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Thermal analysis of bifacial photovoltaic modules with single-axis trackers in a large power plant: Modeling by symbolic equations in tropical climates

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Abstract. The thermal behavior of the single-axis tracked bifacial photovoltaic (PV) module is important for efficient energy extraction in large-scale power plants, especially in tropical regions under high irradiation and high ambient temperature. However, it is difficult to accurately predict their operating temperature due to the complex interaction between environmental variables and the characteristics of solar tracking. The available models, ranging from empirical correlations and computational fluid dynamics (CFD) simulations to machine learning methods, face challenges in terms of accuracy, interpretability, and computational load. This gap is addressed in this study, with the development of a modeling methodology based on symbolic regression (SR) utilizing genetic algorithms (GA) towards obtaining an explicit, interpretable Equation for the prediction of the PV module temperature in single-axis tracking systems. One year of data was collected at 5-minute intervals from a 19.9 MW PV plant located in San Marcos, Colombia, consisting of measurements for solar radiation, ambient temperature, wind speed, and module temperature. The constructed SR GA model achieved satisfactory prediction accuracy compared to classic models with the best root mean square error (RMSE = 4.14 °C) and R^2 (0.91) on the test data set. These results compare favorably with results from MLR (RMSE = 4.31 °C, R^2 = 0.90), the standard industry NOCT model (RMSE = 8.59 °C, R^2 = 0.60), and the empirical Skoplaki I model (RMSE = 5.92 °C, R^2 = 0.81). The resulting symbolic equation directly characterizes the effects of nonlinear solar radiation, ambient temperature, and wind speed, providing greater physical insight into the thermal dynamics of the system. An important finding is that the maximum temperature of the bifacial module is reached around 14:00h, probably due to the accumulation of temperature caused by solar tracking, which contrasts with what occurs in fixed-tilt monofacial technology. This study demonstrates that the symbolic regression technique with a genetic algorithm kernel can produce accurate, interpretable, and computationally economical models for advanced photovoltaic systems.

Keywords: PV temperature prediction, Bifacial Photovoltaics, Single-axis trackers, Genetic algorithms, symbolic regression

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1. Introduction

Solar power is widely accepted as an indispensable part of the world's transforming energy systems (Obaideen *et al.,* 2023). This is important as it is large, renewable, and clean, and therefore an alternative to fossil fuels (Ponnada *et al.,* 2022). New PV module technologies have just made solar even more efficient, more economical, and more accessible (Fan *et al.,* 2017). This is a significant advancement for global energy solutions, environmental impact, and clean energy conversion (Masrur *et al.,* 2021). Bifacial PV modules are a mature technology in PV plants around the world (Lara-Vargas *et al.,* 2025a). These modules can capture sunlight from both the front and rear sides of the module. Their energy yield is higher than that of a conventional single-face module (Bera *et al.,* 2024). Together with solar trackers, they provide significant benefits to gather appropriate solar irradiance in daylight hours (Burnham *et al.,* 2019).

Compared to conventional PV modules, bifacial PV modules are designed to operate as double-sided collectors and are, therefore, primarily used with solar trackers, as the tracker orients both sides of the module so that the maximum direct sunlight is incident on the modules (Abe *et al.,* 2023). The main high implication of this combination of bifacial modules with a solar tracking system is to ensure maximum solar capture, especially during cases of intermittence, solar radiance, and especially at different hours of the day (Ali *et al.,* 2021). Comparatively, the thermal analysis of bifacial PV modules with

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solar trackers is far more complicated because the thermal behavior of bifacial PV modules is dependent upon the relationship with three primary parameters: the intensity of solar radiation, the ambient temperature, and the wind speed (Patel *et al.*, 2020). Such an analysis needs to be performed to optimize the design and deployment of bifacial PV systems in different environments (Yakubu *et al.,* 2022). Although the combination of bifacial PV modules with solar trackers offers considerable gain in energy, it also makes modeling and interpretation difficult (Becerra *et al.*, 2024). Solar tracking systems utilize bifacial PV modules, the temperature of which is difficult to predict due to the simultaneous influence of environmental and solar tracker parameters that have complex interactions (Kaplani & Kaplanis, 2014). These challenges result in considerable gaps between simulation and measured temperatures, negatively impacting the overall accuracy of energy performance predictions (Mannino *et al.,* 2022). The thermal treatment of bifacial modules is poorly characterised by available models, which capture little of the interaction between module characteristics and environmental conditions (Raina *et al.,* 2023). Such an approximation gives rise to significant errors in the temperature prediction, especially under variable tropical climates (Raina *et al.*, 2023). However, while in the case of static ground-mounted systems, the irradiation and thermal dynamics of the bifacial PV module are specific to a given orientation (including angle normal to the incident radiation), the dynamic operation of solar tracking systems adds an additional layer of complexity, as the orientation of the panels changes throughout the day (Tina *et al.,* 2020).

On the other hand, most of the models for temperature prediction were originally developed on the basis of monofacial modules and extrapolated to the case of bifacial ones, not paying adequate attention to their peculiarities (Mannino *et al.,* 2022). Many methods are currently in use, ranging from empirical models to energy balance approaches to machine learning (ML) methods, each of which has benefits and disadvantages. For instance, Meflah *et al.*, (2023) developed empirical models that provide a coefficient of determination (R^2) over 0.90 and root mean square error (RMSE) under clear sky conditions of over 3.8 °C (Meflah *et al.,* 2023). Nonetheless, in their structure, these models suffer from a linear assumption of radiation and ambient temperature to module temperature, resulting in an underestimation of their capability to represent a complex non-linear interaction. A few studies adopted the normal operating cell temperature (NOCT) model provided by the producer of the PV module (Mattei *et al.*, 2006). Kaplani & Kaplanis developed an energy balance algorithm taking into account PV system arrangement and heat transfer by natural and forced convection (Kaplani & Kaplanis, 2020). Although the forecasted temperature patterns are in close agreement with the observed data, showing annual temperature variations mostly within ± 5 °C, the testing duration is limited to just six days. Zaimi *et al.,*(2019) provided analytical expressions for electrical parameter variations of the module as a function of temperature and irradiance (Zaimi *et al.*, 2019). However, their model intercomparison was confined to a single day and may not account for interannual variability in environmental conditions. Haeberle *et al.*,(2022) proposed an energy balance-based approach to achieve a mean absolute error (MAE) of less than 8.5% under NOCT (Nominal Operating Cell Temperature) conditions, even while accounting for conduction, convection, and radiation processes including conduction, convection, and radiation effects (Haeberle *et al.*, 2022). However, these models are computationally intensive due to the numerical iterations involved and the high number of variables, and may limit their applications in real-time and dynamic scenarios. One more study employed a Computational Fluid Dynamics (CFD) model, obtaining an RMSE of 4.2 °C sample ranges of 10 minutes using data from the simulation day. The simulation only takes into account the effect of a single module, without including considerations of configurations closer to the real ones, as well as the computational costs associated with highly detailed models (Johansson *et al.,* 2022). The multiple linear regression model has also been employed to predict the temperature of PV modules, achieving RMSE results of 0.4. However, it was developed exclusively for one month, on sunny days, and only for measurements exceeding 850 W/m² (Tripathi *et al.,* 2021). Furthermore, Kayri & Aydin, (2022) applied artificial neural networks (ANN) to simulate module temperature with excellent metrics (MAE = 1.45°C, RMSE = 2.07°C, MAPE = 6.37%, correlation = 98.87%) (Kayri & Aydin, 2022). Furthermore, the average RMSE of 1.67 °C and R^2 of 0.95 are excellent error metrics, but the "black box" nature of ANNs makes it difficult to physically understand how much each individual environmental variable affects the module temperature. Finally, Sanchìs-Gómez *et al.*, (2025) conducted a performance comparison of 22 mathematical models for forecasting the temperature of bifacial PV modules (Sanchís-Gómez *et al.,* 2025). The best model was the Skoplaki I with a value of 0.25 °C (Skoplaki *et al.,* 2008). But these measurements were not continuous across the year, but sampled within each climatic season.

