates that the power output declines with increasing the ambient temperature whereas it increases as the R.H. rises, highlighting an inverse relationship with the ambient temperature and a direct relationship with the R.H. These figures are aligned with the outcomes presented in the Perturbation Plot shown in Figure 10.

Finally, the normal plot of residuals was created, as shown in Figure 12.

Creating a normal plot of residuals is crucial in validating the accuracy and the normality of the developed statistical model during this study. This graphical representation is instrumental in assessing how the residuals, the differences between the measured values and those predicted by the model, distribute across different levels of the expected values.

The plot compares each data point's residual (its vertical distance from the expected line) to a normally distributed expectation.

Figure 12 demonstrates that the presented data points closely align with the expected normal distribution, indicating the model's strong validity. The range of residuals shown in the figure was from 32.156 to 90.861. In addition, a comprehensive comparison between the measured and predicted values was conducted as demonstrated earlier in Figure 8.

It was found that the average deviation between these two values is only 7.35%, which confirms the model's robustness and reliability in forecasting the power output of solar PV panels under the study's conditions. This analysis reinforces confidence in using this statistical approach to understand and optimize solar PV panels' performance.

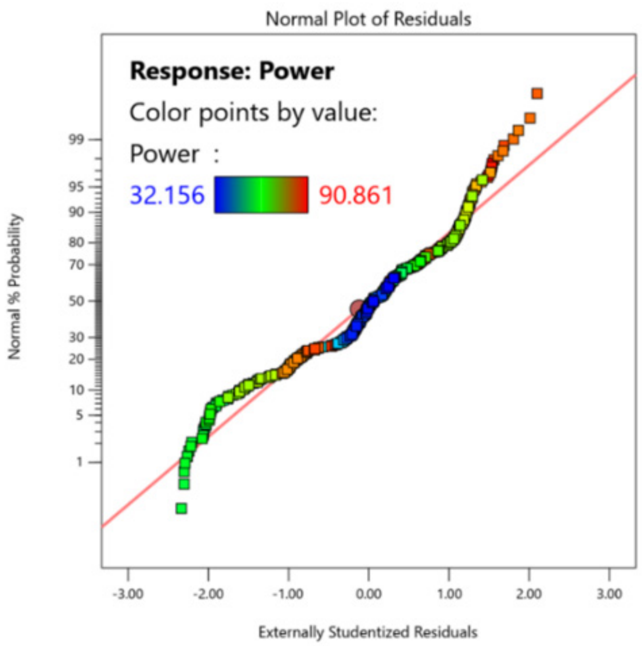


Figure 12. Normal Plot of Residuals.

Comparisons between the present work and previous studies are summarized in Table 4.

The table lists the application along with the approach utilized. The location where the study was conducted, input variable, and the average error are also presented.

Table 4 Comparisons between the present work and previous studies.

Reference	[11], 2023	[12], 2020	[13], 2020	[17], 2013	[26], 2020	Present work
Application	Solar PV system	Solar PV power	Solar PV power	Global solar radiation	Solar PV	Solar PV
Location	UAE	India	Italy, Germany, UK & Belgium	Iran	UAE	Ras Al Khaimah, UAE
Testing period	Short term	Short-term	Long-term	Long-term	Short-term	Short-term
Approach	Fuzzy Logic	ANN	ANN	ANN	RSM	ANOVA & fit summary
Input variables	Light intensity; Ambient temperature; Dust intensity	Different climates: Composite, Warm & humid; Moderate; Hot & dry; Cold & cloudy	Global radiation; Solar azimuth angle; Air temperature; Wind speed	Max, min, mean temperatures; Relative humidity; Sunshine duration; Precipitation	Conduction heat coefficient; Mass flow rate;ZnO volume concentration; Number of tubes	Global radiation; Relative humidity; Ambient temperature
Output variable	Output power	Output power	Output power	Daily global solar radiation	Thermal efficiency; Electrical efficiency	Output power
Software	MATLAB	MATLAB	Not Mentioned	NeuroSolutions 5.0	Not mentioned	Stat-ease
Average error	r = 0.97, = 0.96 Hottel's model = 0.76 Ashrae model	MAPE = 0.0019% - 0.109%	MSE = 0.040	r = 0.968 RMSE =3.09 MAE = 2.57	R2 = 0.9888 for therm. Efficiency = 0.9908 for elec. Efficiency	7.35%
MSE: mean squared error, MAPE: Mean Absolute Percentage Error, MAE: mean absolute error, RMSE: root mean square error, r: correlation coefficient, R2: coefficient of determination.						

