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Parametric optimization and sensitivity analysis of photovoltaic modules: seasonal performance evaluation and emission reduction for sustainable environment

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ABSTRACT

Solar energy can fulfill global energy demand and improve the environment, economy, and energy security of a country. Solar energy systems are very sensitive to meteorological variables, and they must be optimized for maximum output. This study investigates the effect of WS, T, and RH on the power production of monocrystalline cleaned and uncleaned PV modules during four seasons. Regression analysis determined the importance of parameters using p-value and t-statistic. To maximize power generation, GA optimization and sensitivity analysis were used. T has a p-value below 0.05 and a t-statistic value over $|\pm 1.96|$, which shows that it is a crucial parameter for optimal module performance. For spring, summer, monsoon, and winter, clean module power production was 41 W, 48.19 W, 40.62 W, and 37.16 W, respectively. The optimal power output for the unclean module was 24.61 W, 35 W, 31.66 W, and 6.43 W for spring, summer, monsoon, and winter, respectively. In the monsoon season, an increase in T by 25 % lowered the power output by 81 % for clean and 87 % for unclean modules, the largest decline of all seasons. The winter season had the lowest power production, 42 % for clean and 13.3 % for unclean modules when a 25 % change in T was considered. CO_2 emissions for modules reached the highest value in summer and dropped in winter. Similarly, seasonal revenue is highest in summer and lowest in winter because of more operating hours in summer and vice versa.

1. Introduction

Almost every country is facing multiple issues related to power production and distribution. Pakistan faced a severe energy crisis over the past decade which disturbed its economic progress. According to a report from the World Bank in 2022, Pakistan's GDP will decrease up to 20 % in 2050 due to severe climate change [1]. After the industrial revolution, the increased dependence on fossil fuels for materialistic development has not only led to their depletion but it has also increased the threats of global warming and climate change, which ultimately results in rising sea levels, increased floods, droughts, and unpredicted rain patterns. Pakistan is one of the countries where solar energy is abundant almost throughout the year as it experiences a prolonged summer season and a relatively shorter winter season [2]. The generation of power through solar technology is dependent on the weather and climatic changes, and its output may vary with changes in ambient T,RH, and WS. At the end of 2030, renewable energy will account for 30 % of Pakistan's energy production, up from 20 % in 2025, following the implementation of an alternative renewable energy policy in 2019 [3]. Pakistan is already on the way towards power generation using solar energy. The development of a 1000 MW solar energy-based power plant in the first phase and an additional 900 MW in the next two phases in Bahawalpur are pieces of evidence of the implementation of the renewable energy policy, which was introduced in 2006 [4].

Solar energy is the most sustainable source of power production. It is estimated that the sun is irradiating the earth with four million exajoules of energy, out of which 14×10^4 EJ can be utilized for solar energy production [5]. Compared to other renewable energy sources like biomass and geothermal, solar energy has the potential to meet global

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Nomenclature

Acronyms

PV	Photovoltaics
GA	Genetic Algorithm
CSP	Concentrated Solar Power
R	Correlation coefficient
GHI	Global Horizontal Irradiance
T	Temperature
WS	Wind Speed
RH	Relative Humidity
CO_2	Carbon dioxide

power production demand, as geothermal energy harvesting is location-dependent and biomass is not readily available everywhere [6]. Solar energy can be generated through solar cells and CSP. As PV module systems have better conversion efficiency and low levelized cost as compared to the CSP, these systems are the ideal candidates for electricity generation because of cost-effectiveness, advanced technology, reliability, and non-greenhouse gas emissions [7,8]. The development of a PV system requires a profound understanding of the sun spectrum and various meteorological factors that affect the capacity of PV modules [9]. Site selection, temporal performance, and annual power output are the basic parameters that must be considered before the installation of a PV project [10].

Many studies have reported the optimization and sensitivity analysis of solar photovoltaic cells. Asim et al. [11] suggested the mathematical models for the T of solar cells, solar irradiation, and design of absorbers for optimization of cooling system for hybrid solar panels using MATLAB and validated the results by using fluid-simulation interaction. This study concluded that when the module T reached 65.86 °C, the efficiency of the PV module dropped to 15.65 %, while in comparison to a water-cooling system, air-based cooling increased the power output and efficiency by 14 %. Sattar et al. [12] used a computational model for a monocrystalline PV module in Lahore and found that by using water as a coolant, T uniformity is achieved, along with higher efficiency and power output. The results of this work showed that the maximum cell T in the designed cooling system was 38.810 at 0.092 m/s wind velocity. Tahir et al. [13] examined the impact of weather variables on the performance of five PV module technologies for different climate conditions and suggested that copper–indium–gallium–selenide has a higher efficiency than others, and the performance of PV modules does not remain same all the time due to environmental stresses. Mughees et al. [14] investigated the effect of physical and climatic factors on the output of PV modules in Pakistan. This study concluded that the power-voltage curve decreases when irradiance decreases and when T surpasses 40 °C, it makes the solar cells least efficient. Yaghoubirad et al. [7] performed a multi-criteria analysis including economic, exergy, and energy analyses for PV systems to understand the effect of the environment on the PV modules. It was suggested that Portland and Chicago had the climates that were best suited for the optimized PV systems with fewer environmental problems. Chantana et al. [15] used regression analysis by utilizing meteorological parameters to comprehend the degradation time and output of the different types of PV modules. The estimation of energy generation in a lifetime of modules roughly came out to be 20–25 years. This study showed that a term of time is crucial for sc-Si, a-Si, and tandem PV modules when degradation with time was considered but this is not true for mc-Si PV modules. Ahmed et al. [16] performed experimentation to study the effect of cooling, wind velocity, and dirt accumulation on PV output in a humid condition. The outcome of this study showed that dirt deposition (42 g) decreased efficiency from 46.81 W to 21 W, while wind velocity (5 m/s) increased the output from 14.8 % to 16.5 %. Kaya et al. [17] used multivariate linear regression to examine the impact of climatic and operational factors on the efficiency of PV modules. This study yielded results of regression close to one which suggested that all the parameters mentioned in the study such as WS, temperature,RH, and fill factor have a strong influence on the output of PV cells. Mustafa et al. [18] investigated environmental effects on the performance of solar PV systems. The effect of four parameters; dust, bird's dropping, water droplets, and WS were observed by measuring the output current and voltage. This study concluded that dirt accumulation decreased the power output by 8.8 %, the WS enhanced the power output by 5.6 %, and birds dropping decreased the module's output by 7.4 %. Pepple et al. [19] observed the effect of temperature, RH and solar radiations on the power output in Port Harcourt. The outcome of this study showed that increment in solar flux and decrease inRH increased the efficiency of PV cells and it drops with increase in operating temperature. Eldin et al. [20] investigated the effect of ambient temperature on various PV cells in Egypt. Results indicated that with the increase in ambient T the efficiency of all types of cells dropped. This research concluded that for locations where ambient T reached more than 40 amorphous thin film type PV modules are better, while for Ts less than 30 monocrystalline PV modules are suitable. Mousa at el. [21] conducted sensitivity analysis and multi objective optimization keeping three objective functions, which were performance, emissions and cost of energy for a combined photovoltaic and solar collector systems for industrial roof tops. Results indicated that the mix of technologies improved all the previously mentioned objectives when compared to the systems considered individually. This study concluded that the mix of technologies in parallel setup improves performance to about 35 % as compared to solar thermal alone and 21 % when compared with Photovoltaics alone. Many of these studies discussed the influence of meteorological parameters on the power output and energy generation optimization. Some for these discussed the sensitivity and cost-benefit analysis for PV modules. However, there is a need of comprehensive study that combines the optimization technique, sensitivity analysis and enviro-economic evaluation to comprehend complex relations between weather variables and power output of module, efficiency improvement and T control with summarization of environmental and economic findings.

A small-scale PV systems in Pakistan lose about 12 % of their yearly revenue because of soiling contamination alongside T variations. The country aims to reach 30 % renewable electricity supply during 2030 while its PV capacity needs to grow by 9 GW across regions with similar climates as Lahore. Several researchers agree that combined studies connecting seasonal meteorological data with cleaning methods and cost models for monocrystalline modules remain insufficient. An integrated approach linking optimisation with sensitivity analysis and energo-enviro-economic assessment allows for energy restoration at 8 to 15 % levels and 0.4 kg CO_2 emission reduction for each kilowatt-hour thus having significant importance for operators and policymakers within the field. The national energy crisis in Pakistan continues to escalate as demand for electricity increases while renewables stand as a solution to achieve their national energy targets. According to the Alternative and Renewable Energy Policy 2019 Pakistan plans to obtain 30 % of its electricity from renewable sources by 2030 while solar power will have a central role because solar irradiance in the country reaches 5.3 $kWhm^{-2}day^{-1}$ [22,23]. Solar PV systems remain susceptible to substantial alterations due to environmental factors in their operational areas. The energy production of PV systems reduces by 10 to 20 % annually due to soiling in regions experiencing extreme dust like Lahore while high Ts exceeding 40 °C decrease efficiency by 0.3 to 0.5 % per degree Celsius [24,25]. Research focused on T effects,RH, and soiling exists independently but lacks a complete analysis which integrates clean and unclean seasonal assessments with optimizers and sensitivity models and environmental-economic assessments for Pakistan's semi-arid climate zone [21,26]. PV systems face deteriorated performance along with financial setbacks because of neglecting these combined effects which work against renewable energy targets [27].

In the present study, regression analysis is performed to observe the relation of three parameters; WS, T, and RH with the power output of mono-crystalline solar panels in both cleaned and uncleaned conditions. An algorithm is utilized to find optimized value of power output, along with sensitivity analysis of the three prior mentioned parameters. Regression analysis is well suited when we are required to predict the solar power output with maximum accuracy, as it takes into consideration the unpredictable influence of climatic conditions on PV power generation [28]. Furthermore, regression analysis serves as a powerful tool for examining the relationship between solar power generation and meteorological variables [29]. Accurate optimization of power output from solar power systems allows power plant operators to effectively manage load demand and reduce system uncertainty [30].

This study aims to find the optimized values of weather variables for maximum power output of cleaned and uncleaned modules and responsiveness of power with the percentage change in variables across seasons. It also discusses the environmental contribution of modules in terms of CO_2 emissions, as well as the cost-effectiveness of PV modules. The study is significant in designing the solar power system, which is compatible with seasonal variations and contributes substantial knowledge to the field of renewable energy.