In this paper, we propose a symbolic regression (SR) approach based on genetic algorithms (GA) for deriving mathematical expressions for the temperature calculation of bifacial PV modules with trackers. The main benefits of this method are listed in :

- Modeling complex relationships: Symbolic regression facilitates the identification of nonlinear relationships among environmental variables without requiring a predetermined functional form (Kaushik *et al.,*2023) quiring a, thus addressing the constraints of empirical and linear models (He & Zhang, 2021).
- Interpretability: The equations obtained are interpretable and help us understand how each parameter, such as solar irradiation, influences the temperature of bifacial PV modules in comparison to ANNs and other machine learning models (Shmuel *et al.,* 2023).
- Symbolic regression has shown a successful capability to capture nonlinear dynamics in energy systems, like the characterization of wind speed in wind power applications (Radwan *et al.,* 2024). However, its possible utilization for thermal characterization of bifacial PV panels is still unexplored.

Empirical or linear approaches simplify the relationship between solar radiation, ambient temperature, and thermal response, leading to errors by failing to capture the specific dynamics of bifacial modules in tracking systems. On the other hand, although accurate, models based on energy balance or computational fluid dynamics require many variables and high computational costs. While ANN-based models are more accurate than the previous ones, their black-box nature does not allow for model interpretability. This gap reflects the need for interpretable, accurate models specifically tailored to bifacial modules with solar trackers under tropical climates, where operating conditions are severe due to high irradiance and elevated ambient temperatures. Within this framework arises the research question: Can genetic algorithm-based symbolic regression be used to generate interpretable and efficient equations that predict the temperature of bifacial photovoltaic modules with solar trackers in tropical climates more accurately than traditional and statistical models?

To fill the existing gap, this paper introduces the idea of constructing the temperature forecasting model with symbolic regression, achieving good accuracy levels as well as algorithmic outreach simplicity. The symbolic regression model based on GA established in this study attempts to fill these gaps by explicitly linking module temperature to solar radiation (W/m²), ambient temperature (°C), and wind speed (m/s) in 5-minute intervals for one year. These are highly relevant parameters to catch thermal behavior under practical use conditions. Statistical models based on multiple linear regression and the NOCT and Skoplaki I models are compared with the SR GA model. RMSE and R^2 (coefficient of determination) are used as metrics for the comparison. The outline of the paper is as follows: the data collection method and the design of the symbolic regression algorithm based on GA are introduced in Section II. The results of this work are presented in Section III. Section IV includes the discussion. Section IV concludes the paper with the conclusions.

2. Materials and Methods

The approach for generating a model through SR using GA is shown in this section. Fig. 2 outlines the big picture (data collection, model proposal, and comparison with other existing models). This starts with the analysis of the features of a bifacial PV plant with solar trackers and the operating parameters that influence energy production. This subsection describes the data processing techniques applied to this research: data filtering, normality check, and the correlation technique established. Later, the setup of the symbolic regression algorithm was verified. Finally, this is the evaluation, interpreting how we could measure the accuracy and performance of the models using metrics like RMSE and R^2. Finally, a sensitivity analysis was conducted to test the robustness of the SR GA model.

2.1 Specifications of the PV system

Data for training and objective prediction were collected from measurements taken at a facility in San Marcos, Colombia, located at the coordinates: 8° 34′ 32.5″ N, 74° 51′ 27.7″ W. San Marcos in Sucre has a tropical climate with lots of sunshine and warm temperatures all year round. The sunniest months get between 5.5 and 6 kWh/m² of sunlight per day, with an annual average of about 5 kWh/m² per day. The temperature typically varies between 28–32 °C, in the dry season it can exceed 38 °C, whereas in the rainy season it is somewhat cooler, between 26–28 °C, and humidity is generally between 70 and 80%, but it can exceed 80% in case of significant rain (República de Colombia, 2005). The system comprises a bifacial PV plant with trackers designed to generate electricity for the Colombian electrical grid. This installation boasts a capacity of 19.9 MW and is equipped with bifacial modules; the azimuth of the PV plant is 0°, see Fig. 1. The specifications and technical characteristics of the PV bifacial modules are described in Table 1.

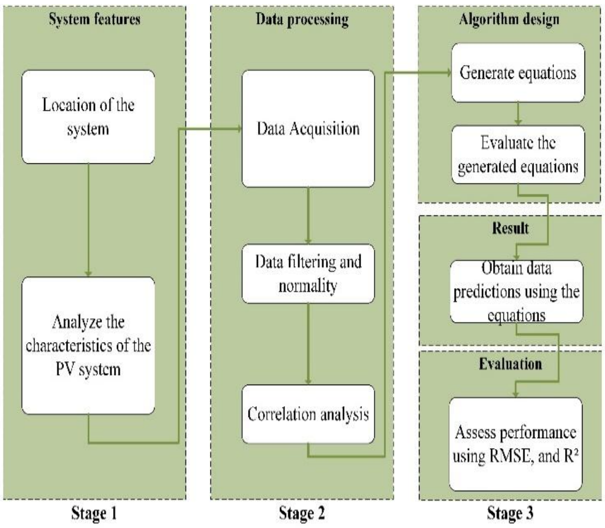


Fig. 2. Summary of methodology for temperature prediction model


Fig. 1. Power generation plants with bifacial solar panels and trackers (Atlantica Colombia, 2023)

Table 1
Technical characteristics of bifacial panels used in PV plant

Item	Number of data
Power rating	400 Wp
Open circuit voltage (Voc)	48.9 V
Short circuit current (Isc)	10.70 A
Maximum power point voltage (Vmp)	40.50 V
Maximum power point current (Imp)	9.97 A
Efficiency (%)	19.5%
Temperature coefficient for Voc	-0.28%/°C
Temperature coefficient for Isc	0.05%/°C
Normal Operating Cell Temperature	25 °C

Source: Authors

2.2 Data processing

The equipment used in the experiment is described in Table 2. The solar tracker operates on a single axis and can move within a range of ±50°, with the 0° position corresponding to midday. Each degree of movement represents 4 minutes, see Fig. 3.

The temperature sensor is located on the rear side of the bifacial PV module, with no solar radiation allowed on it. The solar radiation sensor, on the other hand, is placed vertically mounted on a weather station and is also perpendicular to the ground. It is important to note that the radiation used for analysis is solar radiation that is incident on a horizontal surface at the site, rather than on the module, as the module travels along its path. Simultaneously, the sensor sits in the weather station. Data collection occurred from January 1, 2023, to December 31, 2023, at five-minute intervals, including solar radiation (W/m²), ambient temperature (°C), wind speed (m/s), and bifacial PV module temperature in (°C). The dataset was analysed through filtering and correlation analysis, among others, in order to accurately predict. For the sake of better performance of the algorithm, the data were filtered out due to nonexistent PV power generation, scheduled maintenance of the generation

Table 2
Technical characteristics of equipment

Equipment	Range	Accuracy
CR 300 data	-41 to +69 °C	±1 min per month
Pyranometer MS-80	0 - 3000 W/m2	10 μV/W/m²
110PV CS Scientific	(-45 to 130 °C)	±0.025 °C
Hygro VUE50	-45 to +72 °C	±0.5 °C
Anemometer CS-1	0 to 170 km/h	±0.5 m/s

Source: Authors

Table 3
Technical characteristics of equipment

Libraries	Characteristics
SymPy v1.1	Symbolic expression
Scikit-learn v1.2	Metric calculations
NumPy v1.24-Pandas v2.0	Management and processing
Matplotlib v3.5	Visualization
Multiprocessing	Parallelization of fitness

