

Comprehensive Analysis of Thermal–Electrical Models for PV Module: A Review of Current Approaches and Challenges

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Abstract

The independent application of conventional electrical or thermal models is, generally, not adequate to model the interdependence between temperature distribution, heat transfer mechanisms, and the electrical performance of Photovoltaic (PV) generators. In this context, coupled thermal–electrical modeling approaches have recently gained increasing importance to accurately simulate the PV performance. This work presents a comprehensive and systematic analysis of electrical, thermal, and coupled thermal–electrical models developed for PV modules. Electrical models are classified into analytical/physical, semi-empirical, and empirical classes, highlighting their assumptions, parameter requirements, computational complexity, and applicability at cell, module, and system levels. Thermal modeling approaches are reviewed by distinguishing lumped parameter and thermal network models from spatially distributed numerical methods. Particular emphasis is placed on the ability of these models to represent non-uniform temperature distributions and transient operating conditions. Furthermore, this review critically examines state-of-the-art coupled thermo-electrical models, focusing on different coupling strategies, feedback mechanisms, and levels of spatial resolution. The advantages and limitations of each modeling approach are discussed in relation to accuracy, computational cost, and suitability for performance prediction, fault analysis, and reliability assessment. Finally, current research gaps and future directions are identified, providing a structured framework to guide the selection of the most appropriate model and the development of more accurate and physically consistent PV modeling strategies under complex and realistic operating conditions.

Keywords: photovoltaic modules; PV performance modeling; thermal mismatch; thermal–electrical modeling; coupled models; non-uniform temperature distribution

Academic Editor: Maria Vicidomini

Received: 16 January 2026

Revised: 13 February 2026

Accepted: 21 February 2026

Published: 26 February 2026

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1. Introduction

Nowadays, Photovoltaic (PV) technology has become one of the most important in the renewable energy systems thanks to its modularity, scalability, reliability [1,2,3], and cost effectiveness. However, the electrical performance and long-term reliability of PV

modules are strongly affected by the real operating conditions (cloud coverage, irradiance, and temperature) [4]. Predicting and optimizing the performance of PV systems in real operating conditions requires a deep understanding of the complex interactions between the thermal and electrical phenomena. The temperature of a PV module might significantly affect its current–voltage (I – V) curve and its most important electrical parameters like open-circuit voltage (V_{oc}), short-circuit current (I_{sc}), and maximum power (P_{max}). Nevertheless, the temperature distribution for the cells of a PV module might be non-homogeneous. In this context, a thermal mismatch might occur between the cells, resulting in voltage and power reductions at the module level [5]. Accurate thermo-electrical models are essential for capturing these temperature-dependent effects due to the non-linear relationships between the electrical parameters and the spatial temperature variations along the module surface. These models take into account factors like solar irradiance, ambient temperature, wind speed, module mounting configuration, and material properties [6] and permit the correct investigation of underperformance [7], as well as the identification of faults or failures in real PV plants [8]. Techniques for thermal modeling include finite element analyses [9], finite difference methods [10,11], and computational fluid dynamics [12], which are increasingly employed to accurately simulate the thermo-electrical behavior of PV modules.

This review aims to provide a comprehensive overview of the current state of the art in thermal–electrical modeling for silicon-based PV modules, which constitute most global PV installations, including some considerations regarding their accuracy, computational efficiency, and applicability to different silicon-based PV module configurations. Specifically, the study systematically compares model categories, identifying their strengths, limitations, and optimal application scenarios, as well as emphasizing the importance of integrating thermal and electrical modeling for accurate performance estimation. This study aims to overcome one of the limits affecting the previous studies in the literature that evaluate PV performance by uncoupling the electrical and thermal modeling of solar cells [13,14]. By discussing the literature on different types of models, this review work provides a guide for model selection to help future researchers in selecting an appropriate technique based on their need for modeling, optimization, and maintenance goals. Moreover, it also discusses future recommendations by identifying research gaps in the literature; hence, it provides a roadmap for improving PV modeling strategies under varying and complex operating conditions.

This review article is organized into five sections. Section 1 discusses the introduction, background, motivation, importance, and contribution of the present work. Section 2 is focused on electrical models, discussing analytical/physical, semi-empirical, and empirical models and evaluating the electrical performance of PV modules through these models. In Section 3, thermal models for the estimation of the temperature spatial distribution for PV modules or of a unique module temperature value are discussed. Section 4 discusses the developed coupled models in the literature. These models utilize different coupling approaches based on electrical and thermal models as well as PV technologies; and finally, Section 5 is the discussion and conclusion section that also presents the summary and future recommendations.

2. Modeling for the Estimation of the Electrical Performance of PV Generators

With the increasing demand for photovoltaic systems, it is crucial to accurately model the conversion of solar power into electrical power through solar cells and modules. It can be helpful for better performance of photovoltaic power plants and monitoring systems, as well as electricity production forecasting [15,16]. In the literature, many electrical

models have been developed for photovoltaic cells, with different levels of detail and numbers of parameters [11,17].

While computing the electrical model for a solar cell, there is a need to solve a non-linear system of equations that involves some unknown parameters [18]. The data provided by the manufacturer of the solar cell/module are operational data under benchmark operating conditions, including a solar irradiance of 1000 W/m² and a module temperature of 25 °C, which is known as Standard Test Conditions (STC) [19].

Depending on the modeling goals and required accuracy, electrical models can be classified into three groups (Figure 1): analytical/physical derived from semiconductor physics theory, empirical, which depends on the regression between the meteorological inputs and experimentally measured PV power, and semi-empirical models that integrate the physics-based models and the optimized experimental data.

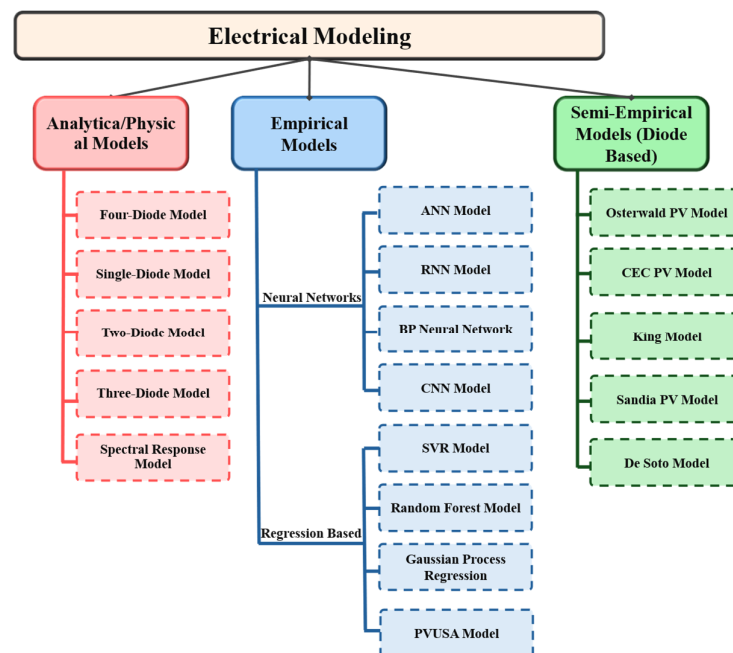


Figure 1. Configuration of electrical models for PV.

Empirical models might result in estimations with high accuracy; however, large datasets are, generally, required to achieve this goal, leading to high computational effort. On the contrary, semi-empirical models offer low computational cost and are easy to implement, but they lack extrapolation capabilities and physical insights into the PV cell/modules. Nevertheless, the application of these two classes of models is, generally, limited to specific PV generators. The analytical electrical models (i.e., diode-based models) are good trade-offs, as they are able to determine the performance of the PV generator under variable conditions with high accuracy without requiring large datasets and computation efforts. The detailed discussion of these electrical models for PV cells/modules is presented in the following subsections.

2.1. Analytical/Physical Models

Analytical/physical models are based on physical laws and semiconductor physics; specifically, these models evaluate the current-voltage (I - V) characteristic curve of the PV cells/modules by considering the charge transport, the recombination, and the junction properties. Physical models include the Single-Diode Model (SDM) [20], the Double-Diode Model (DDM) [21], the Triple-Diode Model (TDM) [22], and the spectral response model.

The electrical behavior of Photovoltaic (PV) cells and modules is commonly represented using equivalent circuit models [23]. The work [24] compared the performance of diode-based models under uniform sunlight and partial shading.