2. Materials and methods

2.1. Experimental setup

For the experimental setup, one monocrystalline solar panel was kept clean in a specific study period, and the other was kept unclean. Monocrystalline modules were used because they have the highest commercially available conversion efficiency and the lowest negative T coefficient; thus, the monocrystalline technology is the most sensitive and best suited for use in the presented seasonal optimisation investigation. Furthermore, monocrystalline panels form over 70 % share for new systems in Pakistan which increases the practical oriented value of the study. They also maintain well-developed performance databases within which can be derived, degradation and lifecycle emission matrices that are crucial in our energo-enviro-economic analysis.

The present study was designed to allow high resolution monitoring of a comparison between one clean and one unclean photovoltaic module under identical conditions. Further increasing modules number would improve statistical robustness, yet several previous studies showed that studying a single clean and a single soiled module is enough to identify soiling effects, seasonal performance variations, and the effects of environment on PV output. Mani et al. [31] performed a very comprehensive soiling impact study using only one clean and one soiled module in desert operation. Sayyah et al. (2014) [24] also based their soiling loss modeling on data obtained from single-module comparisons. A comprehensive review carried out by Sarver et al. [32] had most of the studies relying on single or two-module setups for clean PV modules and dust accumulation assessments and their effect on PV performance. Adinoyi et al. [33] studied the effects of environmental parameters on PV efficiency by using an experimental setup of only one module at a time. Also, Kimber et al. [34] showed that detailed monitoring of individual modules can detect key degradation and soiling behaviors with very high fidelity. Hence, it is methodologically justified to use one clean and one unclean module to evaluate the objectives of this study.

The technical details of the modules are displayed in Table 1. The experimental site for this research was located in Lahore Pakistan which lies between 31.5°N, 74.3 °E at 214 m above sea level. The experimental setup operated within the city at a distance of 12 km from the main observation station of the Pakistan Meteorological Department. Lahore contains no significant height differences as a flat urban area so meteorological data obtained from this region proves suitable for experimental site needs. The annual mean T in this region reaches approximately 24 °C although the summer months frequently reach Ts exceeding 45 °C from May to June and winter Ts occasionally drop to 2 °C during December and January. Monthly rainfall amounts to 715 mm whereby 65–70 % occurs in July through September while the other months experience dry conditions with dust. The annual regional average of GHI reaches 5.3 kWh m^{-2} day^{-1} which produces approximately 2,800 sunshine hours for the year. The dominant WS during non-monsoon months registered at a low level (2 m s^{-1}) while blowing from the northwest direction. The place and weather conditions at this location create varied hot and moist conditions alongside windy and soiled conditions allowing PV performance testing throughout different seasons.

Table 1
Specifications of PV modules used in the study.

Power capacity	150 W
Maximum Voltage	30.32 V
Maximum Current	9.12 A
Dimensions (L × W × H)	1480 × 680 × 40 mm
Number of cells in series	36
Cell dimensions	156 × 156 mm
Efficiency	16–17 %
T coefficient	−0.45 % per °C
Fill Factor	80 %

The modules were installed permanently onto ground-rack infrastructure at the test facility. The experimental setup received a tilt of 31 ± 1° parallel to the local horizontal thus achieving maximum annual radiation through south orientation at 180 ± 2° azimuth. The lower end of the array frame elevated 1.2 m above the roof while the array kept a 15 cm gap behind for passive cooling. A spacing of 0.5 m separated the two similar modules while one remained clean and the other accumulated natural environmental dirt as part of the experiment. The measurement area received no shading during both sunrise and sunset throughout the entire testing period.

Each module received dry-wiping of a standard 10 cm × 10 cm test area followed by a conversion of weight into grams per square metre for tracking cleanliness measurements. A minimum dust load threshold of ≤ 0.5 gm^{-2} served to designate the clean module while personnel cleaned the panel surface with de-ionised water twice a week to avoid exceeding this cleanliness mark. The unclean module did not undergo any cleaning steps while its dust accumulation was quantified using the same gravimetric patch method that took place weekly. During the study period the unclean module accumulation rates amounted to 3.8 gm^{-2} in the spring, 5.1 gm^{-2} in summer and 4.4 gm^{-2} in the winter months while monsoon rains washed away 2.0 gm^{-2} of dust.

The study collected 10,224 records from all measured variables across one year from 1 November 2014 to 31 December 2015 with readings taken once per hour. The duration of one hour signifies the lowest measuring period within this research framework. A robust 10,224 time-stamped records were divided into the seasonal periods of spring (1,416 observations) and summer (2,184) along with monsoon (2,208) and winter (4,416) for statistical analysis purposes.

After collecting the required data for various seasons during the year, the data was imported into MINITAB statistical software to develop a relationship between power, which was considered as a response variable, and the other three variables were used in the study as independent variables.

The measurement equipment received factory-calibration as the first step before its field deployment. Module temperature was measured using a factory-calibrated Pt-100 resistance thermometer (4-wire transmitter, Omega; accuracy ± 0.5 °C, as presented in Table 2). Measurements were initially recorded at one-minute intervals and subsequently averaged to hourly values using trapezoidal numerical integration, consistent with the procedure applied to pyranometer measurements. A 4-wire Pt-100 RTD was preferred over traditional K-type thermocouples due to its superior absolute accuracy, lower susceptibility to lead-wire resistance, and reduced long term drift, making it more suitable for PV module surface temperature measurements

Table 2
Specifications of equipment used to measure weather variables.

Parameter	Equipment	Manufacturer	Accuracy
GHI	Pyranometer	Kipp & Zonen	± 2 %
Module T	4–wire transmitter	Omega	± 0.5 °C
RH	CapacitiveRH–T transmitter	Vaisala	± 3 %
WS	Three–cup anemometer	NRG Systems	± 0.1 ms^{-1}
Voltage and current	Multimeter	Fluke	± 0.025 % for both current and voltage
Power	Digital wattmeter	Yokogawa	± 0.1 %

[35,36]. The temperature sensors and data acquisition system were factory-calibrated and periodically verified under field conditions to maintain measurement reliability. The capacitive probe measured RH within ± 3 % RH accuracy and the WS anemometer functioned with ± 0.1 m s^{-1} or ± 2 % of reading accuracy with the electrical power measurement conducted through a class-1 digital wattmeter with ± 1 % of reading accuracy. The WS sensor installed at 2 m above rooftop level and 4 m above ground level aimed to operate in natural airflow conditions outside nearby structures. Following Banda et al. [37] The accuracies provided by the manufacturer (Table 2) were converted to standard uncertainties by considering the rectangular distribution, and the resulting values were merged to obtain the combined standard uncertaint. Expanded uncertainties (k = 2, ≈95 % confidence) are reported for the principal measured quantities. Bases on the instrument specifications (GHI ± 2 %, Module T ± 0.5 °C, RH ± 3 %, WS ± 2 %, Power ± 0.1 %) provided in the Table 2, the module-temperature accuracy was converted to a relative value using a representative operating temperature of 315 K, the resulting combined standard uncertainty was obtained as 2.38 %, corresponding to an expanded uncertainty (k = 2) of 4.76 %. The largest contributions to the combined uncertainty arose from RH, WS, and irradiance.

The assessment of analytical uncertainty was conducted by statistical tests on the non-linear regression model. The statistical data from the four seasonal datasets produced R values ranging from 0.87 to 0.94, with p values below 0.05 supported by absolute t statistics above 2. The equipment used in the study is listed in Table 2.

A Kipp & Zonen CMP 11 secondary-standard pyranometer served to detect solar radiation (spectral range 285–2800 nm) with a sensitivity of 7–14 μV W^{-1} m^2 and a reading accuracy of ± 2 % of reading. The pyranometer sensor received installation placement on the same solar module surface at 31° elevation and facing due south. One-minute signals from the sensors were integrated using the trapezoidal rule to determine hourly values which then became the basis for calculating daily insolation values (kWh m^{-2}). The PV system received annual factory calibrations together with bi-quarterly field tests with reference cells to verify the drift stayed under 1 % (Fig. 1).

2.2. Statistical analysis

Sensitivity analysis is a methodological approach in which key input parameters are systematically varied to evaluate their effects on the output of the model. In this study, a sensitivity analysis was performed to assess the photovoltaic performance. Every key parameter varied within realistic range by keeping other parameters constant, and the subsequent change in PV output was observed. This technique identifies the factors that have greater influence on the output of PV. This technique also helps to evaluate the robustness of model's prediction by demonstrating the translation of uncertainty of every input parameter to the output of the model.

Regression equations derived from the technical requirements of the modules showed the relationship between the dependent and independent variables. Kim et al. [38] also used the correlation method for the prediction of PV performance by considering environmental variables. The independent-dependent connection was estimated using regression analysis; the analysis was used for forecasting and to develop the correlation between variables..

The non-linear regression algorithm was applied after observing non-linear scatter patterns between power output and the meteorological variables (GHI, T,RH, and WS) to accurately represent the power output and meteorological variable relationship. The reliability of the fitted model was examined through the standard statistical diagnostics of p–values, t–statistics, and R-value.