Source: Authors

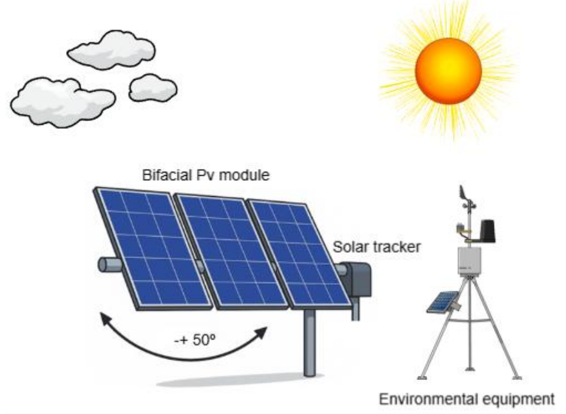


Fig. 3. Measuring equipment and solar tracker

plant, and empty data sets. Also, the data were constrained to the 6:00 and 18:00 hours, because no power was generated for the grid after this period. Out of the dataset, which consisted of 420,480 records, 10,260 (2.44%) of the entries were found incomplete because of bad weather/state pick-up, or system interruptions. All these records were filtered out in the data preparation process before analysis to ensure the correctness of the analysis. The exclusion process was conducted systematically as follows:

- Outliers: To identify outliers, the highest and lowest values of each variable were scrutinized to find and remove any irregularities, thereby maintaining uniformity in the dataset.
- No Imputation: To avoid spurious distortion, missing values were not imputed. Such a perspective is in consonance with previous recommendations (Singha Roy *et al.,* 2020), which emphasizes preserving data integrity over imputation, particularly for high-precision modeling applications (Storlie *et al.,* 2020).
- Focus on normal operations**:** Data from maintenance-related time periods or from times when the system was not functioning properly were eliminated so that records represent only stable operating periods. Thus, the selected filtering improved the dataset with respect to the relevance and accuracy of the modeling.

Analyzing the correlation among variables requires examining the interconnections between these. The corresponding statistical analysis through the correlation coefficient (like Spearman's) tells about the nature and the strength of the relationships between these variables, which form the basis of the symbolic regression model (Sheta *et al.*, 2023). Finding strong correlations between the variables indicates how each is interacting with others to alter the heating of the bifacial PV module. The dataset for training and testing the models was created using 75% for training and 25% for testing data, as suggested by other studies (Kinaneva *et al.,* 2021). To enhance prediction accuracy, it is essential to conduct preliminary data filtering and eliminate singular data points that could lead to prediction errors. The results of the Anderson-Darling normality test play a significant role in deciding which correlation method should be used (Aslam & Algarni, 2020). The correlation between variables was assessed to be adequate and unaffected by the data's non-normality. Selecting an appropriate correlation method allowed for an accurate evaluation of the relationships among the study's variables. Pearson's correlation method is suitable for evaluating linear relationships when the data follows a normal distribution. On the other hand, Spearman's rank correlation method is used when the data does not adhere to normality. The Spearman correlation coefficient, symbolized by ρ, spans from -1 to +1, with values nearer to -1 or +1 signifying a stronger monotonic (Ballina & li, 2025). The computational experiments were carried out on a personal computer. Table 3 describes the libraries used.

2.3 Proposed Algorithm

Symbolic regression is an approach for modeling complex nonlinear relationships between variables, allowing for the identification of the best-fitting (Obaideen *et al.,* 2023). Its importance is highlighted by its . This method relies on the use of genetic algorithms that mimic evolutionary processes to refine mathematical solutions (Angelis *et al.,* 2023). To construct the model employing symbolic regression, the following steps were undertaken, see Table 4.

- Data upload: Upload the file with the data in Excel for the analysis development.
- Initial population generation: The initial population size affects how thoroughly the search space is explored: a larger population enables a more comprehensive exploration but also demands more computational resources. The population can range from 1000 to 10000, so a middle-ground population of 1000 is selected.
- Assessment: The effectiveness of each Equation was evaluated by how well it matched the experimental data. RMSE was used as the primary measure to determine the accuracy of each proposed solution.
- Optimal solution and validation: When the convergence criterion is satisfied, the best solution is chosen as the equation that offers the most accurate fit.

The execution of the algorithm described in Section 2.3 evolved into an explicit and interpretable equation to predict the temperature of a bifacial PV module with a solar tracker. The expression is described in Equation 1.

$$\boldsymbol{T_m = T_a + \sqrt{\left|\sin(10G_s) - |G_S * \cos(T_a * 0.3)|\right|} - E_w} \quad (1)$$

Table 4
Pseudocode for the RS GA algorithm

```
Symbolic Regression with Genetic Algorithms Algorithm

1. Load the regression dataset and select the independent variables (X, Y) and the dependent variable (Z).
2. Generate an initial population with N randomly constructed equations within the search space.
3. Define termination criteria (maximum iterations OR RMSE = 0 OR user stop).
4. Initialize iteration counter, BestFit = INFINITY, BestCandidate = NULL, BestEquation = NULL.
5. FOR each iteration t = 1 to maxIter DO:
  5.1. Select two random Equations (eq1, eq2) from the population.
  5.2. Evaluate eq1 and eq2 with the real data using RMSE (error1, error2).
  5.3. IF error1 < error2 THEN:
      5.3.1. BestCandidate = eq1
      5.3.2. ErrorBestCandidate = error1
      ELSE:
      5.3.3. BestCandidate = eq2
      5.3.4. ErrorBestCandidate = error2
  5.4. Generate a copy of BestCandidate (mutated_copy).
  5.5. Apply random mutation to mutated_copy (modify operators, constants, or Equation structure).
  5.6. Replace the worst-fit equation with mutated_copy.
  5.7. IF ErrorBestCandidate < BestFit THEN:
      5.7.1. BestFit = ErrorBestCandidate
      5.7.2. BestEquation = BestCandidate
      5.7.3. Show BestEquation and BestFit
  5.8. Increment iteration counter.
6. END FOR
7. Return the best Equation, best fitness value, and convergence information.
```

Source: Authors

$\boldsymbol{T_m}$, is the bifacial PV module temperature in (°C), $\boldsymbol{G_S}$ is the solar radiation in (W/m²), the variable $\boldsymbol{T_a}$ represents the ambient temperature in (°C), while $\boldsymbol{E_w}$ denotes the wind speed measured in meters per second (m/s). The term that is contained in the square root is called a nonlinear term.The measurement related to trigonometric functions is in degrees.

2.4 Model evaluation

The RMSE and R² metrics are used to evaluate the model. RMSE: This parameter evaluates those absolute error values in the differences between the predicted values *Vpredicted* and the actual values *Vtarget*. This corresponds to developing a sum of the squares of the differences of these values divided by the sample number *N*, and then taking the root of the result of that operation. The lower the RMSE, the more accurate the model. Equation 1 illustrates the computation method (Hodson, 2022):

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(Vpredicted - Vtarget)^2}{N}} \quad (2)$$

R² (Coefficient of determination): This metric expresses the percentage of the variance of the measured values that can be predicted from the independent variables in the model; it is computed as 1 minus the ratio of the sum-of-squares differences between the actual measured values *yi,actual* and the predicted values *yi,predicted* and the sum-of-squares of the difference between the actual measured values and the average of these values *ȳ,actual*. N is the number of samples of the calibration set or of the validation set. Considering the same concentration range, the closer R is to 1, the higher the degree of fit of the regression or prediction result (Hodson, 2022). The R² was calculated using Equation 2.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(yi,actual - yi,predicted)^2}{\sum_{i=1}^{N}(yi,actual - \bar{y},actual)^2} \quad (3)$$