2.1.1. Four-Parameter Model

The four-parameter model [25] consists of a current source representing the photo-current generated by incident solar irradiance, I_{ph} , a diode with reverse saturation current, I_0 , and the ideality factor, n , representing the behavior of the p-n junction like a diode and a series resistance, R_s , accounting for resistive losses in the contacts. This model neglects the contribution of leakage currents through the lateral surfaces of the cells [26], modeled with the shunt resistance, R_{sh} (Figure 2).

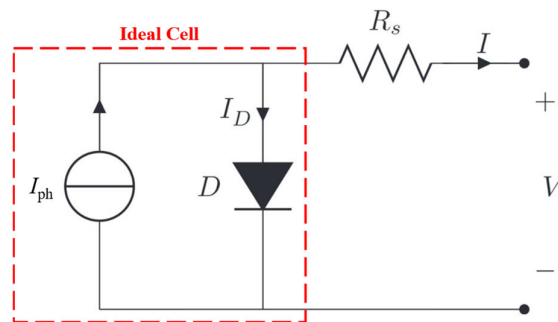


Figure 2. Four-parameter model for a solar cell.

The I – V characteristic curve for the four-parameter model can be evaluated as follows:

$$I = I_{ph} - I_0 \cdot \left(e^{\frac{(V+R_s \cdot I)}{n \cdot V_t}} - 1 \right) \quad (1)$$

where I is the cell current, V is the cell voltage, I_0 is the reverse saturation current, n is the diode ideality factor, and $V_t = kT/q$ is the thermal voltage, with k being the Boltzmann constant ($1.38 \cdot 10^{-23}$ J/K), T the absolute temperature of the cells, and q is the elementary charge.

2.1.2. Single-Diode Model

Diode-based models aim to model the current–voltage (I – V) characteristic curve of the PV cell/module, simulating its performance under variable operating conditions [27]. Among the models based on electrical equivalent circuits, the Single-Diode Model (SDM) is the most used thanks to its optimal compromise between simplicity, high accuracy, and low computational burden [28]. Recent works in the literature proved that the four-parameter model is preferred under uniform solar irradiance thanks to its lower complexity and lower computational burden with respect to the SDM, although a comparable accuracy of I – V curve tracing is achieved. On the contrary, the five-parameter model [29] (Figure 3) might lead to more accurate estimations under unstable operating conditions (such as a cell/module under shadowing), where the leakage contribution due to the shunt resistance is not negligible [30].

The I – V relationship for the single-diode model is given by the following:

$$I = I_{ph} - I_0 \cdot \left(e^{\frac{(V+R_s \cdot I)}{n \cdot V_t}} - 1 \right) - (V + R_s \cdot I)/R_{sh} \quad (2)$$

The SDM parameters are the following [31]: the photocurrent, I_{ph} , is directly proportional to the incident solar irradiance. The saturation current, I_0 , is related to diffusion and

recombination mechanisms within the depletion region of the p-n junction; n is the diode ideality factor. The series resistance, R_s , accounts for losses due to the resistance of the semiconductor material, metallic contacts, and interconnections. The shunt resistance, R_{sh} , represents leakage currents through the cell [28].

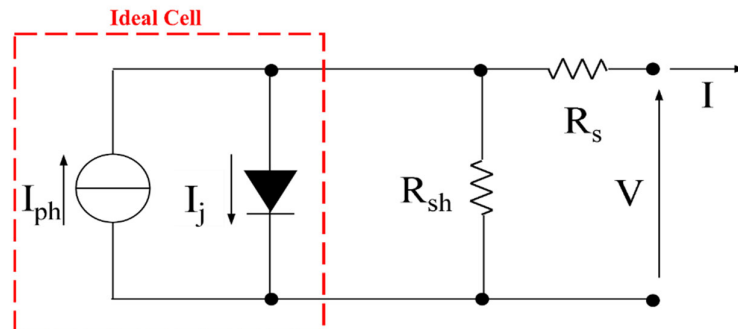


Figure 3. Single-diode model for a solar cell.

2.1.3. Double-Diode Model

The two-diode model extends the single-diode model by adding a second diode in parallel with the first, as can be seen in Figure 4. This second diode accounts for recombination losses in the space charge region, which are not adequately represented by the single-diode model, especially at lower voltages [32].

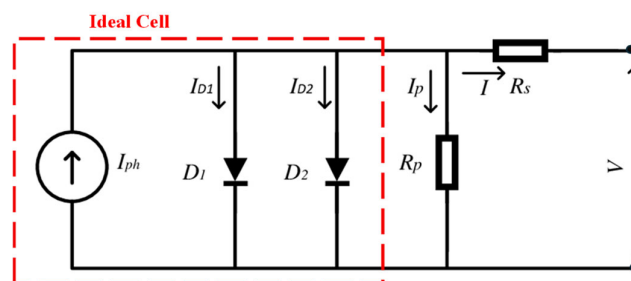


Figure 4. Double-diode model for a solar cell.

The I - V equation for the two-diode model is the following:

$$I = I_{ph} - I_{01} \cdot \left(e^{\frac{(V+R_s \cdot I)}{n_1 \cdot V_t}} - 1 \right) - I_{02} \cdot \left(e^{\frac{(V+R_s \cdot I)}{n_2 \cdot V_t}} - 1 \right) - (V + R_s \cdot I) / R_{sh} \quad (3)$$

Here, I_{01} and I_{02} are the saturation currents of the first and second diodes, respectively, and n_1 and n_2 are their respective ideality factors [33]. Typically, n_1 is close to 1, representing the diffusion current, and n_2 is close to 2, representing the recombination current [34]. The two-diode model generally provides a more accurate representation of the I - V curve, particularly near the open-circuit voltage, but at the cost of increased complexity in parameter extraction. The parameters of both models are directly related to the physical properties of the PV cell. For example, higher-quality silicon with fewer defects will generally exhibit a lower saturation current, I_0 , and a higher shunt resistance, R_{sh} , leading to improved performance. Similarly, minimizing contact resistance and optimizing the cell geometry will reduce the series resistance, R_s , further enhancing performance.

2.1.4. Triple-Diode Models

The single-diode model provides a good balance between accuracy and cost. In contrast, the double-diode model considers the effect of recombination losses, which increases

accuracy but also complexity and computational cost. In addition to SDM and DDM, the triple-diode model considers the diffusion current, recombination in the depletion layer, and recombination in the grain boundaries, represented by three parallel diodes [35], as can be seen in Figure 5 and represented by Equation (4). This model also accounts for the varying series resistance to capture non-linear resistive effects at high currents.

$$I = I_{ph} - I_{01} \cdot \left(e^{\frac{(V+R_s \cdot I)}{n_1 \cdot V_t}} - 1 \right) - I_{02} \cdot \left(e^{\frac{(V+R_s \cdot I)}{n_2 \cdot V_t}} - 1 \right) - I_{03} \cdot \left(e^{\frac{(V+R_s \cdot I)}{n_3 \cdot V_t}} - 1 \right) - (V + R_s \cdot I) / R_{sh} \quad (4)$$

where n_3 is the ideality factor for the third diode, with a value greater than 2.

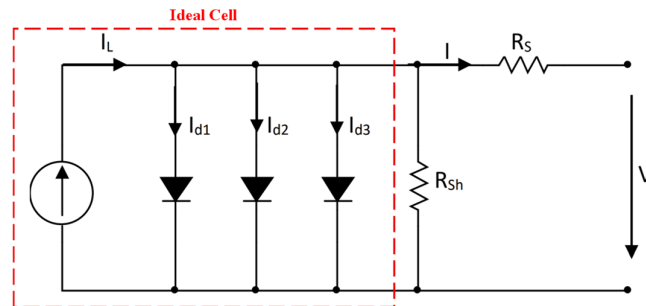


Figure 5. Triple-diode model for a solar cell [36].