4. CONCLUSIONS

This study utilized a statistical approach to develop a mathematical prediction model based on experiment results. Analysis of variance (ANOVA) was the primary tool used in this research. The selected PV module in this study was Solar-module-100W-Mono-CL-100-WM. It has 36 solar cells serially connected to the specified module. Three input parameters were used in developing the model: Global Radiation [W/m²], R.H. [%], and Ambient Temperature [oC]. As conclusions:
1. The global radiation plays a critical role in determining the power output of solar PV panels. This factor is essential for understanding the efficiency and performance of solar energy systems.
2. Analyzing actual data using rigorous statistical methodologies provides a more precise and detailed understanding of the observed phenomena.
3. Adopting a statistical approach to analyze the data yields results with remarkable accuracy, evidenced by a predicted R^2 (coefficient of determination) value of 90.44%. This high R^2 value indicates that the proposed statistical model can explain a significant portion of the variance in the dependent variable.
4. The findings demonstrate a high degree of accuracy in the model's predictions, with an average percentage error of just 7.35% between the actual measured outputs and the
outputs predicted by the present model. This small discrepancy underscores the reliability of the model in forecasting solar PV panels' performance.
5. The analysis determined that the maximum power output achieved was 91 W. This optimum

value signifies the peak performance observed under the specific conditions and parameters of the study.

6. This analysis reinforces confidence in using this statistical approach to understand and optimize solar PV panel performance.

Author Contributions: M.H.: Conceptualization, methodology, formal analysis, writing—original draft, H.A.: writing—review and editing, resources, project administration, validation. K.H.: writing—review and editing, project administration, validation. All authors agreed to publish the current version of the manuscript.

Funding: This work did not receive any external funding.

Data Availability Statement: Data will be available upon request.

Conflicts of Interest: The authors declare that they have no conflict of interest.

REFERENCES

[1] Lo Brano, V., Ciulla, G., and Di Falco, M., "Artificial neural networks to predict the power output of a P.V. panel", International Journal of Photoenergy, 2014, pp. 1–12, 2014.

[2] Statista, "Cumulative installed solar PV capacity worldwide from 2000 to 2022", [Online]. Available: https://www.statista.com/statistics/280220/global-cumulative-installed-solar-pv-capacity/ [Accessed: May 12, 2024].

[3] Khatib, T., Mohamed, A., & Sopian, K., "A review of solar energy modeling techniques", Renewable and Sustainable Energy Reviews, 16(5), pp. 2864-2869, 2012.

[4] Adenle, A., "Assessment of solar energy technologies in Africa-opportunities and challenges in meeting the 2030 agenda and sustainable development goals", Energy Policy, 137, pp. 111180, 2020.

[5] Obaideen, K., Olabi, A., Al Swailmeen, Y., Shehata, N., Abdelkareem, M., Alami, A., & Sayed, E., "Solar energy: Applications, trends analysis, bibliometric Analysis and research contribution to sustainable development goals (SDGs)", Sustainability, 15(2), pp. 1418, 2023.

[6] Obaideen, K., AlMallahi, M., Alami, A., Ramadan, M., Abdelkareem, M., Shehata, N., & Olabi, A., "On the contribution of solar energy to sustainable development goals: Case study on Mohammed bin Rashid Al Maktoum Solar Park", International Journal of Thermofluids, 12, pp. 100123, 2021.

[7] Senthil, R., "Recent innovations in solar energy education and research towards sustainable energy development", Acta Innovations, 42, pp. 27-49, 2022.

[8] Yousef, B., Obaideen, K., AlMallahi, M., Alajmi, N., Radwan, A., Al-Shihabi, S., & Elgendi, M., "On the contribution of concentrated solar power (CSP) to the sustainable development goals (SDGs): A bibliometric analysis", Energy Strategy Reviews, 52, pp. 101356, 2024.

[9] Belgasim, B., Aldali, Y., Abdunnabi, M., Hashem, G., & Hossin, K., "The potential of concentrating solar power (CSP) for electricity generation in Libya", Renewable and sustainable energy reviews, 90, pp. 1-15, 2018.

[10] Elia, A., Kamidelivand, M., Rogan, F., & Gallachóir, B., "Impacts of innovation on renewable energy technology cost reductions", Renewable and sustainable energy reviews, 138, pp. 110488, 2021.

[11] Lurwan, S., Mariun, N., Hizam, H., Radzi, M., & Zakaria, A., "Predicting power output of photovoltaic systems with solar radiation model", In 2014 IEEE International Conference on Power and Energy (PECon), Kuching, Malaysia, pp. 304-308, 2014. doi: 10.1109/PECON.2014.7062461.

[12] Hazza, M., Attia, H., & Hossin, K., "Fuzzy Logic approach based predicting power output of P.V. panel in desert environment", 2023 Advances in Science and Engineering Technology International Conferences (ASET), Dubai, UAE, pp. 1-4, 2023. doi: 10.1109/ASET56582.2023.10180507.

[13] Perveen, G., Rizwan, M., Goel, N., & Anand, P., "Artificial neural network models for global solar energy and photovoltaic power forecasting over India", Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 15(2), pp. 1-26, 2020.

[14] Barrera, J., Reina, A., Maté, A., & Trujillo, J., "Solar energy prediction model based on artificial neural networks and open data", Sustainability, 12(17), pp. 6915, 2020.