The variables in multiple regression are correlated as shown in Eq. (1)

$$P_i = \beta_o + \beta_1 X_{i1} + \beta_2 {X_{i2}}^2 + \beta_2 {X_{i2}}^3 + \cdots + e_i \tag{1}$$

e_i is the statistical error for the i^{th} observation and this equation assumes that all the variables are independent of each other. The multiple regression equation represents the dependent variable as sum of intercept and influence of each parameter along with the error term. Different statistical parameters were considered to check the relation of dependent variables with independent variables. The R-square value plays an important role in determining the fitness of a linear model to the data, and higher values mean better prediction [39]. P-value lower than the confidence interval (0.05 used for analysis) exhibits that the null hypothesis can be rejected. In other words, it shows that changes in predictors contribute to changes in the response variable [40]. t-statistics value also helps to understand the likelihood of the influence of the

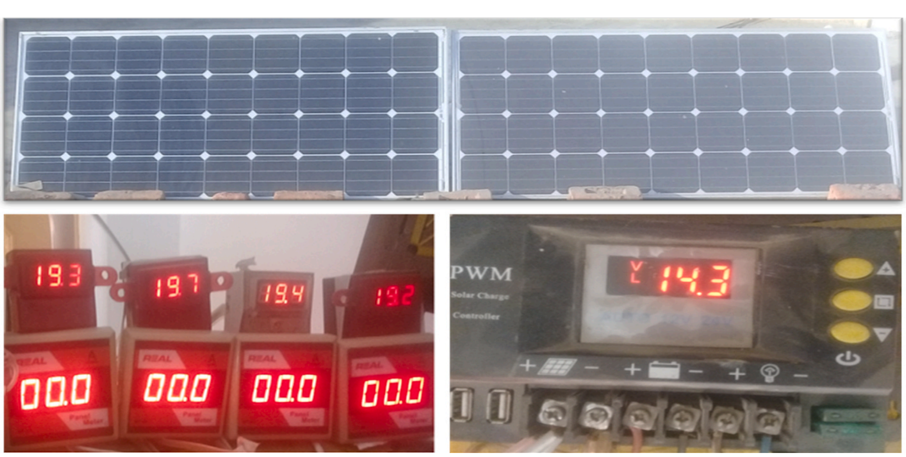

Fig. 1. Cleaned (Left) and uncleaned (Right) PV modules used in the experimental setup.

variable on the output. t-statistics value could be calculated by Eq. (2) for the hypothesis testing:

$$t = \frac{\overline{X} - \mu}{\frac{s}{\sqrt{n}}} \tag{2}$$

In Eq. (2), $\overline{X}$ Represents the average of the sample, μ the average of the population, s the standard deviation, and n the total number of observations used for comparison. The t-statistic value provide information on whether the effect of independent variable is statistically significant or not.

The experimental data was then incorporated in MINITAB and a regression analysis was used to investigate the effects of each independent parameter on a dependent parameter, and a subsequent equation was obtained along with other statistical parameters. After obtaining the equations using linear regression, MATLAB was employed to optimize the data and find the optimized values for each data set using GA.

2.3. Genetic algorithm

The use of GA for power output optimization has also been reported in the literature. Ismail et al. used the optimization ability of GA for the PV module and compared the output of the model with a data sheet that was based on the experimentation [41]. Zagrouba et al. [42] presented a numerical method based on GA to test variables such as current, voltage, and resistance for PV modules and solar cells. The purpose of this optimization was to find the optimal conditions under which the module gave maximum power output for each data set. The total number of variables needed to be defined along with the higher and lower data boundaries, which are 'highest' and 'lowest' values of the variables. According to the statistical relations between the dependent and independent variables calculated from regression equations, optimization resulted in the optimum values for each independent variable. Eq. (3)–(9) shows the step-by-step procedure followed by GA to find the optimum values for each variable:

$$P_{max} = f(X_{i1}, X_{i2}, \cdots\cdots\cdots, X_{in}) \tag{3}$$

$$X_i = (X_{i1}, X_{i2}, \cdots\cdots\cdots, X_{in}) \tag{4}$$

$$fit(X_i) = P_{max}(X_i) \tag{5}$$

$$P_{Selected}(t) = Select(P(t), fit) \tag{6}$$

$$X_{Child} = Crossover(X_{parent1}, X_{parent2}) \tag{7}$$

$$X_{Mutated} = Mutate(X_{Child}) \tag{8}$$

$$P(t+1) = Replace(P(t), P_{Selected}(t), P_{child}(t)) \tag{9}$$

GA algorithm starts by randomly selecting the set of initial population from the data as presented in Eq. (3). Eq. (4) determines the expected power output, and each parameter is scored by using this equation. The parameter with better fitness represents the most significant parameter to achieve maximum power output. Eq. (6) shows the selection criteria of GA and a probability term is assigned to the each solution corresponding to its fitness value. Eq. (7) represents the mutual information sharing between two parent solutions and create new offspring. Eq. (8) provides the details that how a set of variable are combined. The convergence of results of GA is represented by Eq. (9) in which GA stops iterations when optimum value of parameter is reached. GA randomly selects the initial population of observations and makes iterations for the potential output. The fitness function helps to identify the quality of power output, which depends on the variables. A pair of power values are selected to contribute to sharing their properties to develop a new generation of values through uniform crossover. The created set of power values undergoes mutation, with small changes in their characteristics. GA halts when the convergence happens in the results of the fitness function and optimum values of variables for maximum power output (Fig. 2).

2.4. Sensitivity analysis

In MATLAB, sensitivity analysis was performed by changing each parameter from 5 % to 25 %, and a response to power output was observed. During analysis, two of the parameters were kept constant, and a change in power output for a change in one parameter was considered at a time. Eq. (10)–(13) are completely conceptualizing the mathematical form of sensitivity analysis. Eq. (10) is the regression equation for this study, consisting of three variables. For the analysis, Eq. (11)–(13) shows the variation of one parameter while keeping the other parameters constant. This analysis helps to comprehend the impact of the most important parameter on power output which in turn helps to optimize the system and performance prediction [43].

$$P_i = \beta_o + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + e_i \tag{10}$$

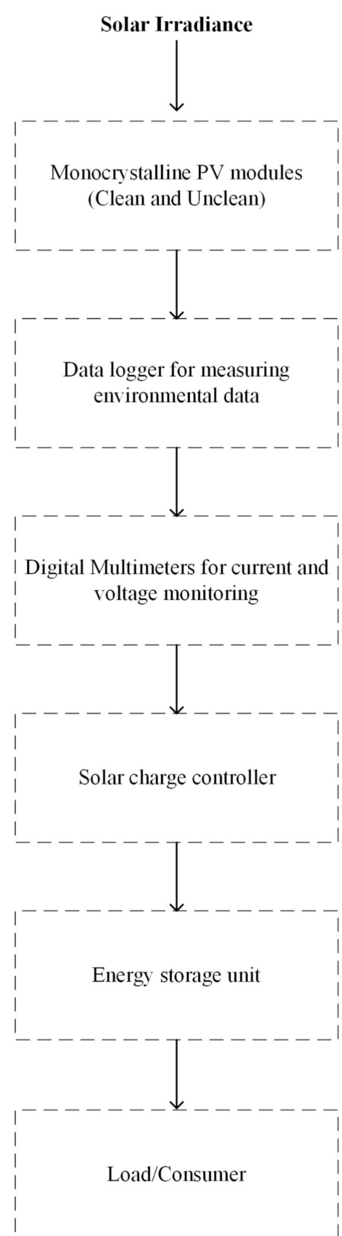

Fig. 2. Single line diagram of experimental setup.

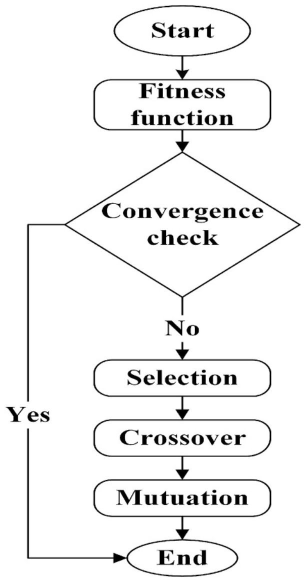

Fig. 3. General scheme of Genetic algorithm.

$$P_i = \beta_o + \beta_1 X_{i1} + C_o \tag{11}$$

$$P_i = \beta_o + \beta_2 X_{i2} + C_o \tag{12}$$

$$P_i = \beta_o + \beta_3 X_{i3} + C_o \tag{13}$$

Eq. (10) shows the regression equation with three variables present in the experimental data relating to the power output. Power output is represented as function of single variable in Eq. (11) while keeping the other variables constant. Similarly, Eq. (12) and (13) represent the power output as a function of second and third variable by keeping all other variables constant.

2.5. Energoenviro-economic analysis

During the installation of a PV system, the main concern is always about the system's energy output, its emissions throughout its lifespan, and its potential savings over time. Policymakers and investors can gain a comprehensive understanding of the feasible risks and returns through analysis based on these metrics. Dust accumulation on the module significantly reduces its output. Eq. (14) can be used to calculate the effect of dust on module efficiency.

$$\eta_{unclean} = \eta_{clean} \times (1 - D) \tag{14}$$

where D is the degradation factor. During normal operation of modules, the degradation factor could be up to 0.75 % [44]. This equation relates the efficiency of unclean module with clean module through a degradation factor and gives a way to get power loss due to dust accumulation.

Energy loss because of lack of cleaning is calculated from Eq. (15) by considering the difference in power output of clean and unclean modules (ΔP) and annual number of operation hours (H). In this analysis, 2000 operational hours were considered for the module. $\in_{loss}$ is the decrease in the power output of the module due to dust which is required for long term performance and maintenance needs.

$$\in_{loss} = \Delta P \times H \tag{15}$$

Revenue generated from the PV system could be determined by the following relation

$$\gamma = P \times t \times C \tag{16}$$

Where t is the operation time and C is the cost per unit of electricity which was 0.071 $ for this analysis [45]. Eq. (16) gives a description of finances for PV output hence helps to estimate the savings for solar power generation. Carbon emission from the module will give a perspective of environmental concerns associated with the usage of PV systems. Eq. (17) provides information about the released emissions from the module:

$$X_{CO_2} = y_{CO_2} \times P \times t \tag{17}$$

where X_{CO_2} is the amount of CO_2 emissions generated annually and y_{CO_2} is the quantity of carbon dioxide emission. Eq. (17) give result of carbon footprint during production of module and operating hours. This helps to understand the ecological changings by quantifying the carbon emission.

For the production of modules; normally 29–35 g of carbon emission is added to the environment per year [46]. In this analysis, 32 g were considered. Lifecycle evaluation assessment of the module is performed based on carbon footprint and to decide on sustainable energy projects, energy analysis is required along with the environmental risks of PV modules. The following equation is used to analyze the cost of carbon footprints for cleaned and uncleaned PV modules:

$$C_{CO_2} = \tau_{CO_2} \times X_{CO_2} \tag{18}$$

where τ_{CO_2} is the reduced price of CO_2 emissions per ton of CO_2 and C_{CO_2} Is the ecological cost-saving factor. Eq. (18) is necessary to use because it tells how much money could be saved by keeping the module clean.

3. Results

The subsequent portion provides the findings derived from our analysis. This section explains how environmental elements affect the performance of both clean and unclean modules.