2.1.5. Spectral Response Model

Spectral response model evaluates the performance of PV modules by assessing their response to the solar spectrum of different wavelengths. For any irradiance condition, the absorption spectrum can be significantly different between indoor and outdoor testing. In such a condition, this model aims to evaluate a spectral mismatch factor to account for these differences. The spectral response is the derivative of the photogenerated current (I_{ph}) of a PV cell or module with respect to the input solar power as a function of irradiance wavelength. This quantity indicates the quality of the conversion from solar power to electrical output power, as stated in the equation [37].

$$SR_{\lambda} = \frac{dI_{ph}(\lambda)}{dG(\lambda)} \quad (5)$$

Whereas, this parameter can also be represented as a function of wavelengths and the Quantum Efficiency (QE_{λ}) in the following way [38]:

$$SR_{\lambda} = QE_{\lambda} \cdot \lambda \frac{q}{hc} \quad (6)$$

where λ is the wavelength of the incoming irradiance; q and h are the electron charge ($1.6021 \cdot 10^{-19}$ C), and Planck constant ($6.6260 \cdot 10^{-34}$ Js), respectively; and c is the speed of light ($2.99 \cdot 10^8$ m/s).

In equivalent circuit models, the I_{ph} can be evaluated as a convolution between the cell's spectral response $SR(\lambda)$ and the incident spectral irradiance $G(\lambda)$:

$$I_{ph} = A \int_0^{\infty} SR(\lambda) \cdot G(\lambda) d\lambda \quad (7)$$

where A is the cell's active area.

R. Daxini et al. [39] calculated I_{ph} using the spectral response model and evaluated the power of the PV module (P_{mod}) using the following relation:

$$P_{mod} = N_s \cdot V_{mp,ref}^{cell} \cdot \min(M_{cell} \cdot I_{ph,ref}^{cell}) \cdot k \cdot (1 + \gamma \cdot (T - T_{ref})) \cdot G_{POA} / G_{ref} \quad (8)$$

where N_s is the number of cells connected in a series for a PV module, $V_{mp,ref}^{cell}$ is the voltage at the maximum power point for each cell under STC conditions, k is the proportionality constant between the current at the maximum power point and the I_{ph} , M_{cell} is the spectral mismatch factor for a cell, $I_{ph,ref}^{cell}$ is the photovoltaic current of the cell at STC, and T is the cell temperature, while T_{ref} is the STC temperature; similarly, G_{POA} is the measured solar irradiance, and G_{ref} is the solar irradiance at STC.

2.2. Semi-Empirical Models

Semi-empirical models are based on physical laws enriched with parameters that are, generally, optimized values from datasets of experimental data. Examples of semi-empirical models are the Osterwald model, Soto model, Sandia PV model, King model, and CEC PV model.

2.2.1. Osterwald Model

The Osterwald model is a semi-empirical model that considers the solar irradiance and temperature to evaluate the output power of the PV module. Although this model has high accuracy without requiring the solution of complex equations, its uncertainty might be high in particular conditions (about 3–6% in PV power estimation). The equation of the Osterwald model is the following [40]:

$$P_{max}(G_{POA}, T) = P_{max,ref} \cdot \frac{G_{POA}}{G_{POA,ref}} \cdot [1 + \gamma \cdot (T - T_{ref})] \quad (9)$$

where P_{max} is the maximum power of the PV module under environmental conditions of irradiance and temperature (G_{POA} , T), and γ is the temperature coefficient for power, while $P_{max,ref}$ is the maximum power of the PV module at STC conditions ($G_{POA,ref} = 1000 \text{ W/m}^2$, $T_{ref} = 25 \text{ }^\circ\text{C}$).

2.2.2. King Model

A semi-empirical model was developed by L. King et al. [41] at Sandia National Laboratories (SNL), based not only on manufacturer data but also on experimental data. The proposed model uses the curve fitting technique to identify the empirical dependence of the most important I – V points for a PV generator with respect to solar irradiance and cell temperature [41]. The empirical equations of the model regarding the short-circuit current I_{sc} , open-circuit voltage V_{oc} , and I – V data at the maximum power point (V_{MPP} and I_{MPP}) are the following:

$$I_{sc} = I_{sc,ref} \left(\frac{G_{POA}}{G_{POA,ref}} \right) (1 + \alpha(T_{cell} - T_{ref})) \quad (10)$$

$$V_{oc} = V_{oc,ref} + N_{cell,s} \cdot V_{th} \cdot \log(G_{eff}) + \beta \cdot (T_{cell} - T_{ref}) \quad (11)$$

$$I_{MPP} = I_{MPP,ref} (C_0 \cdot G_{eff} + C_1 \cdot G_{eff}^2) \cdot (1 + \alpha(T_{cell} - T_{ref})) \quad (12)$$

$$V_{MPP} = V_{MPP,ref} + C_2 \cdot N_{cell,s} \cdot V_{th} \cdot \log(G_{eff}) + C_3 \cdot N_{cell,s} \cdot (V_{th} \cdot \log(G_{eff}))^2 + \beta \cdot (T_{cell} - T_{ref}) \quad (13)$$

where I_{sc} is the short-circuit current for a PV cell; $I_{sc,ref}$ is the short-circuit current of the cell at STC; V_{oc} and $V_{oc,ref}$ are the open-circuit voltage and the STC open-circuit voltage for each cell, respectively; I_{mpp} and $I_{mpp,ref}$ are the current at maximum power point at and maximum power point current at STC, respectively; similarly, V_{MPP} and $V_{MPP,ref}$ are the voltage at maximum power point and the STC value; V_{th} is the thermal voltage; α and β are the temperature coefficients for the short-circuit current and the open-circuit voltage, respectively; and (C_0 – C_3) are the empirically determined coefficients whose values are reported in Table 1. These parameters are determined by NIST (National Institute of Standards and

Technology) and Sandia National Laboratory [19]. Finally, the quantity, G_{eff} , is the effective irradiance that the PV module can convert into electricity, and it can be calculated as follows:

$$G_{\text{eff}} = \frac{I_{\text{ph}}}{I_{\text{ph,ref}}(1 + \alpha(T_{\text{cell}} - T_{\text{ref}}))} \quad (14)$$

The King model neglects the influence of the spectral mismatch factor and optical effects on the output power of the PV module, which limits its applications.

Table 1. Empirical coefficients of the King model.

Coefficient	Mono-Crystalline Technology	Poly-Crystalline Technology
c0	0.9994	1.0144
c1	0.0026	−0.0055
c2	−0.5385	−0.3211
c3	−21.4078	−30.2010

2.2.3. Sandia Model

Another numerical PV model was developed at Sandia National Laboratories, which investigates PV performance under different ambient conditions [41]. Using Sandia's model, key parameters such as short-circuit current, open-circuit voltage, and maximum power point for current and voltage can be obtained for various commercial PV modules [42]. The Sandia PV model is an extended version of the King model and uses the same empirical relations as King's model, with the additional parameters to investigate the spectral effects, angle of incidence, and thermal effects. This model evaluates cell temperature from ambient conditions and makes geometrical corrections to overcome the limitation of King's model. The modified relation for the evaluation of short-circuit current is given as:

$$I_{ph} = I_{ph,STC} \cdot f_1 \left(\frac{f_2 G_{\text{beam}} + f_d G_{\text{diffuse}}}{G_{\text{POA,ref}}} \right) \cdot (1 + \alpha \cdot (T_{\text{cell}} - T_{\text{ref}})) \quad (15)$$

where f_1 is the 4th order polynomial function for spectral effects, f_2 represents the 5th order polynomial function of the angle of incidence, and f_d is the fraction of diffuse irradiance reaching the module (generally, set equal to 1 [43]). These quantities can be evaluated as follows:

$$f_1(AM_a) = a_0 + a_1 AM_a + a_2 (AM_a)^2 + a_3 (AM_a)^3 + a_4 (AM_a)^4 \quad (16)$$

$$f_2(AOI) = b_0 + b_1 AOI + b_2 (AOI)^2 + b_3 (AOI)^3 + b_4 (AOI)^4 + b_5 (AOI)^5 \quad (17)$$

The values of $(a_0, a_1, a_2, a_3, a_4)$ and $(b_0, b_1, b_2, b_3, b_4, b_5)$ are given in [19], indicating the impact of the spectral effects on photogenerated current. Typical values of such coefficients are provided in Table 2 for modules with mono-crystalline and poly-crystalline technology. They are computed with empirical correlations starting from the absolute air mass, AM_a , and the angle of incidence, AOI .

The Sandia model is dependent on module parameters and operating conditions that vary with PV technology and environmental conditions and limits the application in untested conditions.

Table 2. Empirical coefficients of the Sandia PV model.