The RMSE and R² were assessed by comparing the derived equation from the symbolic regression algorithm with the actual data measured in the PV module. The set of data used for the comparison was a group of test data. Using these metrics to measure and compare the performance of the symbolic regression model with the other allows for a critical evaluation of the model's ability to predict temperature behavior. The choice of the following models for comparison with the symbolic regression model is justified by the need to evaluate the new method in a wide range of approaches, from the most basic and generalized to the most specific. This validates the accuracy and usefulness of the proposed model in different contexts and demonstrates its innovative potential and ability to improve the prediction and understanding of the behavior of PV modules with solar trackers. The SR model was compared to a multiple linear regression (MLR) model using the same training dataset. MLR is a statistical method that examines the connection between a dependent variable and multiple independent variables (Sunday *et al.,* 2017). The objective is to identify the line that best fits and minimizes the sum of squared differences between the observed and predicted values of the dependent variable (Jiang, 2022). In addition, a multiple linear regression model was developed using training data and evaluated with a test data set. The analysis will reveal the corresponding coefficients in Equation 4.

$$\text{MLR} = 9.35 + 0.35 * G_S + 0{,}7 * T_a + 0.28 * E_w \quad (4)$$

Furthermore, the model was evaluated against the NOCT model. The cell temperature, Tc (°C), is generally calculated using the NOCT specified by the PV module manufacturer (Nolay, 1987). The connection between Tc and the surrounding temperature Ta (°C), as well as solar radiation G (W/m²), as explained in (Bharti *et al.,* 2009), is expressed as follows in Equation 5:

$$\mathrm{Tc} = \mathrm{Ta} + \frac{\mathrm{G}}{800}(\mathrm{NOCT} - 20\ °\mathrm{C}) \quad (5)$$

The Skoplaki I model relates the environmental variables through Equation 6 (Skoplaki *et al.,* 2008).

$$\mathrm{Tc} = \mathrm{T}_a + \frac{0.32G}{(8.91+2\mathrm{E})} \quad (6)$$

T_a is the ambient temperature (°C), G is solar radiation (W/m²), and E is the wind speed in (m/s). The comparison criteria were the RMSE and R^2. A comparison of the results of the symbolic regression model with those of other models is essential to confirm the efficiency and accuracy of our proposed model. This comparison facilitated the identification of the advantages and disadvantages of the symbolic regression method across various datasets and contexts. Because of the volume of data acquired, the day with the highest irradiance (November 4, 2023) of the test data was chosen to plot the graphical difference between the symbolic regression model, the actual temperature of the solar PV module, and the other models. In addition, a violin plot, box plot, and bagplot were used to represent the performance of the models with the test data group and the temperature measured in the bifacial module. In addition, a sensitivity analysis was developed to confirm whether the SR GA model was consistent in its predictions. Sensitivity analysis is a fundamental tool for evaluating the robustness of model results, as it examines how variations in input parameters affect the results (Tarantola *et al.*, 2024). The one-at-a-time (OAT) sensitivity analysis is a simple method where one input parameter is altered while all other parameters remain unchanged, enabling the examination of the effects on the output (Zand *et al.*, 2023).

3. Results and Discussions

This section outlines the primary findings of this research. It is organized into two parts: an analysis of variable correlations and an assessment of the model.

3.1 Correlation of analysis variables

The statistical analysis of the data obtained from the measuring equipment described in Table 2 forms the basis for understanding the physical interrelations that govern the temperature of a bifacial module with a solar tracker. Table 5 describes the data distribution, where out of a total of 420,480 annual records, 574 were identified as blank or erroneous, and 4,582 records had no values because the equipment was under maintenance. These practices are in line with previous studies (Storlie *et al.*, 2020). More than 98% of the available data was obtained for the development of the study. For the specific analysis, 207,662 records corresponding to the PV plant's daytime operating periods were selected (06:00 a 18:00 h). From this latest dataset, 75% that is, 155,747 records, were used to train the model, while the remaining 25%, or 51,915 records, were set aside for independent model validation. This is a standard practice that ensures an unbiased assessment of predictive performance (Kinaneva *et al.,* 2021). The nature of the interactions between the environmental variables and the temperature of the bifacial module with solar tracker was analyzed through a correlation analysis. Prior to this, since the Anderson-Darling normality test indicated that the data were not normally distributed according to the p-value < 0.05, the Spearman correlation method was chosen for the analysis, a robust and non-parametric methodology suitable for cases where the data do not meet the assumption of normality (Aslam & Algarni, 2020).

Table 5
Acquired data distribution statistics.

Item	Number of data
Total data calculated for the year	420,480
Overall data for the study	420,480
Blank data	574
No data for maintenance activity	4,582
Filtered data for the study	415,324
Total data from 6:00 to 18:00	207.662
Training data	51,915
Test data	25,973

Source: Authors

The results shown in Table 6 indicate highly significant correlations. Correlation provides information about some of the factors that determine the behavior of the bifacial PV module. The extremely strong and monotonic correlation between the module temperature and solar radiation, at ρ = 0.88, is, to a certain degree, normal, since the incident irradiance is the main source of energy absorption and, therefore, of the heating of bifacial PV modules. However, the strength of the correlation is significantly higher than that obtained by Díaz-Bello *et al.*, (2024) in their studies with a different climate (Spain), with ρ = 0.48 (Díaz-Bello *et al.*, 2024). It could be assumed that the discrepancy is due, at least in part, to the intense and constant radiative forcing relevant to the tropical location. Subsequently, this forcing is intensified by the dynamic footprint of the axis follower, which is constantly adjusting to track the sources of irradiance, changing its position throughout the day. The secondary correlation, although extremely strong, with ambient temperature at ρ = 0.83, establishes this parameter as the thermal baseline. On the other hand, wind speed exhibits a moderate correlation with ρ = -0.39, confirming its role as a convective cooling mechanism. However, it proves to be significantly less influential, representing one of the crucial operational challenges for photovoltaics in tropical climates. Fig. 4 shows a three-dimensional scatter plot, in which the highest values of solar radiation are found in regions above 1200 W/m² and the highest ambient temperature is close to 37.5°C. On the other hand, wind speed is mostly below 3 m/s.

Fig. 5 shows the average hourly evolution of solar radiation, module temperature, tracker angle, and solar time. An interesting finding is that the maximum temperature of the bifacial module with a tracker does not occur at solar noon, but rather around 14:00 h, that is, there is a delay or thermal lag of approximately two hours with respect to the irradiance peak. These results differ from those obtained when measuring the temperature in a monofacial solar module without a solar tracker at 8° tilt and 0° azimuth at latitudes very similar to that of the

Table 6
Solar hour, Solar radiation, PV module temperature correlation coefficients

	Wind speed	Ambient temperature	Solar radiation	PV module temperature
Wind speed	1			
Ambient temperature	0.30	1		
Solar radiation	0.34	0.59	1	
PV module temperature	-0.39	0.83	0.88	1