3.1. Statistical significance

The research conducted statistical significance analysis through regression techniques to quantify the influence levels of environmental elements. The evaluation utilized statistical regression methods to provide quantitative measurement of the effects these environmental factors have on PV system output.

3.1.1. Spring season

A clean PV module in spring season generates energy output based on a 0.25 correlation with WS, a 0.73 correlation with T, −0.82 correlation withRH, and a 0.99 correlation with GHI. The results revealed that WS had an R-value of 0.29 while T exhibited an R-value of 0.76 andRH showed a value of −0.84 for the unclean PV module. The R-value of GHI for unclean module also showed a strong correlation with value of 0.99.

The statistical results of the clean PV module during spring season showed that the WS p-value equaled 6.16×10^{-13} with a t-statistic value of 6.62 and the T p-value equaled 5.42×10^{-13} while its t-statistic value was 26.49 and the RH p-value was 5.12×10^{-13} and t-statistic value was −35.77 and GHI p-value was 7.53×10^{-13} alongside a t-statistic value of 705.65. The analyzed p-values for WS from the unclean PV module indicated 7.71×10^{-13} and a corresponding t-statistic of 7.65. The p-value for the T was 5.83×10^{-13} with a t-statistic of 30.58 while RH analysis yielded 2.94×10^{-13} and −41.51 and GHI produced 7.30×10^{-13} and 876.28.

3.1.2. Summer season

The analysis of a clean module in the summer season showed that WS affected power production by correlation of 0.21 while T contributed 0.78 with −0.67 correlation impact fromRH and 0.99 correlation came out for GHI. The data demonstrated that for an unclean module WS had

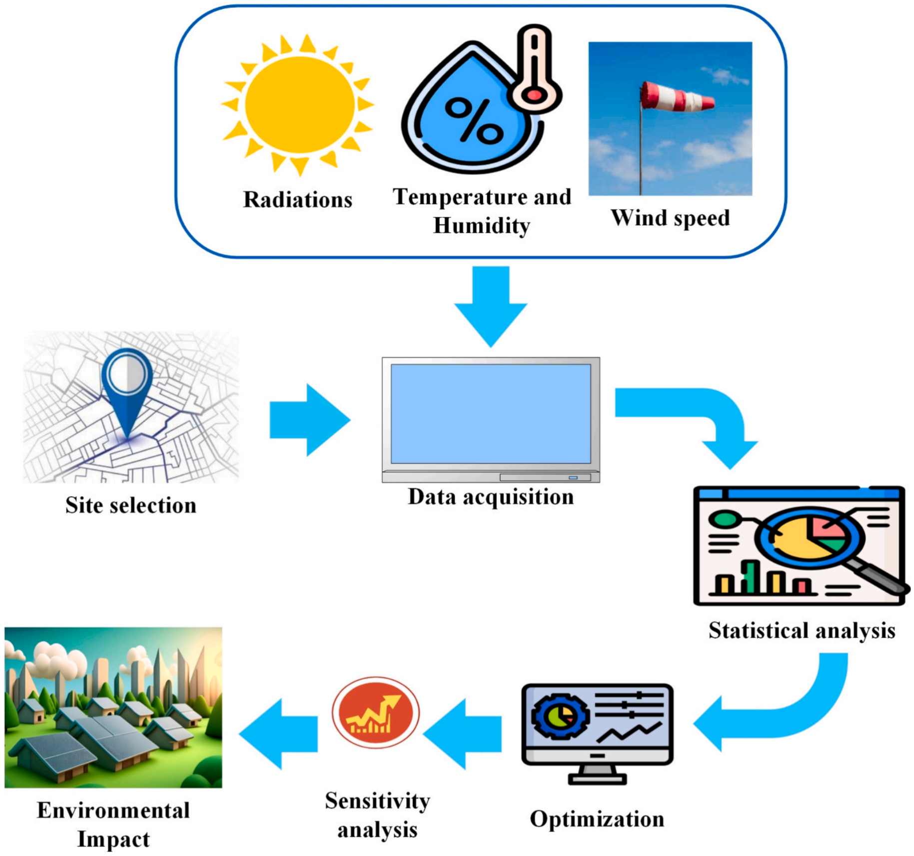

Fig. 4. Flowchart of methods used in the analysis.

an effect of 0.24 on performance, T impacted 0.74 andRH generated −0.62 change while the GHI influence remained at 0.99 during the summer season.

During summer season, clean PV module regression analysis produced WS results of 8.01 × 10^{-13} and a corresponding t-statistic value of 5.76 and the T results of 3.22 × 10^{-13} with a t-statistic value of 32.14 and RH results of 2.88 × 10^{-13} with a t-statistic value of −25.95 and GHI results of 1.32 × 10^{-13} with a t-statistic value of 843.46. The statistical analysis of the unclean PV module produced a WS p-value of 5.15 × 10^{-13} and t-statistic of 6.57 while T reported a p-value of 9.91 × 10^{-13} and corresponding t-statistic value of 26.98 and RH demonstrated a p-value of 9.98 × 10^{-13} together with a t-statistic value of −21.95 and GHI gave a p-value of 2.94 × 10^{-13} with a t-statistic value of 757.03.

3.1.3. *Monsoon season*

A clean PV module in monsoon season showed WS had 0.33 correlation, T had 0.78 correlation whileRH with −0.77 and GHI had 0.99 correlation coefficient. The results revealed that the WS showed correlation of 0.36 while T by 0.80 andRH had correlation coefficient of 0.69 for the unclean module during monsoon season.

During monsoon season, the statistical analysis of the clean PV module revealed that WS had a p-value of 1.41 × 10^{-14} and t-statistic value of 10.75 while the T showed a p-value of 3.40 × 10^{-14} with t-statistic value 40.48 and RH had a p-value of 4.18 × 10^{-14} along with a t-statistic value of −38.93 and GHI exhibited a p-value of 4.98 × 10^{-13} and t-statistic value of 1156.91. The analysis of the unclean PV module yielded a WS p-value of 1.41 × 10^{-14} and a corresponding t-statistic of 10.75 while the T p-value was 3.40 × 10^{-14} and its t-statistic was 40.48 and RH p-value amounted to 4.18 × 10^{-13} with a t-statistic of −38.93 and GHI p-value equaled 2.96 × 10^{-14} and had a t-statistic of 1081.46.

3.1.4. *Winter season*

The results suggest the module's power output relates to WS at 0.37 and T values at 0.79, GHI at 0.99 andRH at −0.82 for a clean PV module. Additionally, WS had an R-value of 0.31 while T showed 0.77 andRH −0.85 meanwhile GHI stood at 0.99 for the unclean PV module during the winter season.

During winter season, the regression analysis on the clean PV module demonstrated that WS had a p-value value of 3.94 × 10^{-13} while its t-statistic value reached 13.03 over the study period and the T presented a p-value value of 5.74 × 10^{-13} coupled with a t-statistic value of 39.45 and RH displayed a p-value value of 3.70 × 10^{-13} paired with a t-statistic value of −45.25 and GHI had a p-value value of 7.79 × 10^{-13} that matched The analysis of the unclean PV module generated p-values of 2.98 × 10^{-13} for WS with a corresponding t-statistic value of 11.05 while its p-value for ambient T was 8.11 × 10^{-13} and the t-statistic value was 33.31. RH showed a p-value of 2.89 × 10^{-13} accompanied by a t-statistic value of −52.32 and the GHI p-value came out to 9.47 × 10^{-13} with t-statistic value of 1262.40.

3.2. *Optimization*

3.2.1. *Spring season*

The optimization findings revealed that the optimized power output for clean panels was 41.09 W at 0.5140 m/s, 305 K, and 57 %, which were the optimized values of WS, T, andRH, respectively, for clean panels, as shown in Fig. 5(a). The optimization findings showed that the optimized power output for unclean panels was about 24.61 W at 0.5140 m/s, 305 K, and 57 %, which were the optimized values of WS, T, andRH, respectively, for unclean panels, as shown in Fig. 5(b).

3.2.2. *Summer season*

The optimization findings revealed that the optimized power output

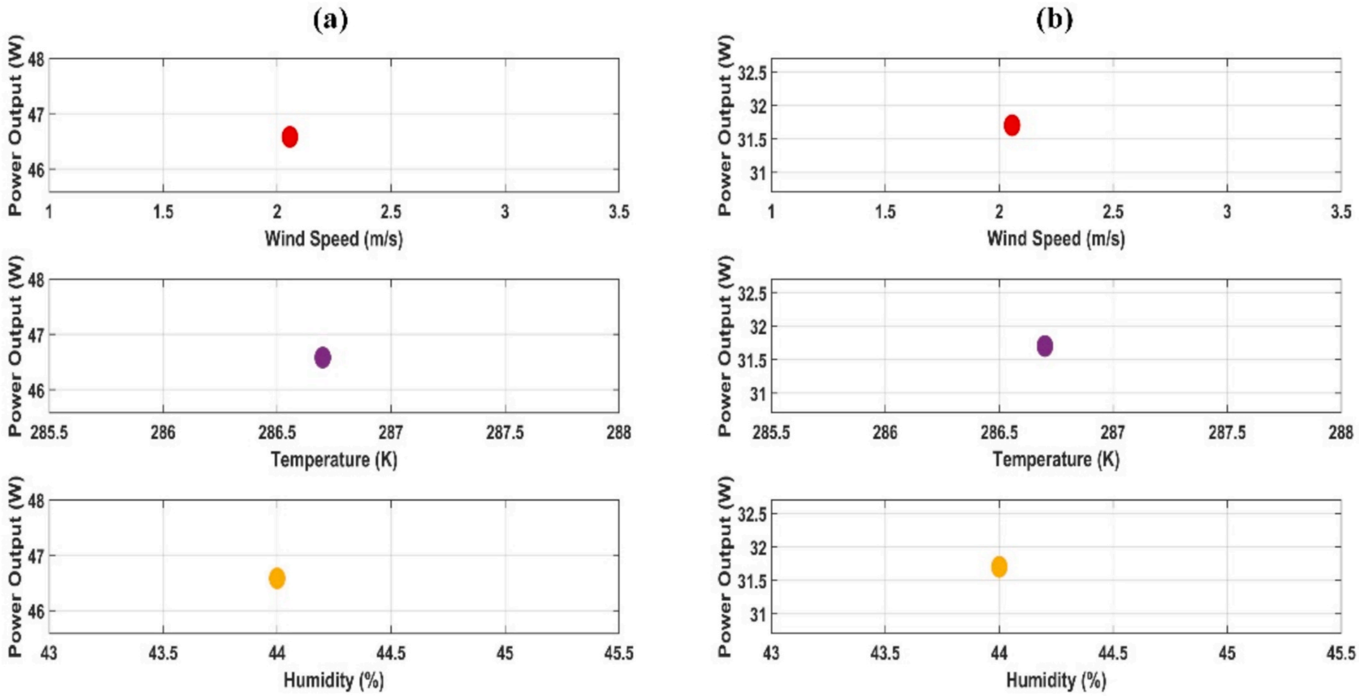

Fig. 5. Optimized values of variables for Spring season (a) clean module (b) unclean module.

for clean panels was 48.19 W at 0.5140 m/s, 322 K, and 56 %, which were the optimized values of WS, T, andRH, respectively, for clean panels, as shown in Fig. 6(a). The optimization findings revealed that the optimized power output for unclean panels was about 35 W at 0.5140 m/s, 305 K, and 56 %, which were the optimized values of WS, T, andRH, respectively, for unclean panels, displayed in Fig. 6(b).