Coefficient	Mono-Crystalline	Poly-Crystalline
a_0	0.935823	0.918093
a_1	0.054289	0.086257
a_2	−0.005677	−0.024459
a_3	0.000527	0.002816
a_4	−0.000011	−0.000126

b_0	1.000341	0.998515
b_1	-0.005557	-0.012122
b_2	$6.553 \cdot 10^{-4}$	$1.440 \cdot 10^{-3}$
b_3	$-2.730 \cdot 10^{-5}$	$-5.576 \cdot 10^{-5}$
b_4	$4.641 \cdot 10^{-7}$	$8.779 \cdot 10^{-7}$
b_5	$-2.806 \cdot 10^{-9}$	$-4.919 \cdot 10^{-9}$

2.2.4. De Soto Model

A semi-empirical model based on the five parameters was developed by De Soto et al. [19] to overcome the limitation of Sandia's model. The proposed model considers both manufacturer data and incoming solar irradiance, as well as cell temperature. The five parameters are photogenerated current (I_{ph}), reverse saturation current (I_0), series resistance (R_s), shunt resistance (R_{sh}), and modified diode ideality factor (n_0) at any temperature (T_{cell}). To evaluate these parameters at reference conditions, the three equations regarding the most important I - V states (short-circuit, open-circuit, and maximum power point) are solved analytically, as follows:

Case 1: Short-Circuit condition ($I = I_{sc,ref}$ and $V = 0$)

$$I_{sc,ref} = I_{ph,ref} - I_{0,ref} \cdot \left(e^{\frac{I_{sc,ref} R_{s,ref}}{n_0}} - 1 \right) - (I_{sc,ref} \cdot R_{s,ref} / R_{sh,ref}) \quad (18)$$

Case 2: Open-Circuit condition ($I = 0$, and $V = V_{oc,ref}$)

$$0 = I_{ph,ref} - I_{0,ref} \cdot \left(e^{\frac{V_{oc,ref}}{n_0}} - 1 \right) - (V_{oc,ref} / R_{sh,ref}) \quad (19)$$

Case 3: Maximum Power Point (MPP) ($I = I_{mp,ref}$ and $V = V_{mp,ref}$)

$$I_{MPP,ref} = I_{ph,ref} - I_{0,ref} \cdot \left(e^{\frac{V_{MPP,ref} + I_{MPP,ref} R_{s,ref}}{n_0}} - 1 \right) - ((V_{MPP,ref} + I_{sc,ref} \cdot R_{s,ref}) / R_{sh,ref}) \quad (20)$$

These equations are numerically solved for $I_{0,ref}$, $R_{s,ref}$, and $R_{sh,ref}$, and these parameters are estimated as functions of the solar irradiance and cell temperature by the following relations [44]:

$$I_{ph} = \left(\frac{G_{POA}}{G_{ref}} \right) \cdot \left(\frac{AM}{AM_{ref}} \right) \cdot (I_{sc,ref} + \alpha \cdot (T_{cell} - T_{ref})) \quad (21)$$

$$I_0 = I_{0,ref} \left(\frac{T_{cell}}{T_{ref}} \right)^3 \cdot \exp \left[\frac{1}{k} \cdot \left(\frac{E_{g,ref}}{T_{ref}} - \frac{E_g}{T_{cell}} \right) \right] \quad (22)$$

$$R_s = R_{s,ref} \quad (23)$$

$$R_{sh} = R_{sh,ref} \cdot \left(\frac{G_{POA,ref}}{G_{POA}} \right) \quad (24)$$

$$n_0 = \frac{N_{cell,s} \cdot n \cdot k \cdot T_{cell}}{q} \quad (25)$$

where $N_{cell,s}$ is the number of cells in series for a PV module, n and k are the diode ideality factor and Boltzmann's constant, T_{cell} is the cell temperature, q is the charge of electrons, AM is the air mass at given conditions, AM_{ref} is the air mass at STC (AM1.5), and E_g is the temperature-dependent bandgap in eV, and, for crystalline silicon (c-Si) technology, is evaluated as follows:

$$E_g(T_{cell}) = E_g(T_{ref}) \cdot [1 - 0.0002677 \cdot (T_{cell} - T_{ref})] \quad (26)$$

Since all the parameters are estimated considering the STC conditions, this may result in a small deviation at MPP under real-world operating conditions.

2.2.5. CEC Model

The CEC model is a modified version of the De Soto model developed at the California Energy Commission (CEC), implemented at the University of Wisconsin—Madison, with an additional adjustment coefficient for the correct evaluation of model parameters as a function of operating conditions [45]. The CEC model is based on the Single-Diode Model (SDM) to include the temperature dependencies of the SDM parameters [7,19].

The modified six-parameter model (n , I_{ph} , I_0 , R_s , R_{sh} , and Adj) was introduced by considering an adjusted (Adj) parameter to modify the temperature dependence of I_{ph} and V_{oc} , which is given as follows [46]:

$$\beta' = \beta_{oc} \cdot (1 - Adj/100) \quad (27)$$

$$\alpha' = \alpha_{sc} \cdot (1 - Adj/100) \quad (28)$$

Under generic environmental conditions, Adj is the tuning parameter that corrects the temperature coefficients for current and voltage (α' and β') till the measured power matches the theoretical power under a certain tolerance level. It not only helps in I - V curve adjustment close to theoretical but also highlights model inaccuracies in real-world conditions.

Considering the adjusted temperature coefficients for the I_{ph} and V_{oc} , the model parameters can be evaluated as follows:

$$I_{ph} = \left(\frac{G_{POA}}{G_{ref}} \right) \cdot (I_{sc,ref} + \alpha' \cdot (T_{cell} - T_{ref})) \quad (29)$$

$$I_0 = I_{0,ref} \left(\frac{T_{cell}}{T_{ref}} \right)^3 \cdot \exp \left[\frac{1}{k} \cdot \left(\frac{E_{g,ref}}{T_{ref}} - \frac{E_g}{T_{cell}} \right) \right] \quad (30)$$

$$R_s = R_{s,ref} \quad (31)$$

$$R_{sh} = R_{sh,ref} \cdot \left(\frac{G_{POA,ref}}{G_{POA}} \right) \quad (32)$$

$$n = \text{constant} \quad (33)$$

$$V_{oc} = V_{oc,ref} + \beta' \cdot (T - T_{ref}) \quad (34)$$

The reference parameters for the CEC model are obtained following the relations of the De Soto model, and n is considered from the CEC database, which varies with the PV module technology.

2.3. Empirical Models

Empirical models rely on statistical relations among input variables from experiments, such as solar irradiance, temperature, and electrical quantities [47,48], and the output parameters, such as current, voltage, and power. Different statistical and machine learning algorithms are used to develop these models based on historical data. Therefore, large datasets need to be available to ensure the robustness and reliability of the models. In the literature, many empirical models are proposed, adopting different algorithms according to the application [49]. In particular, the most used empirical models are artificial neural networks and regression models.

2.3.1. Artificial Neural Networks

Artificial Neural Networks (ANNs), inspired by the human brain, configure the model considering four performance parameters, namely, delay, number of neurons, activation function, and multi-parameter, to establish the neural network architecture [50]. Considering the applications in photovoltaics, ANNs are trained for the PV performance

forecasting and estimation, fault detection, and maximum power point tracking under dynamic operating conditions. The PV power estimation (P_{out}) through ANNs can be mapped as a non-linear function of the plane of array irradiance, G_{POA} , and module/cell temperature, T_{mod} .

The performance of the PV system is evaluated through the primary layers of the ANNs, as follows:

- Input Layer:

This layer is populated with the input features (x), such as wind speed, cell/module temperature, ambient temperature, solar irradiance, and time.

- Hidden Layers:

This layer consists of neurons, including non-linear transformations through activation functions $\phi(x)$, and, for each j^{th} neuron, the equation is the following:

$$h_j = \phi \left(\sum_{i=1}^n w_{ij} x_i + b_i \right) \quad (35)$$

where w_{ij} is the weight of each i^{th} input variable, and b_i is the bias term that captures the offsets.

- Output Layer:

The model is trained through the field datasets to evaluate the non-linear interaction between the transformation function of each neuron in the hidden layer and the output variables (PV power), which can be mathematically computed as follows:

$$P_{\text{out}} = \sum_{j=1}^m w_{j,\text{out}} \cdot h_j + b_{\text{out}} \quad (36)$$

where $w_{j,\text{out}}$ is the weight of each j^{th} neuron on the output, and b_i is the bias considering the offsets.