Source: Authors

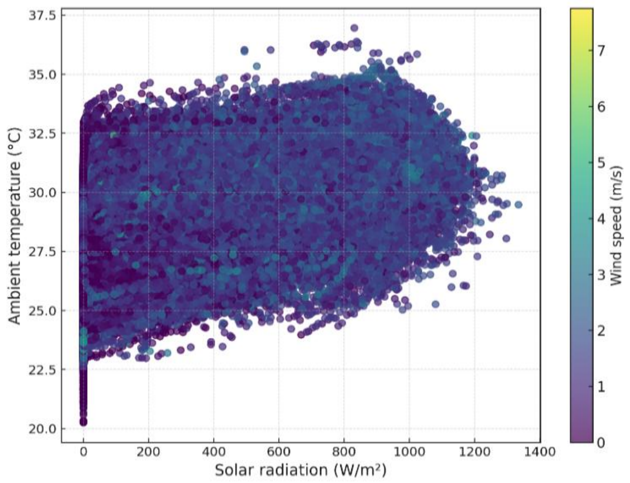


Fig. 4 Scatter plot of solar radiation versus ambient temperature and wind speed

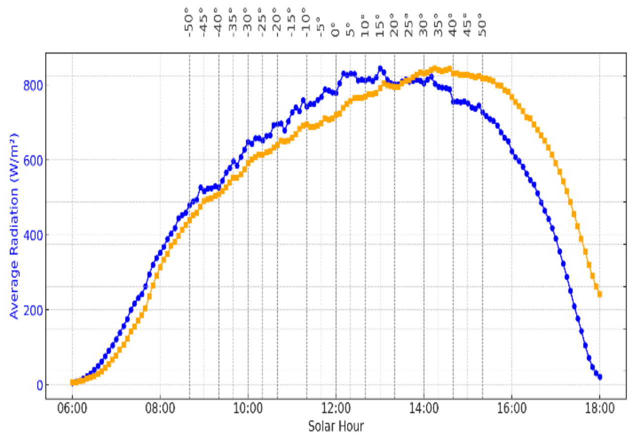


Fig. 5 Radiation and module temperature as a function of solar time and tracking angle

plant under study, where the maximum temperature is reached at midday (Lara Vargas *et al*., 2025b). This phenomenon could be attributed to the combination of three main factors: a) the thermal inertia of the module materials and their mounting structure, which delays the response to the irradiation peak, b) the continuous contribution of reflected radiation on the rear side, which is maximized by the tracker's orientation even after midday, c) and the high ambient temperatures characteristic of the tropical climate, which reduce the efficiency of thermal dissipation, as well as the high humidity at the plant site, which ranges between 70 and 80%, as studied in section 2.1. This delay coincides with the observations of Wang *et al*.,(2022) who noted that trackers can prolong the period of energy capture and, consequently, heat accumulation (Wang *et al.,* 2022). This result highlights the need to develop specific models, such as the one proposed in this work, that take into account the particular dynamics generated by the use of solar tracking.

2.2 Model evaluation

The symbolic regression algorithm with genetic algorithms (SR GA) is configured with the parameters detailed in Table 7. The algorithm evolved until it found Equation 1 presented in Section 2.3. The total processing time of the algorithm was 20 minutes and 10 seconds. A computationally reasonable time for the volume of training data, and given the complexity of the relationships between the variables, especially when the resulting model is a simple algebraic expression with instant evaluation, as opposed to the costly numerical models of computational fluid dynamics that require more than the three variables used by the RS GA model (Haeberle *et al.,* 2022).

The predictive performance of the model was evaluated using the test data and compared with three reference models, as shown in Table 8. The proposed model achieved the best performance with an RMSE of 4.14 °C and an R^2 of 0.91. These results indicate that the RA GA model explains 91% of the variance in the temperature of the bifacial module with a solar tracker. The next best model is the MLR, with an RMSE of 4.31 °C and an R^2 of 0.90, outperforming the empirical NOCT models with an RMSE of 8.59 °C and an R^2 of 0.60, and the Skoplaki I model with an RMSE of 5.91 °C and an R^2 of 0.81. The superior performance of the RA GA model lies in its ability to capture nonlinearities and interactions among the variables analyzed, aspects that the reference models do not consider, as they overlook the dynamics introduced by the type of PV module used and by the solar tracker (Mannino *et al.,* 2022 ; Tina *et al.*, 2020). Table 8 summarizes the various data obtained from the models used about the actual temperature of the PV module.

Figure 6a allows us to visualize the individual contribution of each component to the measured module temperature *(Tm),* taking into account Equation (1). It can be seen that the ambient temperature *(Ta)* provides a thermal baseline for the RS GA model. The nonlinear term (the expression inside the square root) adds the heating caused by solar radiation *(Gs),* which displays a nonlinear response modulated by ambient temperature through the sine function. Likewise, the effect of wind speed is presented as a cooling effect of constant magnitude that is subtracted linearly from the result. This decomposition offers insight into the importance of each variable in the heating of the bifacial solar module with a solar tracker, which aligns with the explanatory capacity of the models derived from symbolic regression (shmuel *et al.* 2023; Angelis *et al.* 2023). Figure 6b, which represents the day with the highest radiation recorded during the testing period, illustrates that the measured temperature of the module and the temperature predicted by the Model SR GA exhibit a similar pattern. This pattern is characterized by a gradual increase from the early hours, reaching a peak around midday, followed by a decline in the afternoon. The convergence of both curves suggests a generally strong correlation, although minor discrepancies are noted during periods of maximum radiation, where the model occasionally diverges from the observed values. This visual

Table 7
Algorithm input parameters

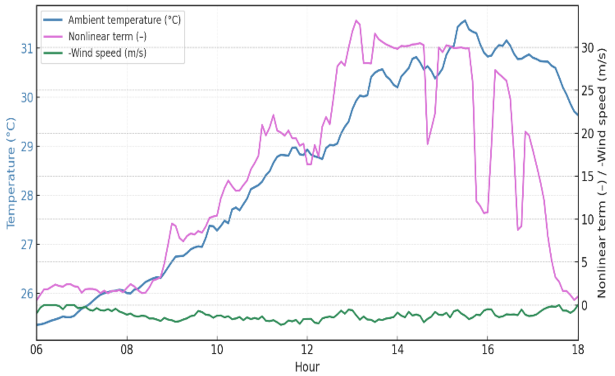
Item	Number of data
Individual set	1000
Evolutions steps	50
Baseline mutation	0.5
Selection ratio	0.5
Hybridization	Subexpression

Source: Authors

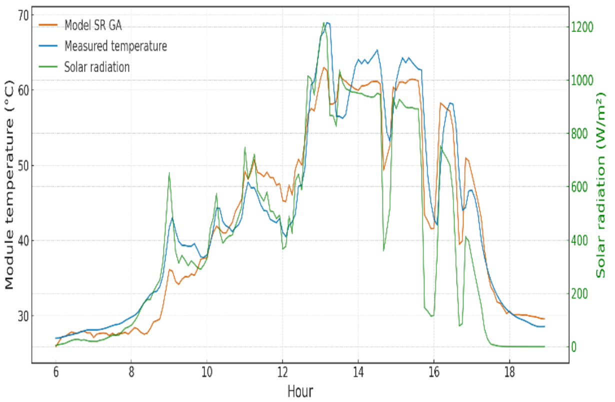
Table 8
Comparison of models

Model	RMSE	R^2
SR GA	4.14	0.91
MLR	4.31	0.90
NOCT	8.59	0.60
Skoplaki I	5.92	0.81

Source: Authors



(a)



(b)

Fig. 6 Components and behavior of the SR GA model. a) Components of the RS GA model symbolic equation. b) Comparison between RS GA model and a clear day

analysis suggests that the SR GA model effectively reproduces the thermal behavior of the module on a day of maximum irradiation, despite slight deviations in the peaks. A comparative analysis is presented in Figure 7, where the performance of the RS GA model is contrasted with the reference models on the day with the highest radiation during the test period. The advantage of the symbolic regression approach is evident. While the NOCT and Skoplaki I models consistently underestimate the temperature of the bifacial OPV module with a solar tracker throughout the day, the NOCT model in particular overestimates it during the hours of highest solar radiation. In contrast, the RS GA model aligns much more closely with the actual temperature of the module, demonstrating its superior ability to generalize under extreme conditions. This behavior confirms that the linear assumption inherent to MLR is insufficient for this nonlinear system and that, while empirical models are useful for preliminary estimates, they lack the accuracy needed for modeling bifacial PV systems with solar trackers.