3.2.3. Monsoon season

The optimization findings revealed that the optimized power output for clean panels was 40.62 W at 2.056 m/s, 308.1 K, and 49 %, which were the optimized values of WS, T, andRH, respectively, for clean panels, as shown in Fig. 7(a). The optimization findings revealed that the optimized power output for unclean panels was about 31.66 W at 2.056 m/s, 308 K, and 69 %, which were the optimized values of WS, T, andRH, respectively, for unclean panels, displayed in Fig. 7(b).

3.2.4. Winter season

As shown in Fig. 8(a), the optimization findings revealed that the

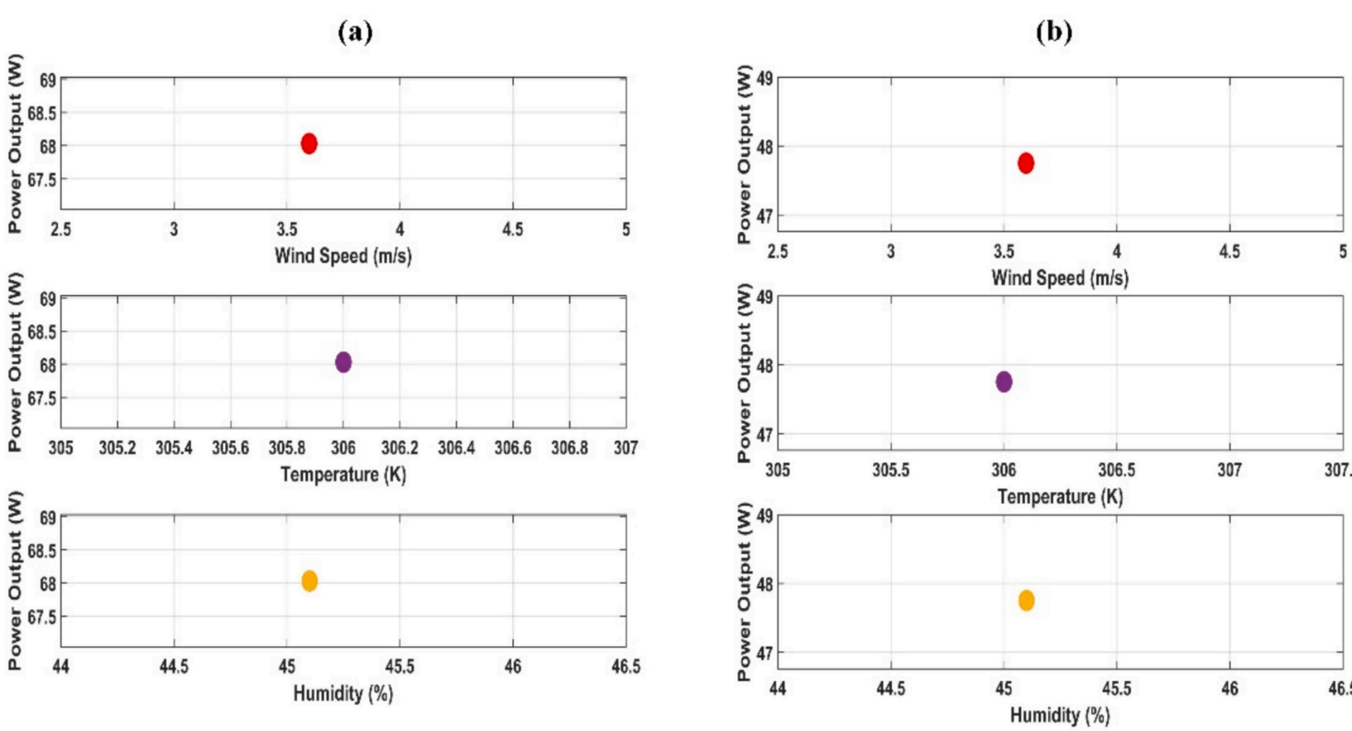

Fig. 6. Optimized values of variables for the summer season (a) clean module (b) unclean module.

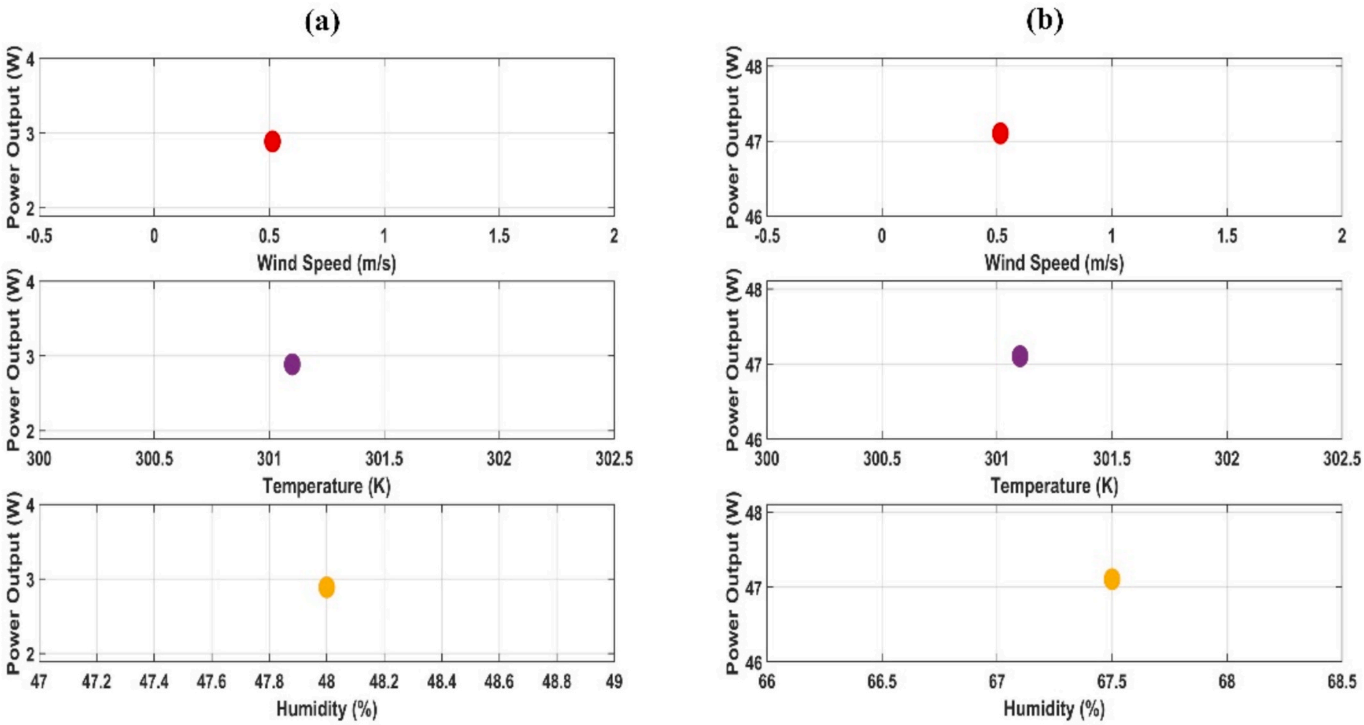

Fig. 7. Optimized values of variables for Monsoon season (a) clean module (b) unclean module.

optimized power output for clean panels was 37.16 W at 0.514 m/s, 317 K, and 55 %, which were the optimized values of WS, T, andRH, respectively, for clean panels. The results of the optimization showed that the best power output for dirty panels was about 6.43 W at 0.514 m/s, 317 K, and 55 %RH. These were the best WSs, T, andRH for dirty panels, displayed in Fig. 8(b).

3.3. Sensitivity analysis

3.3.1. Spring season

In a sensitivity analysis for clean PV modules during the spring season, adjusting WS values from 5 % to 25 % resulted in only a marginal change in power output. Conversely, T variations of 5 % to 25 % led to a rapid reduction in power output from 40.28 W to 27.95 W,