The process of the training the ANNs with experimental data involves three steps, namely, *data processing*, where the input data is filtered and normalized; *data partitioning*, where the processed datasets are organized as training, testing, and validation datasets; and *Training Phase*, which considers and evaluates the weight and bias terms to minimize the error, usually through the estimation of the Mean Squared Error (MSE) between the predicted output power and the actual measured power.

$$MSE = \frac{1}{N} \cdot \sum_{i=1}^N (P'_{\text{out}} - P_{\text{pred}})^2 \quad (37)$$

where P'_{out} is the actual output power, P_{pred} is the predicted output power, and N is the total number of samples.

2.3.2. Back Propagation Neural Network

A Back Propagation Neural Network (BPNN) Model utilizes the backpropagation algorithm to forecast the performance of the PV systems. BP neural networks are dynamic models that have the capability of parallel processing and adaptability to adjust according to several input datasets [51]. Back propagation network models are trained with a large amount of historical datasets for many input variables, including wind speed, plane of array solar irradiance, ambient and module temperatures, relative humidity, and mounting structure [52].

The learning process of the backpropagation algorithm involves minimizing the Root Mean Square Error (RMSE) between the actual measured power P'_{out} and the predicted power P_{pred} , given as follows:

$$RMSE = \sqrt{\frac{1}{N} \cdot \sum (P'_{out} - P_{pred})^2} \quad (38)$$

The gradient descent method [53] adjusts the weights to achieve the minimum $RMSE$, and each weight vector, w_{ji}^t , at the training step, t , is updated by considering the partial derivative of the error with respect to the weight vector, as follows:

$$w_{ji}^{t+1} = w_{ji}^t - \eta \cdot \frac{\partial E}{\partial w_{ji}} \quad (39)$$

where η is the learning rate defined by the user.

In summary, the BPNN model evaluates the non-linear interaction between the environmental variables and output power, making it flexible for power estimation of different PV technologies and operating conditions.

2.3.3. Convolutional Neural Network

A Convolutional Neural Network (CNN) is a deep learning architecture that jointly carries out convolution and pooling operations to determine spatial features from structured data. In the case of PV installations, the features might be the spatial distribution of variables like solar irradiance, module temperature, and others like the albedo, the cloud patterns, or other PV performance [54].

A typical CNN for the prediction of PV power consists of one input layer, one or more convolutional layers, one or more pooling layers, and at least one fully connected (dense) layer. The input layer receives the spatial distributions of interest and the convolutional layer employs filters named kernels to generate feature maps. The filters have variable sensitivity to different patterns like irradiance gradients, hot spots, or shading phenomena.

For a kernel, k , the output of the convolution at position (i,j) before activation, $z_{ij}^{(k)}$, is defined in the following way:

$$z_{ij}^{(k)} = \sum_{m=1}^M \sum_{n=1}^N w_{mn}^{(k)} \cdot x_{(i+m) \cdot (j+n)} + b^{(k)} \quad (40)$$

where x is the spatial feature distribution, $w_{mn}^{(k)}$ is the kernel weight for the k th filter of map size $M \times N$, and $b^{(k)}$ is the bias term.

After the calculation of the pre-activation output, a non-linear activation function is employed (typically, the Rectified Linear Unit, ReLU). The output of the function is the activated feature map of the k th filter, $h_{ij}^{(k)}$, which is the maximum value between zero and the pre-activation output, $z_{ij}^{(k)}$. The function preserves positive outputs to emphasize spatial regions with strong patterns.

The pooling layer reduces the resolution of the spatial distribution while maintaining the most useful information to reduce the number of parameters and estimations. The max pooling is commonly used, and the mathematical formulation of the pooled output corresponding to the l th feature is the following:

$$p_{ij}^{(l)} = \max_{(u,v) \in window_{ij}} (h_{uv}^{(l)}) \quad (41)$$

where $window_{ij}$ is the pooling region centered around or associated with the location (i,j) . This step aims to maintain the most important local patterns while removing noise and measurement variability.

After the application of convolutional and pooling layers, the feature maps are converted into a one-dimensional feature vector p . Then, fully connected layers integrate the spatial features into a global prediction (e.g., the AC power of a PV system).

In the case of a model with one output (electrical power P_{el}), the mathematical equation for a fully connected layer is as follows:

$$P_{el} = \sum_j v_j \cdot p_j + c \quad (42)$$

where p_j is the j^{th} component of the feature vector after the pooling layer; v_j is the weight for the feature p_j to the output neuron; and c is the bias of the output neuron.

With these operations, the fully connected layer quantifies the effect of the spatial distribution and of the pattern intensity on the electrical power.

The CNN parameters $\{w_{mn}^{(k)}, b^{(k)}, v_j, c\}$ are empirically obtained after the minimization of a loss function. In particular, the Mean Squared Error (MSE) can be estimated starting from N samples in a dataset, in which each sample i has input distributions and a measured electrical power $P_{el,i}$:

$$MSE = \frac{1}{N} \cdot \sum_{i=1}^N (P_{el,i} - P_{pred,i})^2 \quad (43)$$

where $P_{pred,i}$ is the related power estimation by the CNN.

The gradients of MSE as functions of the weights and of the biases are estimated by backpropagation. Then, a gradient-based optimization algorithm (e.g., stochastic gradient descent or Adam) is applied to update the parameters.

2.3.4. Recurrent Neural Network

Recurrent Neural Networks (RNNs) are neural networks tailored for sequential data. In PV applications, RNNs can be trained on time series of plane-of-array irradiance, air and module temperature, wind speed, and PV power data, to predict the AC power production of the system [55]. These neural networks maintain an internal state that is updated at each time step through a feedback loop. The inputs of the RNN consist of a vector containing the most important variables x_t (mainly, solar irradiance and modules temperature) at the generic time instant t , along with the hidden state from the previous time step, h_{t-1} . Then, the new hidden state h_t is computed.

The simplest RNN can be described as follows:

$$h_t = f_h(x_t w_{hx} + h_{t-1} w_{hh} + b_h) \quad (44)$$

$$P_{out,t} = f_p(h_t w_{ph} + b_p) \quad (45)$$

where w_{hx} is the matrix weighting the input x_t to the hidden state, b_h is the bias vector for the hidden layer, w_{ph} is the matrix relating the hidden state with respect to the output (typically, PV power), b_p is the output bias, f_h is the hidden activation function (for example, hyperbolic tangent, tanh, or ReLU), f_p is the output activation function (typically, linear for the PV power prediction).

The operation of the network starts from an initial hidden state, h_0 , typically set to zero or learned during training. Then, for a sequence of input quantities, x , the hidden states, h and the outputs are iteratively computed. This structure permits the RNN investigating dependencies over time, such as the variations in cloud cover and ambient temperature, which affect the short-term PV forecasting.

The parameters of the network $\{w_{hx}, w_{hh}, w_{ph}, b_h, b_p\}$ are determined from historical data by minimizing a loss function. In the PV context, the Mean Squared Error (MSE) between the measured PV power at time step i ($P'_{out,i}$) and the predicted power ($P_{pred,i}$):

$$MSE = \frac{1}{N} \cdot \sum_{i=1}^N (P'_{out,i} - P_{pred,i})^2 \quad (46)$$

where N is the number of experimental data. The variations in the MSE with respect to the parameters of the network are computed by backpropagation through time (BPTT), which is an extension of the conventional backpropagation technique. Similar to convolutional neural networks, gradient-based optimizers are adopted to update the network parameters.

2.3.5. Support Vector Regression

SVR investigates non-linear relationships between the input variables (weather quantities like solar irradiance and module temperature) and the PV power output. This technique permits managing noise effectively from experimental data and, generally, smaller training datasets are required with respect to other neural networks. Consequently, good forecasting accuracy can be achieved with lower computational effort and a small set of input variables [56].

In this technique, the following regression function is investigated:

$$P_{pred} = w^T \cdot \phi(x) + b \quad (47)$$

where P_{pred} is the predicted PV power for the input set x , w is the weight vector, ϕ is the non-linear feature mapping, and b is the bias contribution. Non-linearities in the input-output relation might occur due to non-linear temperature effects, clipping of inverter power, or mismatch. These contributions are determined by the function ϕ , which is, typically, implemented implicitly through a kernel function K . The loss function, L_ϵ , is calculated considering the measured power, P_{out} , is the power prediction P_{pred} , as follows:

$$L_\epsilon = \begin{cases} 0 & \text{if } |P'_{out} - P_{pred}| \leq \epsilon \\ |P'_{out} - P_{pred}| - \epsilon & \text{otherwise} \end{cases} \quad (48)$$

where ϵ is the desired tolerance.