Fig 8 delves deeper into the analysis of the test data, the RS GA model, and the reference models by means of box plot and violin plot distributions. It is observed that the RS GA and RLM models show narrower distributions centered around the measured temperature values, indicating a better fit in terms of accuracy and dispersion. In contrast, the NOCT model shows a greater deviation from the measured temperature, with a more distant and wider distribution, confirming its lower ability to represent real conditions under a tropical climate and using a solar tracker. The Skoplaki I model offers intermediate performance, better than NOCT but with greater dispersion than RS GA and RLM. These results are consistent with previous

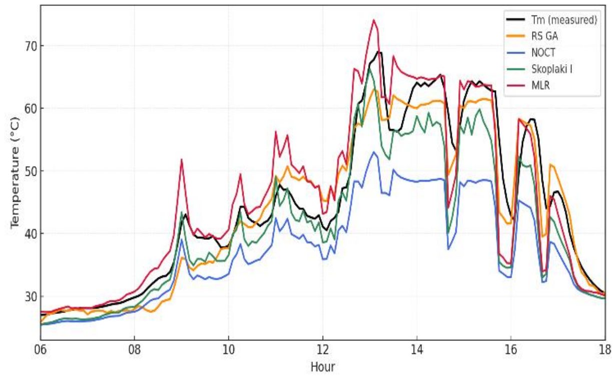


Fig. 7 Behavior of models on the day with the highest solar radiation

studies that pointed out the limitation of the NOCT model in capturing thermal interactions in bifacial modules in tropical climates (Mannino *et al*., 2022). Finally, the one-at-a-time (OAT) sensitivity analysis, performed on Equation (1) in Figure 9, provides a physical validation of the model and confirms its robustness: The nonlinear relationship between the bifacial module temperature (*Tm*) and solar irradiance (*Gs*) (a) is consistent with the physical phenomenon known as thermal saturation, where at very high irradiance levels, heat dissipation efficiency decreases, leading to less than proportional increases in module temperature (Kaplani & Kaplanis, 2020). The non-monotonic response of the ambient temperature (Ta) in part (b), with slight variations in the slope, is the most interesting result due to the use of a trigonometric term inside the square root of Equation (1). This behavior suggests that the model captures a complex interaction where the ambient temperature modulates the effectiveness of irradiance in heating the bifacial module, likely related to changes in the thermal conductivity of air or to radiative losses in different temperature regimes. This level of interpretation is typical of symbolic regression models and would be impossible to obtain in a black box model such as a neural network (Kayri & Aydin, 2022). The influence of wind speed *(Ew)* in part (c) is approximately linear and of moderate magnitude, which aligns with its role as a convective cooling mechanism (Meflah *et al*., 2023), whose effectiveness at this tropical site, with predominantly low winds, is limited. These results highlight the importance of mitigation strategy (tracking angle management to limit thermal peaks, geometric separation to promote convective sweeping) targeted specifically for

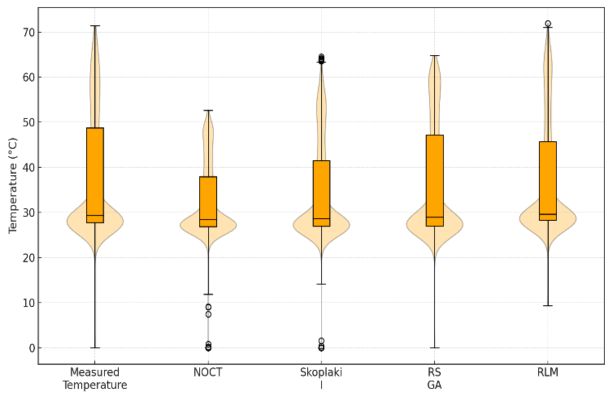


Fig. 8 Data distribution of the different models and the temperature measured in the bifacial PV module

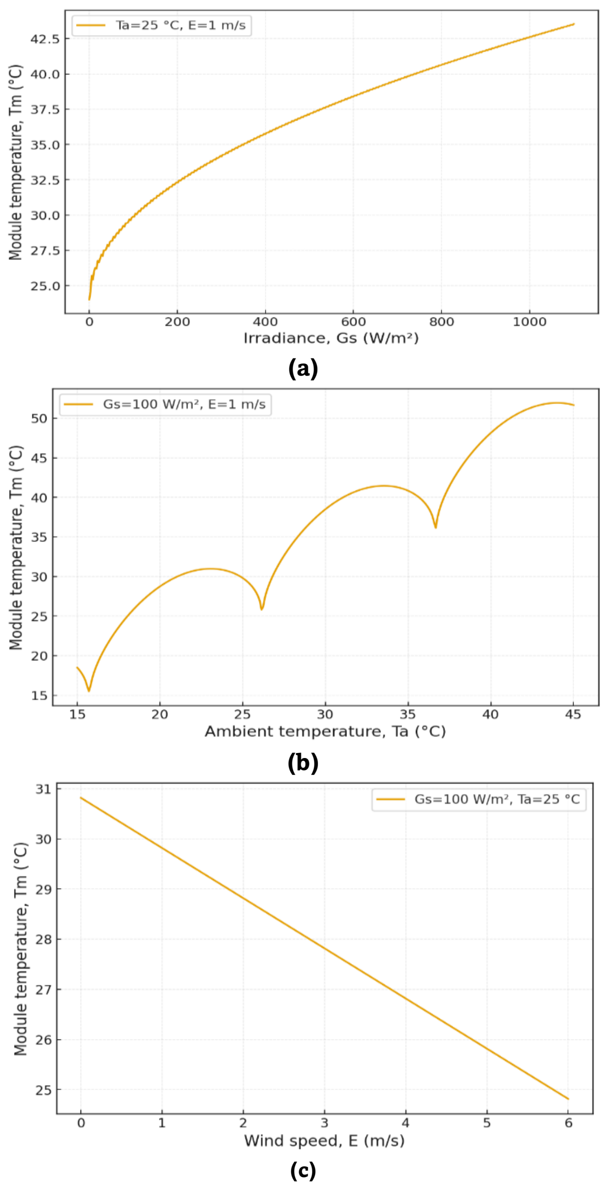


Fig 9. Sensitivity of module temperature to a) irradiance, b) ambient temperature, and c) wind speed

bifacial modules with tracking, which have been recommended by others through empirical analysis (Wang *et al.,* 2022).

The results complement and extend the existing literature on thermal modeling of PV modules that use solar trackers. The RS GA model conducts an analysis with a greater number of records at a high precision (every 5 minutes), analyzing data from an entire year in duration, unlike other models. (Kaplani & Kaplanis, 2020; Johansson *et al*., 2022 ; Sanchís-Gómez *et al*., 2025) and Black Box Models (e.g., Neural Networks - (Kayri & Aydin, 2022). A key benefit of the RS GA model is that it exceeds the accuracy of the RLM and approaches the prediction capabilities of much more complex models, but with the added benefit of physical interpretability. On the other hand, when comparing the RS GA model with the Skoplaki I (Sanchís-Gómez *et al*., 2025), the end result was an RS GA model that was 30% more accurate than the prior best Skoplaki I model. In addition, it achieved better accuracy than the model by Kaplani & Kaplanis,(2020) whose accuracy ranges between ± 5 °C (Kaplani & Kaplanis, 2020) and the computational fluid dynamics (CFD) model, which obtained an RMSE of 4.2 °C (Johansson *et al.,* 2022). As such, this study addresses a gap in the literature that can be summed up as an absence of a precise, interpretable, computationally cheap model for bifacial modules with trackers in the tropics.