[15] Pang, Z., Niu, F., & O'Neill, Z., "Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons", Renewable Energy, 156, pp. 279-289, 2020.

[16] Elsheikh, A., Sharshir, S., Abd Elaziz, M., Kabeel, A., Guilan, W., & Haiou, Z., "Modeling of solar energy systems using artificial neural network: A comprehensive review", Solar Energy, 180, pp. 622-639, 2019.

[17] Yaïci, W., Entchev, E., Longo, M., Brenna, M., & Foiadelli, F., "Artificial neural network modelling for performance prediction of solar energy system", In 2015 International Conference on Renewable Energy Research and Applications (ICRERA), Palermo, Italy, pp. 1147-1151, 2015. doi: 10.1109/ICRERA.2015.7418589.

[18] Ramedani, Z., Omid, M., & Keyhani, A., "Modeling solar energy potential in a Tehran province using artificial neural networks", International Journal of Green Energy, 10(4), pp. 427-441, 2013.

[19] Thulasiram, R., Murugapoopathi, S., Surendarnath, S., Nagappan, B., & Devarajan, Y., "RSM-Based Empirical Modeling and Thermodynamic Analysis of a Solar Flat Plate Collector with Diverse Nanofluids", Process Integration and Optimization for Sustainability, pp. 1-14, 2024.

[20] King, E., Otieno, S., & Standridge, C., "Modeling Solar Energy Data using Periodic Regression", International Journal of Renewable Energy Research (IJRER), 10(3), pp. 1246-1254, 2020.

[21] Patrizi, Z., Karami, H., Golpour, I., Kaveh, M., Szymanek, M., Blanco-Marigorta, A. M., ... & Darvishi, Y., "Modeling and optimization of energy and exergy parameters of a hybrid-solar dryer for basil leaf drying using RSM", Sustainability, 14(14), 8839, 2022.

[22] Haitham, O., Jamel, M., & Ihab, S., "Statistical analysis and mathematical modeling of modified single slope solar still", Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 43(21), pp. 2788-2806, 2021.

[23] Hossain, M., Rahim, N., Aman, M., & Selvaraj, J., "Application of ANOVA method to study solar energy for hydrogen production", International Journal of Hydrogen Energy, 44(29), pp. 14571-14579, 2019.

[24] Samy, M., Almamlook, R., Elkhouly, H., & Barakat, S., "Decision-making and optimal design of green energy system based on statistical methods and artificial neural network approaches", Sustainable Cities and Society, 84, pp. 104015, 2022.

[25] Al-Shamisi, M., Assi, A., & Hejase, H., "Estimation of global solar radiation using artificial neural networks in Abu Dhabi city, United Arab Emirates", Journal of solar energy engineering, 136(2), pp. 024502, 2014.

[26] Rejeb, O., Ghenai, C., Jomaa, M., & Bettayeb, M., "Statistical study of a solar nanofluid photovoltaic thermal collector performance using response surface methodology", Case Studies in

Thermal Engineering, 21, pp. 100721, 2020.

[27] Tahir, M., Tzes, A., & Yousaf, M., “Enhancing PV power forecasting with deep learning and optimizing solar PV project performance with economic viability: A multi-case analysis of 10 MW Masdar project in UAE”, Energy Conversion and Management, pp. 311, 118549, 2024

[28] Hachicha, A., Al-Sawafta, I., & Said, Z., “Impact of dust on the performance of solar photovoltaic (PV) systems under United Arab Emirates weather conditions”, Renewable Energy, 141, pp. 287-297, 2019.

[29] Salimi, M., Hosseinpour, M., & Borhani, T., “Analysis of solar energy development strategies for a successful energy transition in the UAE”, Processes, 10(7), pp. 1338, 2022.

[30] Hossin, K., & Attia, H., “Water-Cooling-Based Approach for P.V. System Performance Enhancement towards UAE Future Energy Efficiency Policies”, International Journal of Energy Economics and Policy, 14(1), pp. 433-440, 2024.

[31] Attia, H., Hossin, K., & Al Hazza, M., “Experimental investigation of photovoltaic systems for performance improvement using water cooling”, Clean Energy, 7(4), pp. 721-733, 2023.

[32] Westech-Solar Energy, “Solar Module 100Wp, 160Wp, 200Wp Mono CL”, [Online]. Available: https://westech-pv.com/WT-Solarmodul-Mono-100Wp-160Wp-200Wp-20V_1 [Accessed: May 15, 2024].

[33] Montgomery, D. C., “Introduction to statistical quality control”. John Wiley & Sons, 2019.

[34] Das, B., Jha, D., Sahu, S., Yadav, A., Raman, R., & Kartikeyan, M., “Analysis of variance (ANOVA) and design of experiments”, In Concept Building in Fisheries Data Analysis, Singapore: Springer Nature, pp. 119-136, 2022.

[35] Ya’u, M., Gele, M., Ali, Y., & Alhaji, A., “Global solar radiation models: A review”, Journal of photonic materials and technology, 4(1), pp. 26-32, 2018.