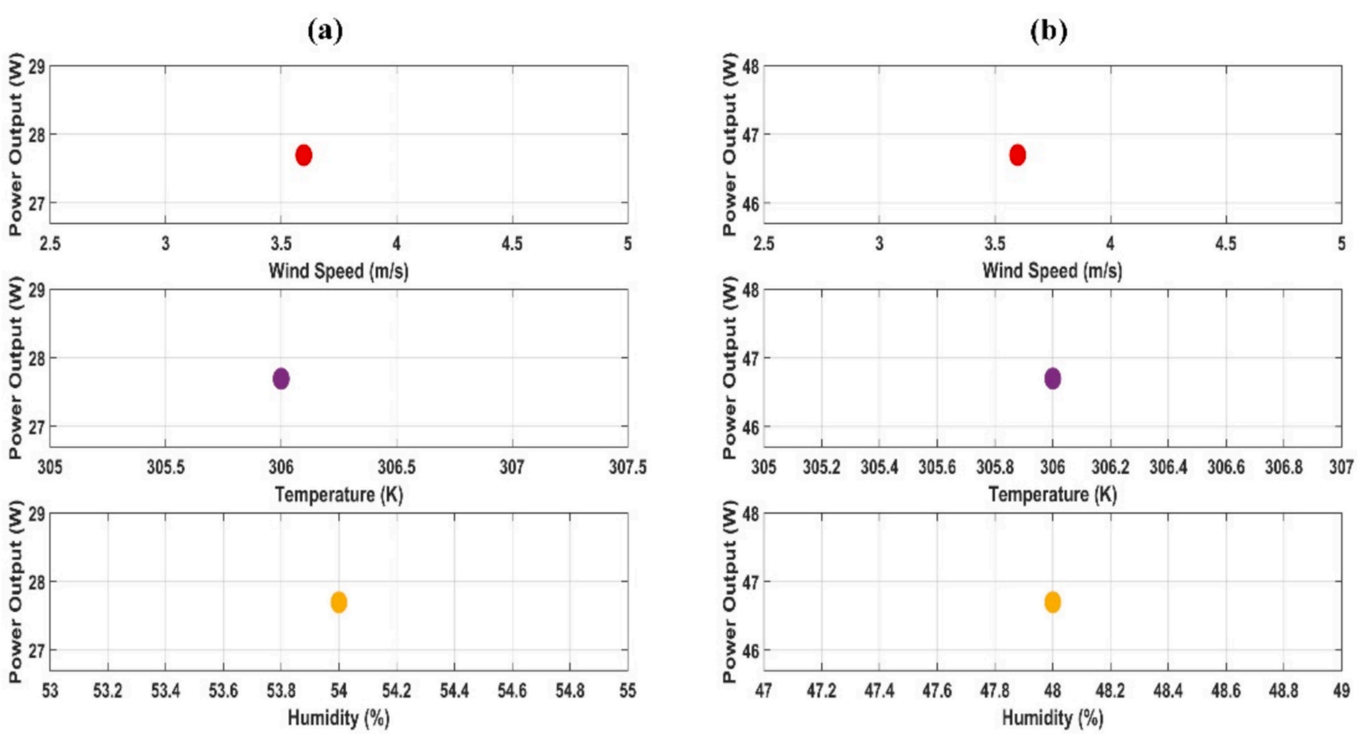

Fig. 8. Optimized values of variables for Winter season (a) clean module (b) unclean module.

whileRH changes in the same range caused a slight decrease in output from 43.27 W to 42.91 W. Fig. 9(a) shows the influence of each variable on clean module's output. Similarly, in a sensitivity analysis for an unclean module, altering WS values from 5 % to 25 % resulted in a small power output change from 27.59 W to 27.71 W. T fluctuations had a more pronounced effect from 22.62 W to 2.88 W, andRH variations caused a decrease from 27.53 W to 27.41 W. Fig. 9(b) shows the influence of each variable on the unclean PV module's power output.

3.3.2. Summer season

According to sensitivity analysis conducted for clean modules during the summer, power output increased from 56.70 W to 56.87 W when WS was changed from 5 to 25 %. Conversely, an increase in T of 5 to 25 % resulted in a change in production from 46.38 W to 5.26 W, while an increase inRH of 5 to 25 % led to a decrease from 54.38 W to 47.51 W. Fig. 10(a) illustrates how each variable affects the clean PV module's power output. According to a sensitivity analysis conducted for the unclean module during summer, power output changed from 40.36 W to 40.67 W when WS was increased from 5 to 25 %. In contrast, a 5 to 25 % increase in T caused a change of 34.61 W to 11.95 W, while a 5 to 25 % change inRH caused a power output decrease of 39.34 W. Fig. 10(b) illustrates how each variable affects the PV module's power output.

3.3.3. Monsoon season

In the sensitivity analysis for clean PV modules during the monsoon season, varying WSs from 5 % to 25 % resulted in a slight decrease in production from 43.85 W to 43.83 W. Conversely, T changes of 5 % to 25 % led to a more significant drop in power output from 30.25 W to 3.03 W, whileRH variations in the same range caused a slight increase in output from 43.87 W to 43.90 W. A similar analysis for unclean modules showed that WS adjustments from 5 % to 25 % resulted in a small power output change from 35.69 W to 35.60 W. T fluctuations had a more pronounced effect from 22.88 W to 2.79 W, andRH changes caused a decrease from 35.46 W to 34.41 W. Fig. 11(a) and Fig. 11(b) illustrate the impact of each variable on clean and unclean PV module power output, respectively.

3.3.4. Winter season

In the sensitivity analysis for clean PV modules during the winter season, altering WS values from 5 % to 25 % resulted in a slight power output increase from 52.48 W to 52.73 W. Conversely, T variations of 5 % to 25 % led to a more significant reduction in power output from 47.36 W to 27.15 W, whileRH changes in the same range caused a slight power output increase from 51.48 W to 47.76 W. Fig. 12(a) represents the influence of each variable on the clean PV module's performance. Similarly, in a sensitivity analysis for unclean modules during winter, adjusting WS values from 5 % to 25 % resulted in a smaller power output change from 28.13 W to 28.17 W. T fluctuations had a more pronounced effect from 27.2 W to 23.56 W, andRH variations caused a power output increase from 28.89 W to 31.98 W. Fig. 12(b) provides insights into the influence of each variable on the unclean PV module's power output.

3.4. Energoenviro-economic results

In spring, due to a lack of cleaning, the efficiency of the module dropped to 26.5 % from 31.4 %, as shown in Table 3. Similarly, the module's efficiency dropped from 34.1 % in the summer season to 26.9 %. During the monsoon season, the module's efficiency decreased to 24 % from 29.4 % due to a lack of cleaning. The efficiency of the module decreased to 18.9 % from 20.7 % during the winter, when it remained in a dusty condition.

The cost-saving factor was 1.50$ for the summer season and 1.29$ for the monsoon season, while 1.38$ and 0.83$ were for the spring and winter seasons, respectively. Fig. 13(a) shows the comparison of CO_2 emissions for seasons. In the spring season, modules released 3.02 kg of CO_2 emission was released by modules. In summer, 3.27 kg of CO_2 emission was added by the module in the environment. Similarly, 2.82 kg of CO_2 emission was released by modules in the monsoon season, and in winter, 1.81 kg of CO_2 emission was added by modules. In the spring season, 14.66 kWh of energy loss was recorded, and 22 kWh and 16.04 kWh of energy loss were recorded for the summer and monsoon seasons, respectively. In winter, energy loss was only 5.34 kWh, as shown in Fig. 13(b).

In terms of economy generation, from the module under consideration, 9.44$ and 7.97$ revenue could be generated from cleaned and uncleaned modules during the spring season yearly, as shown in Fig. 14. In summer, 10.23$ and 8.07$ revenue could be generated from cleaned and uncleaned modules yearly, and 8.83$ and 6.2$ revenue could be generated in the monsoon and winter seasons when modules were kept clean. As shown in Fig. 14, due to dust collection on the module, 7.22 and 5.6 dollars of revenue could be made in the monsoon and winter seasons, respectively.

4. Discussion

The statistical significance of parameter regression coefficients was evaluated based on p-value and t-statistic value, and these values are evidence of how these parameters contribute to the regression model [47]. For all the seasons, the coefficient of T has a p-value less than the confidence interval. This suggests that T is the key parameter to consider

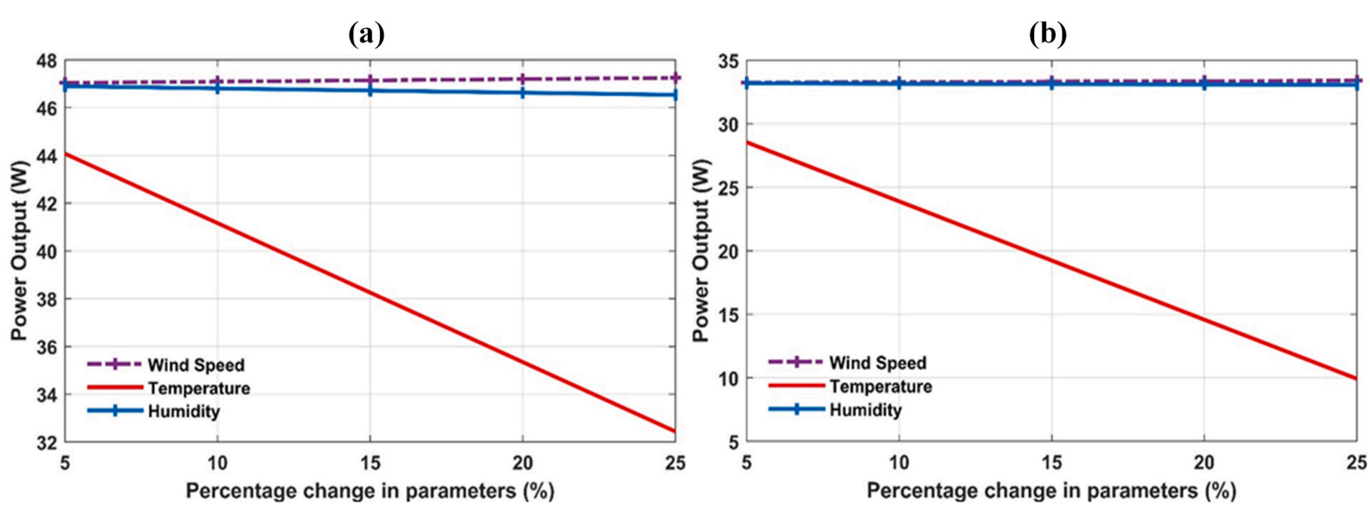

Fig. 9. Change in Power output with percentage change in variables for spring season (a) clean module (b) unclean module.