2.3.6. Gaussian Process Regression

Gaussian Process Regression (GPR) is a machine learning model that can be used for mean power forecasting, uncertainty quantification, fault detection, I - V curve modeling, and energy yield estimation. Its main applications regard small training datasets is relatively small due to its relatively high computational effort [57].

With respect to other networks, additional inputs can be integrated according to the application (e.g., analysis of losses in PV plants, fault events, or degradation phenomena).

The measured and the predicted PV power profiles are jointly modeled by a multivariate Gaussian distribution. Considering a training set (X, y) with X as the matrix of the training inputs, y as the array of experimental power data, and a test input x^* , the joint distribution over training outputs and the latent function f^* at the test input can be expressed as follows:

$$\begin{bmatrix} y \\ f^* \end{bmatrix} \sim N \left(0, \begin{bmatrix} K(X, X) + \sigma_n^2 I & K(X, x^*) \\ K(x^*, X) & K(x^*, x^*) \end{bmatrix} \right) \quad (49)$$

where $K(X, X)$ is the covariance matrix between training inputs, $K(X, x^*)$ is the covariance vector between the training inputs and the test input, $K(x^*, X)$ is the transposed vector of $K(X, x^*)$, $K(x^*, x^*)$ is the variance at the test input, σ_n^2 is the variance of measurement noise, and N is the multivariate Gaussian distribution.

The latent function $f(x)$ is expressed as a Gaussian Process (GP), as follows:

$$f(x) \sim \text{GP}(m(x), k(x, x')) \quad (50)$$

where $m(x)$ is the mean function (generally, set equal to zero, or assumed as a linear function of solar irradiance and temperature), and $k(x, x')$ is the covariance function quantifying the similarity of the output variable under two conditions x and x' (in PV application, similar irradiance and module temperature).

2.3.7. Random Forest

Random Forest (RF) is an ensemble machine learning method relying on decision trees, and it is applied for short-term PV power prediction considering inputs like solar irradiance, ambient or module temperature, relative humidity, system design, and wind speed. This approach determines multiple regression trees starting from independent bootstrap samples drawn from the original training dataset. At each node of a tree, a random subset of features is considered, and the best split is considered according to the reduction in variance or mean squared error [58]. This operation improves the generalization capability of the technique. The power prediction, P_{pred} , for the input vector, X , is determined as the average prediction among the predictions for the same input X from the N trees. The prediction error is minimized by applying splitting criteria that identify similar operating conditions in terms of solar irradiance and module temperature. In particular, the split with the largest reduction in the Mean Squared Error (MSE) is identified, with the metric defined according to [47].

2.3.8. PVUSA Model

The Photovoltaics for Utility Scale Applications (PVUSA) is a model defined in the 1990s to characterize the performance of PV systems, currently used for PV power forecasting and performance monitoring [59]. In this model, the AC power P_{AC} is an empirical function of plane-of-array irradiance G_{POA} and module temperature T_{PV} as follows:

$$P_{\text{AC}} = G_{\text{POA}} \cdot (\alpha_0 + \alpha_1 \cdot G_{\text{POA}} + \alpha_2 \cdot T_{\text{PV}}) \quad (51)$$

where $(\alpha_0, \alpha_1, \alpha_2)$ are empirical coefficients obtained by regression on experimental data. The quantity α_0 is affected by the rated efficiency of the PV system; the parameter α_1 includes non-linear irradiance effects on PV power, like fill factor and efficiency variations under low irradiance conditions; the term α_2 takes into account the influence of temperature on PV power, including the performance reduction at high cell temperatures. Generally, these coefficients are identified using linear regression on historical operating data after adequate filtering.

Table 3 presents a summary of the most diffused electrical models for estimating the PV power by highlighting their advantages, drawbacks, and accuracy performance.

Table 3. Summary of electrical models for PV modules.

Model Name	Input Parameters	Advantages	Drawbacks	Uncertainty ($\pm$ %)
Analytical/Physical Models				
Four-Parameter Model	Irradiance, cell temperature, I_{ph} , I_0 , R_s	- Simple formulation - Low computational cost	- No leakage current paths considered - Poor accuracy under mismatch	$\pm 4\text{--}6\%$
Five-Parameter/Single-Diode Model (SDM)	Irradiance, temperature, R_s , R_{sh} , n	Good balance accuracy vs. complexity	Sensitive to input parameters	$\pm 2\text{--}5\%$

		Widely adopted and validated	Calibration effort required using measured data	
Double-Diode Model (DDM)	SDM + recombination parameters	- Improved accuracy close to V_{oc} - High accuracy under low-irradiance	- High complexity - Difficult parameter extraction from I–V curve	$\pm 1\text{--}3\%$
Triple-Diode Model	Multiple diode currents and ideality factors	Captures complex recombination mechanisms	- Many parameters reduce reliability - Limited accuracy gain, high calibration complexity	$\pm 1\text{--}2\%$
Spectral Response Model	$SR(\lambda)$, $G(\lambda)$, A , Temperature, Thermal coefficient for maximum power, Module layout	- Spectral mismatch included - Physically rigorous	- Requires detailed spectral data - Sensitive to air mass	$\pm 2\text{--}5\%$
Semi-Empirical Models (Diode Based)				
Osterwald Model	Plane-of-array irradiance, module temperature	- Extremely simple - Suitable for fast yield estimation	Empirical model parameters	$\pm 3\text{--}6\%$
CEC Model	De Soto parameters + correction factor	Improved temperature modeling	Requires tuning factor	$\pm 2\text{--}3\%$
King Model	Irradiance, temperature coefficients	- Captures non-linear power vs. irradiance behavior - Field-tested	- Empirical coefficients - Limited extrapolation	$\pm 2\text{--}4\%$
Sandia PV Model	Irradiance, AOI , air mass, temperature	- Includes optical and spectral effects - High field accuracy	Technology-specific calibration	$\pm 2\text{--}3\%$
De Soto Model	SDM parameters, temperature	- Physically meaningful - Robust temperature correction	STC-based parameters	$\pm 2\text{--}4\%$
Empirical Models (Neural Network Based)				
ANN-Based Models	Historical environmental data	- High predictive capability - Handles non-linear irradiance, temperature, and I–V effects	- Accurate predictions without physical interpretability - Data-dependent	$\pm 1\text{--}3\%$
RNN Model	Time-series irradiance, temperature	Captures temporal dynamics	- Requires sequential data - High training complexity	$\pm 1\text{--}3\%$
BP Neural Network	Time-series irradiance, temperature	- Stable classical training - Moderate complexity	- Stable classical training - Moderate complexity	$\pm 1\text{--}4\%$
CNN Model	Spatial irradiance/temperature data	- Captures spatial patterns - Robust feature extraction	Computationally heavy	$\pm 1\text{--}3\%$
Empirical Models (Regression-Based)				

SVR/GPR Models	Environmental and system data	Effective with limited datasets	Model performance varies with Kernel selection	$\pm 2\text{--}4\%$
Random Forest Model	Environmental variables	- Robust - Includes non-linearities	Large dataset required	$\pm 1\text{--}4\%$
PVUSA Model	Irradiance, temperature	- Simple regression-based - Low data requirement	Limited accuracy under variable conditions	$\pm 4\text{--}6\%$

3. Modeling for the Estimation of the Temperature Distribution of PV Generators

Thermal modeling is crucial for understanding and predicting the performance and reliability of photovoltaic (PV) modules. Elevated temperatures negatively impact the efficiency of PV modules and accelerate degradation processes. The correlation of variation in the electrical efficiency with the increase in the operating temperature of the PV module can be found in the literature. Due to different ambient conditions, configuration and materials of PV modules, non-uniform temperature distributions can be easily found, affecting power production and efficiency.

For these reasons, thermal models are required to investigate temperature distributions and losses [10,60–62]. Various approaches are used, ranging from Thermal Network (TN) approaches and Lumped Parameter Models (LPMs) to spatial distributed numerical models. Common examples of TNs and LPMs are the NOCT/Ross model, the Sandia/King model, the Faiman model, and the Mattei and Duffie–Beckman relations. LPMs can be stationary, which evaluate the steady state temperature under constant operating conditions, and can be time-dependent, which include the thermal capacitance under dynamic operating conditions.