Despite the promising results, this work presents some limitations that must be acknowledged: a) Geographical generalization: The model was built and validated based on a unique region (San Marcos, Colombia). It is yet to be validated in climates where solar radiation patterns, humidity, or wind differ radically (e.g., arid, temperate, or cold). b) Computational cost: While the final model is a simple one, the RS GA was run on a large population (1,000 individual population size) and took a of processing time (20 minutes). That might make it less practical for certain applications that require constant retraining, without the optimal compute hardware to back it up (Sanchís-Gómez *et al.,* 2025). The implications of this research are both practical and academic. The derived equation provides a simple tool for engineers and PV plant designers to predict system operating temperatures to maximize efficiency and lifespan in tropical environments. Eventually, long-term studies (≥ 5 yr) could be done to compare the temperature predictions of the model with actual observed module performance degradation data on a yield basis to create predictive models of service life.

5. Conclusion

This study demonstrates the potential of symbolic regression as a technique for modeling physical phenomena applied to renewable energy, specifically the temperature of a bifacial module with a solar tracker located in a tropical region. The RS GA model outperformed traditional and statistical methods in modeling the temperature of a bifacial module, achieving an RMSE of 4.14 °C and an R^2 of 0.91. The main contribution is the derivation of Equation (1), which models the thermal behavior of the bifacial module. An important finding was that the bifacial module with a solar tracker reaches its maximum temperature around 14:00h, in contrast to fixed monofacial modules in similar tropical latitudes. This behavior highlights the need for specific prediction models for systems with solar trackers.

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References

Abe, J. Batista Dias, G. Notton, G. -A. Faggianelli, G. Pigelet and D. Ouvrard. (2023). Estimation of the Effective Irradiance and Bifacial Gain for PV Arrays Using the Maximum Power Current. *IEEE J Photovolt* 13:. https://doi.org/10.1109/JPHOTOV.2023.3242117.

Ali, M.M., Rokonuzzaman, M. D. Z,. Shuvo, A., Das, M., Islam, M., Rahman, M.M.(2021). Performance Investigation of Bifacial Module Based Time Varying Multilevel Solar Panel System. In: *Conference Record of the IEEE Photovoltaic Specialists Conference*. https://doi.org/10.1109/PVSC43889.2021.9518456

Angelis, D., Sofos, F., Karakasidis, T.E. (2023). Artificial Intelligence in Physical Sciences: Symbolic Regression Trends and Perspectives. *Archives of Computational Methods in Engineering* 30. https://doi.org/10.1007/s11831-023-09922-z

Aslam, M., Algarni, A. (2020). Analyzing the solar energy data using a new anderson-darling test under indeterminacy. *International Journal of Photoenergy*. https://doi.org/10.1155/2020/6662389

Atlantica Colombia.(2023). Get to know our Plants. In: https://atlanticacolombia.com/en/nuestras-plantas/

Ballina, J., Yun, L. (2025). Quantification and Comparative Analysis of Environmental Factors to Large-Scale Solar Plant's Energy Performance via Regression and Linear Correlation Models. *Journal of Energy and Power Technology*; 7(1), 001; https://doi.org/doi:10.21926/jept.2501001.

Becerra, V.G., Valdivia-Lefort, P., Barraza, R., García, J.G.(2024). Electrical Model Analysis for Bifacial PV Modules Using Real Performance Data in Laboratory. *Energies (Basel)*, 17, 5868. https://doi.org/10.3390/en17235868.

Bera, C., Premachandra, K.W.R.S, Sujeewan, G., Rathwaththa, J.D.R.R, Abejeewa, P.A.I.S, Priyadarshana, H.V.V, Koswattage, K.R. (2024). A Comparative Experimental Performance Analysis for Fixed Solar PV Systems and Solar Tracker PV Systems in a Tropical Region. *International Journal of Research and Innovation in Applied Science* IX, 476–480. https://doi.org/10.51584/IJRIAS.2024.909041

Bharti,. R, Kuitche, J,, Tamizhmani, M.G. (2009). Nominal Operating Cell Temperature (NOCT): Effects of module size, loading and solar spectrum. *Conference Record of the IEEE Photovoltaic Specialists Conference*. https://doi.org/10.1109/PVSC.2009.5411408

Burnham, L., Riley, D., Walker, B., Pearce, J.M. (2019). Performance of Bifacial Photovoltaic Modules on a Dual-Axis Tracker in a High-Latitude, High-Albedo Environment. *Conference Record of the IEEE Photovoltaic Specialists Conference*

Díaz-Bello, D., Vargas-Salgado, C., Alcázar-Ortega, M., Solar-Alfonso, D. (2024). Optimizing Photovoltaic Power Plant Forecasting with Dynamic Neural Network Structure Reenement Optimizing Photovoltaic Power Plant Forecasting with Dynamic Neural Network Structure Refinement. *Scientific Reports*, 15, 3337 https://doi.org/10.21203/rs.3.rs-3835055/v1

Fan, X., Liu, W., Zhu, G. (2017). Scientific linkage and technological innovation capabilities: international comparisons of patenting in the solar energy industry. *Scientometrics* 111:. https://doi.org/10.1007/s11192-017-2274-5

Haeberle, F., Dias, J.B., Cardoso Junior, J.T., Abe, C., Notton, G. (2022). Estimativa da temperatura do módulo fv a partir de um modelo de balanço de energia. *Anais Congresso Brasileiro de Energia Solar - CBENS*. https://doi.org/10.59627/cbens.2022.1122.

He, M., Zhang, L. (2021). Machine learning and symbolic regression investigation on stability of MXene materials. *Comput Mater Sci* 196:. https://doi.org/10.1016/j.commatsci.2021.110578.

Hodson, T.O. (2022). Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. *Geosci Model Dev* 15. https://doi.org/10.5194/gmd-15-5481-2022

Jiang, J. (2022). Multiple Linear Regression. *Applied Medical Statistics*. John Wiley & Sons, Ltd, 345–367. https://www.wiley.com/en-us/Applied+Medical+Statistics-p-9781119716822

Johansson, F., Gustafsson, B.E., Stridh, B., Campana, P.E. (2022). 3D-thermal modelling of a bifacial agrivoltaic system: a photovoltaic module perspective. *Energy Nexus*, 5. https://doi.org/10.1016/j.nexus.2022.100052.

Kaplani, E., & Kaplanis, S. (2014). Thermal modelling and experimental assessment of the dependence of PV module temperature on wind velocity and direction, module orientation and inclination. *Solar Energy* 107. https://doi.org/10.1016/j.solener.2014.05.037

Kaplani, E., & Kaplanis, S. (2020). PV Module Temperature Prediction at Any Environmental Conditions and Mounting Configurations. In: Sayigh, A. (eds) Renewable Energy and Sustainable Buildings. Innovative Renewable Energy. Springer, Cham. https://doi.org/10.1007/978-3-030-18488-9_77

Kaushik, A.R., Padmavathi, S., Gurucharan, K.S., Raja, S.C. (2023). Performance Analysis of Regression Models in Solar PV Forecasting. *2023 3rd International Conference on Artificial Intelligence and Signal Processing*, AISP 2023. https://doi.org/10.1109/AISP57993.2023.10134943

Kayri, I., Aydin, H. (2022). ANN Based Prediction of Module Temperature in a Single Axis PV System. *IEEE Global Energy Conference, GEC* 2022. https://doi.org/10.1109/GEC55014.2022.9986829

Kinaneva, D., Hristov, G., Kyuchukov, P., Georgiev, G., Zahariev, P., Daskalov, R.(2021). Machine Learning Algorithms for Regression Analysis and Predictions of Numerical Data. In: HORA 2021 - 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications, Proceedings. https://doi.org/10.1109/HORA52670.2021.9461298

Lara Vargas, FA, De la Ossa Rivera, J., Jaramillo Mira, S., Vargas Salgado, C. (2025a). Optimización del rendimiento de plantas solares en azotea mediante monitoreo IoT de bajo costo: Un estudio de caso en Montería, Colombia. *Entre Ciencia e Ingeniería*, 19, 71–78. https://doi.org/10.31908/19098367.3106

Lara-Vargas, F.A., Vargas-Salgado, C., Águila-León, J., Díaz-Bello, D. (2025b). Optimizing Bifacial Solar Modules with Trackers: Advanced Temperature Prediction Through Symbolic Regression. *Energies (Basel)* 18. https://doi.org/10.3390/en18082019.