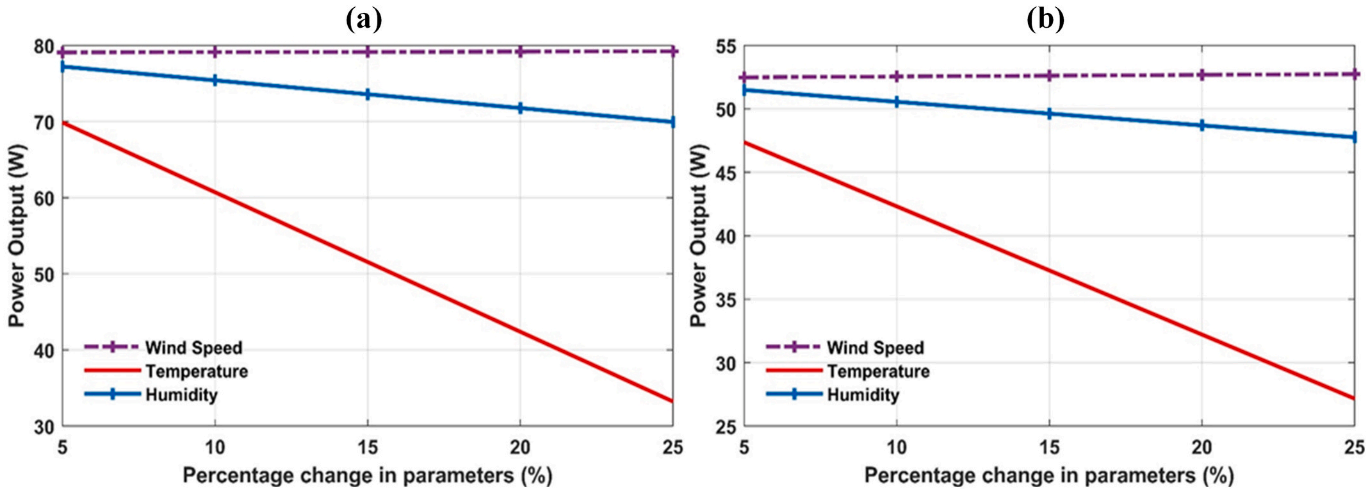

Fig. 10. Change in Power output with the percentage change in variables for summer season (a) clean module (b) unclean module.

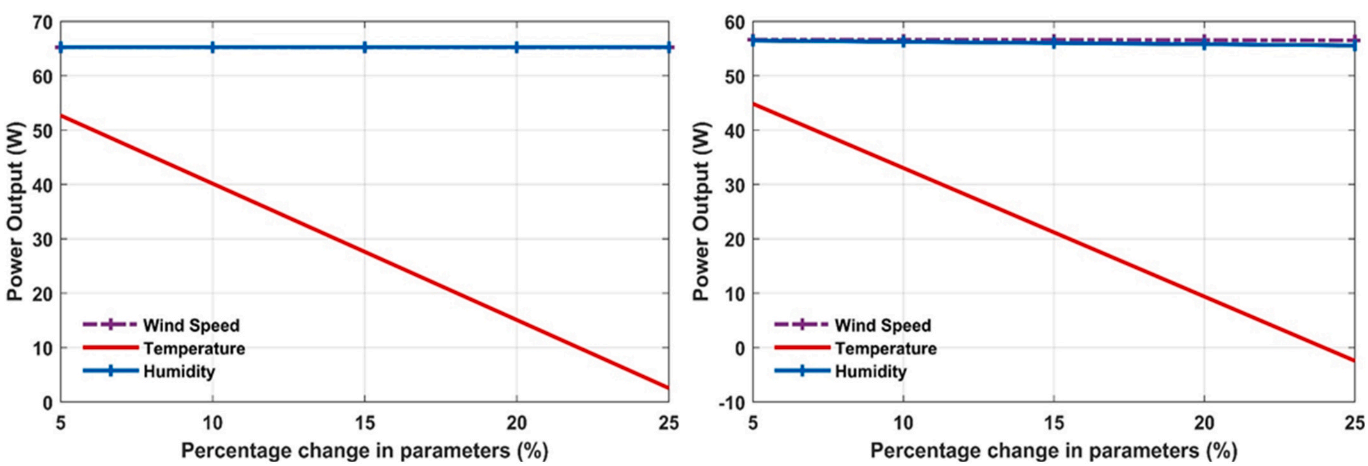

Fig. 11. Change in Power output with the percentage change in variables for monsoon season (a) clean module (b) unclean module.

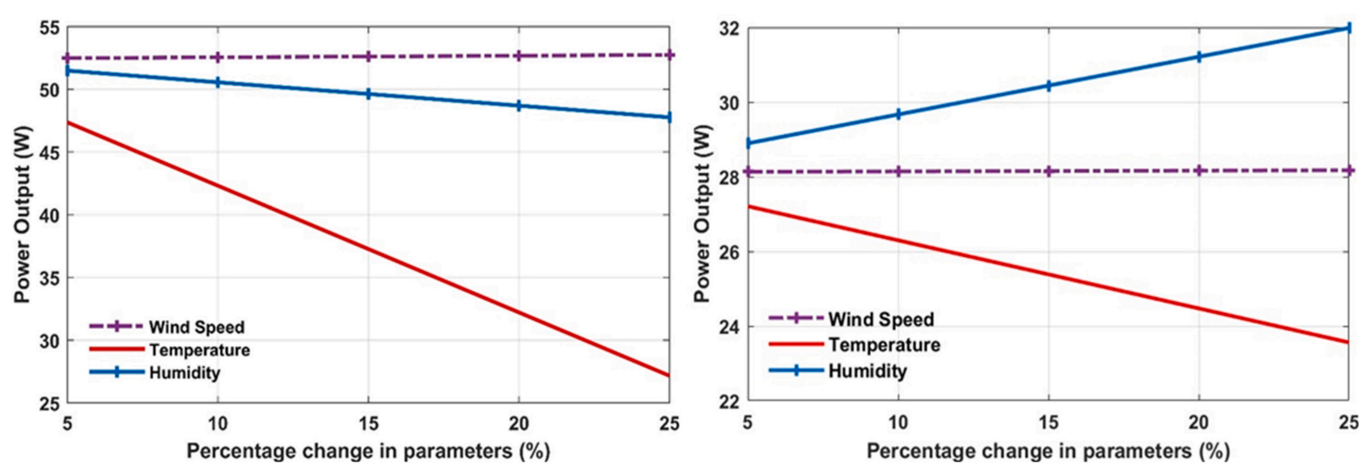

Fig. 12. Change in Power output with percentage change in variables for winter season (a) clean module (b) unclean module.

in the design of solar energy-based power systems for all seasons. Similarly, the coefficient of T has a t-statistic value more than $|\pm 1.96|$, indicating that T is the most important parameter among the three parameters used in this study [48]. The p-value and t-statistic values for WS andRH indicate that these parameters are less important than T. Moreover,RH is a more statistically significant parameter than WS, when considering the yield of the PV module. The same results related to WS andRH were reported by Zainuddin et al. [49]. This study concluded that the effect ofRH is more pronounced on the working of PV modules than the WS.

Table 3
Efficiency and cost saving factor of modules across seasons.

Metrics	Spring	Summer	Monsoon	Winter
Efficiency of cleaned module	31.4 %	34.1 %	29.4 %	20.7 %
Efficiency of uncleaned module	26.5 %	26.9 %	24.0 %	18.9 %
Ecological cost-saving factor	1.38$	1.50$	1.29$	0.83$

Studies reported in the literature demonstrates that GHI plays the primary role in PV output which reflects the results obtained in the current study. The performance of PV modules mainly depends on GHI as Skoplaki et al.[50] proved it through experimentation under different climatic situations. Benghanem [51] validated the close matching between PV energy yield and irradiance data using experimental data modeling methods. The negative connection betweenRH levels and power generation capacity matches the research findings presented by Mekhilef et al. [52], who demonstrated that higherRH levels decrease both solar radiation levels and system operational effectiveness. Dubey et al. [53] described how increased Ts typically reduce the efficiency of PV modules, while this study validated their findings. Similar findings on WS-related power increase and T reduction appeared in Tonui and Tripanagnostopoulos' study [54].

The regression model produces similar results to modern PV modeling approaches. The irradiance-power relationship within the current study exhibits an R value of 0.94, which confirms polynomial regressions from Yang et al. [55]for commercial monocrystalline systems. The T coefficient of −0.45 % per °C obtained from this study agrees with the findings of Kimber et al. [56] who analyzed 1.2 million data points from utility-scale plants during a multi-year period. The approach used in this study performs with the transformer-based model of Huang et al. [57] while using 50 % less computing resources to deliver R values of 0.93 compared to 0.95. Regression models serve as the fundamental operational prediction system for PV systems because they demonstrate robust reliability according to the IEEE Standard 1812–2023 [58].

Figs. 3 (a) and 3(b) show optimal values of parameters that are necessary to obtain the optimal power output in the spring season for both clean and unclean panels. When no cleaning method is employed for PV modules, more than a 16 % reduction in power output is observed for the same optimized values of parameters. In the spring season, there are a lot of dust storms and an increase in pollen levels, which ultimately causes a reduction in the output of PV modules when no maintenance is carried out for a longer period [59]. Figs. 4 (a) and 4(b) show the optimal values of parameters that produce optimal power output for the summer season in cleaned and uncleaned conditions of PV modules. Keeping the optimized parameters the same, there is a 13.1 % reduction in the power output when compared with the power output of the clean module. In summer, limited rainfall causes soiling on the modules which acts as a barrier and impacts the energy production of modules [60,61]. Figs. 5(a) and 5(b) display the optimized values of parameters for optimal energy yield from PV modules in the monsoon season. During this season, almost 9 % of power output is reduced when the PV module is in an unclean state. The lower reduction in power output for unclean panels during this season, compared to other seasons, could be attributed to the removal of soiling caused by rainfall [62]. Optimized values of parameters for optimal power output in the winter season are displayed in Figs. 6(a) and 6(b) for clean and unclean PV modules respectively. In winter, when the module is unclean reduced daylight hours lead to a decrease in the power output drastically when no care is taken in the cleaning of the PV module [63,64]. For the same parameters, the power output of an unclean module decreases by up to 30 % in the winter season.

Fig. 7(a) shows the influence of each parameter on the working of a clean PV module in the spring season. There is almost negligible impact of WS on the power output, while a 25 % increase in T reduces the power output up to 30 %. However, a 25 % increase inRH results in a much lower reduction in power output. For an unclean panel in the spring season, WS does not affect the power output but a 25 % increase in T

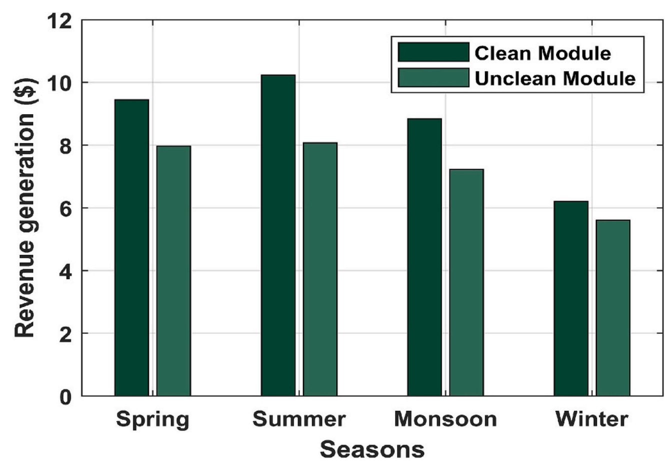

Fig. 14. Revenue generation comparison of cleaned and uncleaned modules.