On the other hand, spatial distributed numerical models evaluate the spatial temperature distribution within the PV module by considering conservation of mass, momentum, and energy in one-, two-, and three-dimensions. Conservation equations can be solved by adopting different numerical methods, such as the Finite Difference Method (FDM) [63], Finite Element Method (FEM) [64], and Finite Volume Method (FVM) [65]. A more advanced approach considers Computational Fluid Dynamics (CFD) [66] to predict the heat transfer of the PV module as immersed in a fluid by solving the governing conservation equations for mass, momentum, and energy [67]. In Spatial distribution models, multi-layer module configurations are considered both in steady-state or time-dependent regimes, and more detailed thermal profiles for the PV modules than TNs and LPMs can be found, making them key for thermo-electric coupled studies, system design, and reliability analyses.

In summary, both the TN/lumped and spatially distributed thermal models provide a comparative framework for estimating PV cell/module temperature under real-world operating conditions, and their applications depend on the level of required details and goals. TN and LPMs are key for quick performance analysis and system-level power predictions, while spatially distributed numerical models are more appropriate and accurate for detailed thermal–electrical interactions. The detailed overview of the classification of these thermal modeling approaches, as given in Figure 6, mathematical relations, required inputs, and limitations are discussed in the following section.

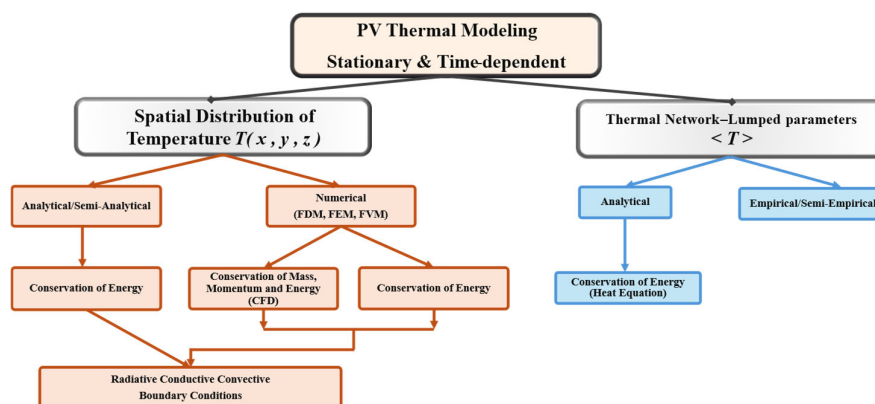


Figure 6. Configuration of thermal models for evaluating the cells' temperature distribution.

3.1. Thermal Network and Lumped Parameter Models

Thermal Network (TN) and Lumped Parameter Models (LPMs) are the most commonly used single-point estimation techniques to evaluate the temperature of the PV cell/module, simplifying the complex heat transfer phenomena into a manageable set of equations. These models assume a uniform temperature distribution within each component of the module, such as the cell, encapsulating layer, and back sheet, eliminating the spatial thermal gradients [68,69].

Simplicity makes them suitable for quick estimations and real-time monitoring applications. They require minimal computational resources and can be easily integrated into electrical performance models. For instance, a simple one-node LPM can provide a rough estimate of the average module temperature based on incident solar irradiance, ambient temperature, and wind speed. However, TNs and LPMs fall short in capturing detailed temperature distributions, especially under dynamic conditions where temperature gradients within the module become significant. This limitation arises from the assumption of uniform temperature, which is often not valid in real-world scenarios. Applications where TNs and LPMs are sufficient include preliminary system design and performance monitoring, where high precision is not required [70,71]. In situations demanding accurate temperature mapping, such as analyzing hotspot formation or optimizing cooling designs, more sophisticated distributed models are necessary.

Thermal network and lumped parameter models are further classified based on mathematical representations and temporal behavior. Analytical models are based on energy balance principles that evaluate the physical relation among the solar irradiance, thermal losses, and thermal capacitance. On the other hand, empirical and semi-empirical models depend on energy balance as well as statistical regression of the experimental data. These models can be stationary, operating under constant environmental conditions, or can be time-dependent, considering the thermal capacitance and time-dependent input parameters such as PV cell/module efficiency.

3.1.1. Steady State Analytical Models

In steady state analytical models, it is simply assumed that, within a short time period, the intensity of the solar radiation and other parameters are constant. To evaluate the temperature of the PV cell/module within constant operating conditions, models such as the Nominal Operating Cell Temperature (NOCT) [72] and the Ross model [73], the equivalent cell temperature model [74], and the Mattei model [75] can be found in the literature. More in detail, the nominal operating cell temperature model, also known as the standard model [72], assumes the following linear relationship:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{T_{\text{cell,NOCT}} - T_{\text{amb,NOCT}}}{G_{\text{POA,NOCT}}} \cdot G_{\text{POA}} \quad (52)$$

Equation (52) represents this relationship by considering *NOCT* ($G_{\text{POA}} = 800 \text{ W/m}^2$, $T_{\text{amb,NOCT}} = 20 \text{ }^\circ\text{C}$, wind speed = 1 m/s) as a reference point [76]. The *NOCT* model does not provide any information about the mounting structures [77], but, according to IEC 61215-2: 2016 [78], this model is developed by considering rock-mounted module configurations.

Similarly, the Ross model is a modification of the *NOCT* model, as follows:

$$T_{\text{cell}} = T_{\text{amb}} + k \cdot G_{\text{POA}} \quad (53)$$

where the Ross coefficient, k [73], has been introduced to account for different mounting configurations, as shown in the Table 4. A different formulation of the Ross model considers the relative solar irradiance instead of absolute solar irradiance, as mentioned in the equation [79], as follows:

$$T_{\text{cell}} = T_{\text{amb}} + A \cdot \frac{G_{\text{POA}}}{G_{\text{POA,STC}}} \quad (54)$$

where $G_{\text{POA,STC}}$ is the plane of array irradiance at *STC* (1000 W/m^2), and A is the temperature offset ($^\circ\text{C}$) according to the mounting structure that defines the thermal profile of the module for a given solar irradiance.

Table 4. Ross coefficient for different mounted structures [80,62].

Mounted Structure k ($^\circ\text{C} \cdot \text{W}^{-1} \cdot \text{m}^2$)	Ross Coefficient
Flat Roof	0.026
Free Standing	0.021
Sloped Roof: Well Cooled	0.02
Façade Integrated: Transparent PVs	0.046
Sloped Roof: Highly Integrated and Poorly Ventilated	0.056
Façade Integrated: Opaque PVs—Narrow Gap	0.054
Sloped Root: Not-So-Well Cooled	0.034

The equivalent cell temperature model, also known as the V_{oc} -based model, has been developed considering the electrical performance of the solar module instead of weather parameters. Experimentally, this method can be useful as it is difficult to determine the average cell temperature. V_{oc} is highly sensitive to the operating temperature of the cell/module and slightly affected by the solar irradiance, as explained in IEC 60904-5. Instead of connecting thermocouples at the back surface, the cell temperature can be obtained by using the following equation:

$$T_{\text{cell}} = T_{\text{cell,STC}} + \frac{1}{\beta} \cdot \left[V_{\text{OC,m}} + \frac{n \cdot k \cdot (T_{\text{cell}} + 273) \cdot N_s}{q} \cdot \log\left(\frac{G_{\text{POA,STC}}}{G_{\text{POA}}}\right) - V_{\text{OC,STC}} \right] \quad (55)$$

where $T_{\text{cell,STC}}$ is the *STC* temperature ($25 \text{ }^\circ\text{C}$); $V_{\text{oc,STC}}$, and $V_{\text{oc,m}}$ are the open-circuit voltage at *STC* and measured voltage in V , respectively; similarly β , n , k , q , and N_s are the V_{oc} temperature coefficient, ideality factor, Boltzmann's constant, electron charge, and the number of series-connected cells.

Mattei et al. [75] developed a thermal model that considers the ambient operating conditions and temperature coefficients of the PV module to predict its thermal profile. The Mattei model is represented in the following equation:

$$T_{\text{cell}} = \frac{U_v \cdot T_{\text{amb}} + G_{\text{POA}} \cdot [\tau \alpha - \eta_{\text{STC}} \cdot (1 + \gamma \cdot T_{\text{cell,STC}})]}{U_v - \gamma \cdot \eta_{\text{STC}} \cdot G_{\text{POA}}} \quad (56)$$

where U_v and γ are the thermal loss coefficient of the module to the ambient environment in $\text{W/m}^2 \text{ }^\circ\text{C}$ and the temperature coefficient for power of the module, in $\%/^\circ\text{C}$, respectively.