Mannino, G., Tina, G.M., Cacciato, M., Todaro, L., Bizzarri, F. (2022). Experimental assessment of temperature estimation models of bifacial photovoltaic modules. *2022 IEEE 49th Photovoltaics Specialists Conference (PVSC). IEEE*, pp 0214–0216. https://doi.org/10.1109/PVSC48317.2022.9938792

Masrur, H., Konneh, K.V., Ahmadi, M., Khan, K., Lutfi, M., Senjyu, T. (2021). Assessing the techno-economic impact of derating factors on optimally tilted grid-tied photovoltaic systems. *Energies* (Basel) 14. https://doi.org/10.3390/en14041044.

Mattei, M., Notton, G., Cristofari, C., Muselli, M., Poggi, P. (2006). Calculation of the polycrystalline PV module temperature using a simple method of energy balance. *Renew Energy* 31, 553–567. https://doi.org/10.1016/J.RENENE.2005.03.010

Meflah, A., Aouchiche, I., Berkane, S., Chekired, F. (2023). Estimation models of photovoltaic module operating temperature under various climatic conditions. *Indonesian Journal of Electrical Engineering and Computer Science* 32. https://doi.org/10.11591/ijeecs.v32.i1.pp13-20

Nolay, P. (1987). Developpement d'une methode generale d'analyse des systemes photovoltaiques. ENMP

Obaideen, K., Olabi, A.G., Al Swailmeen, Y., Shehata, N., Ali, M., Hai, A., Rodriguez, C. E. (2023). Solar Energy: Applications, Trends Analysis, Bibliometric Analysis and Research Contribution to Sustainable Development Goals (SDGs). *Sustainability* (Switzerland) 15. https://doi.org/10.3390/su15021418

Patel, M.T., Vijayan, R.A., Asadpour, R., Varadharajaperumal, M,, Khan, R., Alam, M.(2020). Temperature-dependent energy gain of bifacial PV farms: A global perspective. *Appl Energy*, 276. https://doi.org/10.1016/j.apenergy.2020.115405

Ponnada, S., Kumari, I., Chinnam, S., Sadat, M., Lakshaman, A., Kumar, L., Bose, R.S.C., Gorle, D.B., Nowduri, A., Sharma, R.K. (2022). Renewable Energy: Introduction, Current Status, and Future Prospects. In: Green Energy Harvesting: Materials for Hydrogen Generation and Carbon Dioxide Reduction. https://doi.org/10.1002/9781119776086.ch1

Radwan, Y.A., Kronberger, G., Winkler, S. (2024). A Comparison of Recent Algorithms for Symbolic Regression to Genetic Programming. *Lecture Notes in Computer Science*, 15172.. https://doi.org/10.1007/978-3-031-82949-9_15

Raina, G., Sharma, S., Sinha, S. (2023). Dynamic Opto-Electric-Thermal Modelling for Performance Assessment of Bifacial PV Modules. *2023 IEEE 3rd International Conference on Sustainable Energy and*

Future Electric Transportation, *SeFet* 2023. https://doi.org/10.1109/SeFeT57834.2023.10245096

República de Colombia (2005). Atlas de Radiación Solar de Colombia. Bogota

Sanchís-Gómez, C., Aleix-Moreno, J., Vargas-Salgado, C., Alfonso-Solar, D. (2025). The novel evaluation method for PV module temperature and string size risk in utility-scale solar projects. *Solar Energy* 295:113520. https://doi.org/10.1016/J.SOLENER.2025.113520

Sheta, A., Abdel-Raouf, A., Fraihat, K.M., Baareh, A. (2023). Evolutionary Design of a PSO-Tuned Multigene Symbolic Regression Genetic Programming Model for River Flow Forecasting. *International Journal of Advanced Computer Science and Applications(IJACSA),* 14 (4). http://dx.doi.org/10.14569/IJACSA.2023.0140489

Shmuel, A., Glickman, O., Lazebnik, T. (2023). Symbolic Regression as Feature Engineering Method for Machine and Deep Learning Regression Tasks. *Mach. Learn.: Sci. Technol.* **5** 025065. https://doi.org/10.1088/2632-2153/ad513a

Singha, R. M., Roy, B., Gupta, R., Das Sharma, K. (2020) .On-Device Reliability Assessment and Prediction of Missing Photoplethysmographic Data Using Deep Neural Networks. *IEEE Trans Biomed Circuits Syst* 14. https://doi.org/10.1109/TBCAS.2020.3028935

Skoplaki, E., Boudouvis, A.G., Palyvos, J.A. (2008). A simple correlation for the operating temperature of photovoltaic modules of arbitrary mounting. *Solar Energy Materials and Solar Cells* 92,1393–1402. https://doi.org/10.1016/j.solmat.2008.05.016

Storlie, C.B., Therneau, T.M., Carter, R.E, Chia. N., Bergquist, J.(2020). Prediction and Inference With Missing Data in Patient Alert Systems. *J Am Stat Assoc* 115:. https://doi.org/10.1080/01621459.2019.1604359

Sunday, V.E., Simeon, O., Anthony, U.M. (2017). Multiple Linear Regression Photovoltaic Cell Temperature Model for PVSyst Simulation Software. *International Journal of Theoretical and Applied Mathematics* 2, 140–143. https://doi.org/10.11648/j.ijtam.20160202.27

Tarantola, S., Ferretti, F., Lo Piano, S., kaslova, M., Lachi, A., Rosati, R., Puy, A., Roy, P., Vannucci, G., Czarnecka, M., Saltelli, A. (2024). An annotated timeline of sensitivity analysis. *Environmental Modelling and Software* 174. https://doi.org/10.1016/j.envsoft.2024.105977

Tina, G.M., Scavo, F.B., Gagliano, A. (2020). Multilayer Thermal Model for Evaluating the Performances of Monofacial and Bifacial Photovoltaic Modules. *IEEE J Photovolt* 10, 1035–1043. https://doi.org/10.1109/JPHOTOV.2020.2982117

Tripathi, A.K., Ray, S., Aruna, M. (2021). Analysis on Photovoltaic Panel Temperature under the Influence of Solar Radiation and Ambient Temperature. *2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT). IEEE,* pp 1–5. https://doi.org/10.1109/ICAECT49130.2021.9392619

Wang, S., Shen, Y., Zhou, J., Li, C., Ma, L. (2022). Efficiency Enhancement of Tilted Bifacial Photovoltaic Modules with Horizontal Single-Axis Tracker—The Bifacial Companion Method. *Energies* (Basel) 15:1262. https://doi.org/10.3390/en15041262

Yakubu, R.O., Mensah, L.D., Quansah, D.A., Adaramola, M,S. (2022). Improving solar photovoltaic installation energy yield using bifacial modules and tracking systems: An analytical approach. *Advances in Mechanical Engineering* 14. https://doi.org/10.1177/16878132221139714

Zaimi, M., El Achouby, H., Ibral, A., Assaid, E., Salaheddine, M., Saadani, R.(2019). Temporal monitoring of temperature and incident irradiance for predicting photovoltaic solar module peak power and efficiency using analytical expressions of model physical parameters. *Proceedings of 2018 6th International Renewable and Sustainable Energy Conference, IRSEC 2018*. https://doi.org/10.1109/IRSEC.2018.8702973

Zand, M., Nasab, M.A., Padmanaban, S., Maroti, P., Muyeen, S.(2023). Sensitivity analysis index to determine the optimal location of multi-objective UPFC for improvement of power quality parameters. *Energy Reports* 10. https://doi.org/10.1016/j.egyr.2023.06.028