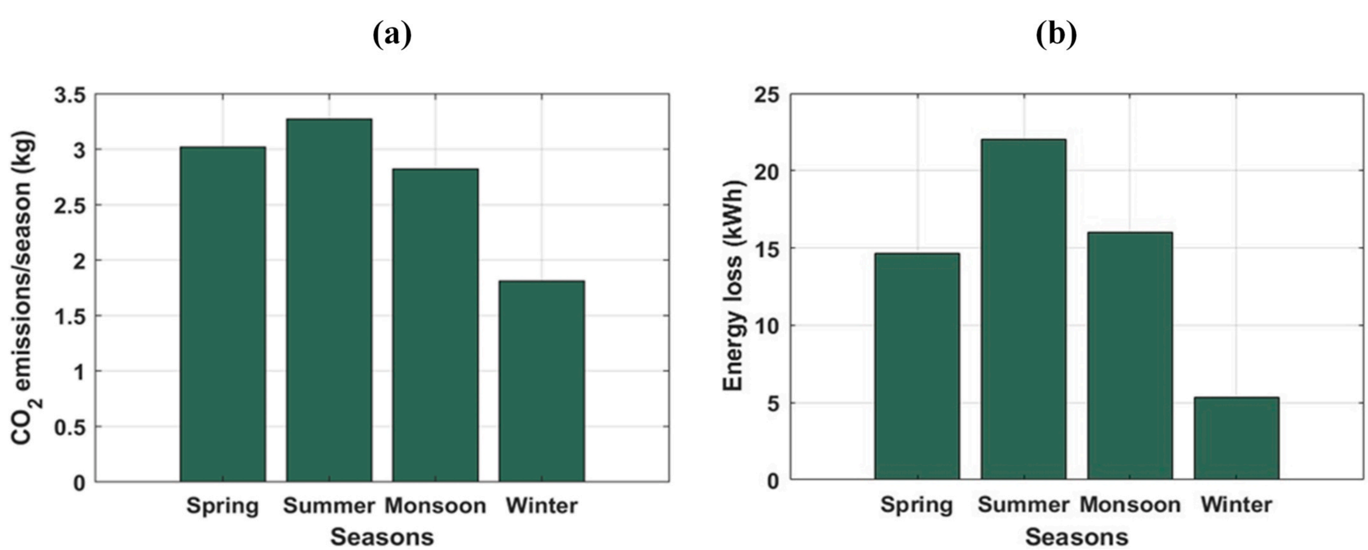

Fig. 13. (a) Carbon emission of module (b) Energy loss across four seasons.

andRH causes a reduction in power output of more than 87 % and 0.4 %, respectively, as shown in Fig. 7(b). During this season, WS has almost no importance for the power of the PV module which may be because it is only contributing to moderate T when WS is below 3 m/s [65,66]. Furthermore, an increase in T causes a drastic decrease in power output because it increases the circuit resistance and ultimately reduces the power output as reported by Sakkaf et al. [67]. However,RH reduces the power output because when moisture mixes with dust, it forms a sticky layer [68]. Fig. 8(a) and Fig. 8(b) show the change in power output of clean and unclean modules when the values of each parameter are increased by 25 % in the summer season. The increase in WS helps to improve the energy production of a clean module by 0.29 % at low WS and 0.76 % when the module is not cleaned. The same trend was observed by Lee et al. [69] who reported that increasing WS by 1.5 times causes a 0.7 W increase in power output. When the module is clean, 25 % increase in T reduces the power output more than 86 %. When the panel is not clean, a 65 % power reduction is observed when the T is increased. Sani et al. [70] reported the same trend between T increase and power output. Similarly, when theRH level increases up to 25 %, the power output of clean and unclean modules decreases by 13.3 % and 9.53 %, respectively. This may be because moisture reflects the sunlight in the case of the clean module and results in a reduction of power output and the case of the unclean module, moisture makes a thick layer with dust and this tenacious layer acts as a barrier for the sunlight [71]. Fig. 9(a) and Fig. 9(b) show the variation of power output concerning the percentage of parameters during monsoon season. In this season, for both clean and unclean modules, the wind has almost no impact on the power generation of modules because the WS may vary during the whole season, but when it remains consistent for a longer period then modules produce the same amount of energy [72]. The T when increased by 25 %, causes a power output drop of 89 % in clean modules and 87 % in unclean modules. Various solar modules have negative solar coefficients and higher Ts cause a reduction in PV output, as reported in literature [73,74]. For a clean module, an increase inRH level leads to an increase in power output by 0.06 % becauseRH excites the evaporative cooling process and lowers the cell T of the module [75]. For the unclean module, a 25 % increase inRH level drops the power output by 2.96 %. Sitthiphol et al. [76] reported that increase inRH level leads to induce degradation of PV modules and increase the leakage current which is the main reason of less power output. Fig. 10(a) and Fig. 10(b) show the variation of power output with respect to percentage of parameters during winter season. WS puts negligible impact on energy generation of both modules while upto 25 % increment in T reduced the output of clean module by 42 % and 13.3 % for the unclean module. Ahmad et al. [77] concluded that when the T of PV modules increases by 35 %, the module efficiency can drop up to 10 %, and it was also reported that every 1 °C increase in T above standard conditions can reduce the output by 0.2 % [78]. This sensitivity analysis identifies the most influential input parameters of PV performance. The changes in solar irradiance influence the output of PV the most. In contrast, operating temperature of module showed moderate effect on PV's output. Other parameters proved to be less crucial compared to solar irradiance and operating temperature of cells. Hence, sensitivity analysis provides valuable insights of relative importance of various parameters and helps to improve PV system efficiency.

In terms of environmental contribution, modules produce less CO_2 emissions in the winter season, whereas emissions are highest during the summer season, as represented in Fig. 11(a). This may be because PV systems are not used frequently in the winter season and their operational requirements decrease, which is not the case in the summer season [79]. Fig. 11(b) shows that the energy loss in the summer season reaches 22 kWh, while 14.6, 16.04, and 5.34 kWh energy losses are recorded for the spring, monsoon, and winter seasons, respectively. In the summer season, dry weather is the cause of high energy loss because dust storms happen frequently in summer, which results in the accumulation of dust layers on the module [80]. Revenue generation for the cleaned module has a higher value of 10.23$ in the summer season, but for the uncleaned module, high revenue of up to 8.83$ is generated in the monsoon season as depicted in Fig. 12. The high solar intensity and more operating hours are the factors for maximum revenue in summer while revenue generation is minimal for both cleaned and uncleaned modules in the winter season because of fewer operating hours [81].

The findings might only apply to monocrystalline technology installed at the Lahore location because the study used a single test site. Natural soiling was left to build up throughout the study without any artificial control measures thus allowing dust type along with rainfall variations and cleaning effectiveness to potentially affect the results throughout the experiment period. The available models still have further potential for improvement but advanced machine learning methods went beyond this work. The final evaluation relied on established local electricity prices together with fixed carbon intensity factors but these parameters could change according to regional variations and time-based factors. The analysis would benefit from additional investigations through research across multiple locations while evaluating multiple PV technologies and by including real-time pricing and environmental data in the research methodology.

5. Conclusions

In this study, the impact of WS, T, andRH on the power output of 50 W cleaned and uncleaned modules is determined. The p-value for the T regression coefficient is less than 0.05 and the t-statistic value is more than $|\pm 1.96|$ for all seasons which shows that T is the most critical parameter for the power output of modules. Optimization of power output and sensitivity analysis are performed to prioritize the parameter that has more influence on power output. The highest optimized power is obtained as 48.19 W during summers when the module is clean at 0.5140 m/s, 322 K, and 56 % which are the optimal values of WS, T, andRH, respectively. Similarly, the lowest power of 37.16 W is generated in winter when the module is clean at the ideal conditions of 0.514 m/s, 317 K, and 55 %RH. During the unclean state, the maximum energy of 35 W is generated in summer at 0.5140 m/s, 305 K, and 56 %RH while during winter, 6.43 W of power is generated by the module at 0.514 m/s, 317 K, and 55 %RH in unclean state. WS ensures a stable power output of modules in both clean and unclean conditions throughout all seasons, except for the summer, when it serves as a cooling agent for PV cells. An increase in T badly impacts the performance of modules in all seasons. During the monsoon season, increases in T drastically reduce power output. In winter, an increase in T leads to better performance because of a clear sky and more irradiance. In unclean conditions, modules show bad performance at highRH levels due to the formation of sticky layers on their surfaces.

CO_2 emissions increase during the summer season, reaching a value of 2.37 kg per year. The winter season limits CO_2 emissions to 1.81 kg due to reduced operational time and demand. In terms of revenue generation, the summer season stands out the best and could generate revenue of up to 10.23$ in cleaned condition and 8.07$ in uncleaned condition. The findings can be useful in designing solar energy systems for different climate zones. Optimization of power output will result in improved module performance, and sensitivity analysis will guide system design, maintenance scheduling, reliability, and resource allocation with consideration of critical parameters such as T.

CRediT authorship contribution statement

Muhammad Asim: Writing – review & editing, Validation, Project administration, Data curation, Conceptualization. **M. Farooq:** Writing – review & editing, Resources, Formal analysis. **Ammara Kanwal:** Writing – review & editing, Software, Formal analysis. **Talha Akhtar:** Writing – review & editing, Resources, Formal analysis. **Awais A. Khan:** Writing – review & editing, Formal analysis, Validation. **Enio. P.B. Filho:** Writing – review & editing, Software, Investigation. **Naeem**

Ullah: Writing – review & editing, Validation, Methodology. **Noreen Sher Akbar:** Writing – review & editing, Software, Methodology, Investigation. **M. Imran Khan:** Writing – review & editing, Software, Resources, Formal analysis. **Fahid Riaz:** Writing – review & editing, Visualization, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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