Radiation effect is neglected in this model, while wind speed is considered as the main source of thermal loss by considering a simple energy balance analysis. It was experimentally investigated, and the researchers noticed that it showed a good agreement for low wind speeds [81], while for the increase in wind speed above 10 m/s, its effect seems less important.

3.1.2. Time Dependent Analytical Models

In real conditions, ambient physical quantities can frequently change over time, mainly the irradiance. Under these conditions, the temperature of PV module cannot be assumed as a time-invariant value and a proper time-dependent energy equation should be considered in order to obtain the transient of the module temperature. The most popular time-dependent LPM model is represented by the Duffie and Beckman model based on the energy balance between the parameters affecting the module's thermal profile [82]. Solar cell/module converts the solar irradiance mainly into electrical and thermal energy, which is then collected by the external circuit [83]. This model considers thermal losses due to convection, conduction, and radiation, and is adopted by the SAM simulation software [84]. The temperature of the cell within the PV module can be expressed as follows [85,82]:

$$T_{\text{cell}} = T_{\text{amb}} + \left(\frac{9.5}{5.7 + 3.8 \nu} \right) \cdot (T_{\text{cell,NOCT}} - T_{\text{amb,NOCT}}) \cdot \left(\frac{G_{\text{POA,STC}}}{G_{\text{POA}}} \right) \cdot \left(1 - \frac{\eta_{\text{NOCT}}}{\tau \alpha} \right) \quad (57)$$

where the term $(5.7 + 3.8 \nu)$ is the value of the convective heat transfer coefficient for free convection and radiation, and the given conditions. This term differs based on the test condition and wind direction [86,87]; similarly, $\tau \alpha$ is the product of transmissivity and absorbance coefficients and this product is, generally, assumed equal to 0.9.

3.1.3. Empirical/Semi-Empirical Models

In the literature, numerous thermal models can be found that are based on energy balance relations, as well as the regression of experimental data to evaluate the temperature of the PV cell/module. These models are the Sandia model [41], Faiman model [88], Servant model [89], Skoplaki model [62], modified NOCT model, modified Sandia model, Keddouda model, and Tamizhmani model [90].

Sandia National Laboratories developed a simplified empirical thermal model named the Sandia model [41]. This model was developed based on energy balance considerations of the thermal mass of the PV module, but it does not consider any electrical connection [91]. This model considers an exponential equation for estimating the module temperature while considering three parameters: wind speed ν_{10} (corrected to a 10 m height), ambient temperature, and the solar irradiance [81], as follows:

$$T_{\text{mod}} = T_{\text{amb}} + G_{\text{POA}} \cdot e^{a + b \cdot \nu_{10}} \quad (58)$$

$$\text{where } \nu_{10} = \nu \cdot \left(\frac{H_{10}}{H} \right)^{\xi} \quad (59)$$

where ν is the wind speed at 2 m above the ground level, H is the height of the anemometer, and H_{10} is the height used for performance at 10 m heights, while ξ is the Hellmann exponent representing the resistance coefficient. Similarly, a and b are the empirical coefficients of the Sandia model [92]. These coefficients are typically negative and decrease under favorable heat exchange conditions. For instance, the values of a and b are -2.81 and -0.0455 for the back-insulated and mounted configurations, while -3.56 and -0.075 for the open rack configuration, considering glass/cell/polymer sheet-based module types, respectively [93].

The Faiman model, also adopted by commercial software PVsyst [94], in [88], was developed using the Hottel–Whillier–Bliss equation that assumes a PV module as a flat-plate solar thermal collector under steady-state conditions [95]. To develop this model, an experimental setup at Sede Boqer in the Negev Desert Peninsula was analyzed. The experimental setup was based on the analysis of multi- and poly-crystalline silicon solar cells with Tedlar back and front glass covers.

The error uncertainty in the power of crystalline modules by the Faiman model is approximately 1% [88]. IEC 61853-2 standards are considered by the Faiman model to specify the environmental boundary conditions [96] to obtain the heat loss coefficients. It can be noticed that this model considers the effect of wind and solar irradiance while neglecting the IR radiation, which exists at low wind speed and irradiance [97], as follows:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{G_{\text{POA}}}{U_0 + U_1 v} \quad (60)$$

Faiman's model was improved by considering the effective radiation, where the electrical efficiency was assumed from an energy balance equation, as expressed by the following equation:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{\alpha \cdot G_{\text{POA}} \cdot (1 - \eta_{\text{STC}})}{U_0 + U_1 \cdot v} \quad (61)$$

where α is the irradiance absorptance and defines the impact of solar irradiance on the module temperature ($\text{W/m}^2 \text{ } ^\circ\text{C}$) of the PV module. Commonly, this quantity can be assumed equal to 0.91, while U_0 is the heat loss coefficient at zero wind speed, and U_1 is the heat loss coefficient per unit wind speed. Coefficients U_0 and U_1 are sensitive to ambient conditions and are obtained through the regression models. They vary according to the technologies and installation sites.

The Faiman model has been modified by considering the dependency of temperature on the efficiency of the solar cell and transmissivity. A collective heat transfer coefficient, $U_{\text{collective}}$, has been introduced. It lacks the precise measurement of wind speed and is dependent on the exact height and location of the modules [98]. In the literature, the Faiman model can be found in two forms [81,98]:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{\alpha G_{\text{POA}} \cdot (1 - \eta_{\text{STC}})}{U_0 + U_1 v} = T_{\text{amb}} + G_{\text{POA}} \cdot \left(\frac{\tau \alpha}{U_{\text{collective}}} \right) \cdot \left(1 - \frac{\eta}{\tau \alpha} \right) \quad (62)$$

$$U_{\text{collective}} = U_0 + U_1 \cdot v \quad (63)$$

$$\eta = \eta_{\text{STC}} \cdot \left(1 + \beta \cdot (T_{\text{cell}} - T_{\text{cell,STC}}) \right) \quad (64)$$

Servant [89] developed another empirical model from a steady-state heat balance of the PV module under solar irradiance, which evaluates weather parameters to estimate the cell temperature, as follows:

$$T_{\text{cell}} = T_{\text{amb}} + 0.0138 \cdot G_{\text{POA}} \cdot (1 + 0.031 \cdot T_{\text{amb}}) \cdot (1 - 0.042 \cdot v) \quad (65)$$

It can also be found in another form that utilizes the solar cell efficiency, as follows:

$$T_{\text{cell}} = T_{\text{amb}} + 0.0138 \cdot G_{\text{POA}} \cdot (1 + 0.031 \cdot T_{\text{amb}}) \cdot (1 - 1.053 \cdot \eta(T)) \quad (66)$$

Skoplaki et al. [62] have developed an explicit semi-empirical thermal model that considers the effect of forced convection instead of natural convection and the radiation effect. It is a three-parameters model, depending on wind speed, ambient temperature, and plane of array solar irradiance as follows:

$$T_{\text{cell}} = T_{\text{amb}} + \Psi \cdot \left(\frac{0.32}{8.91 + 2.0 \cdot v} \right) \cdot G_{\text{POA}} \quad (67)$$

where $\Psi = \frac{K_I}{K_f}$ is the mounting coefficient and depends on the coefficient of the Ross model; it is the ratio of the Ross coefficient for the integrated configuration, K_I to the coefficient for free-standing, K_f .

Recent advancements in PV industries enable researchers to develop bifacial PV (bPV) modules that can also generate electricity on the rear sides from reflective solar irradiance [99]. Bifacial modules convert the reflected solar irradiance into useful electrical energy by utilizing the back side of the PV module, and therefore, it has gained a production superiority over the mono-facial (mPV) modules [100,101]. The reflected solar irradiance is highly dependent on the ground surface type and impacts the rear spectral response for the bifacial PV modules [100]. This ground impact was compared by Muehleisen et al., as well as the performance of bifacial PV modules. For a flat white roof, bPV produces up to 17% more electrical energy and mPV [102]. The standard NOCT model is only valid for mPV modules, which only consider the solar irradiance on the front, but in bPV modules, both front and back radiation contribute to electrical and thermal energy. Therefore, the modified NOCT model is described by the following equation:

$$T_{\text{cell}} = T_{\text{amb}} + \frac{T_{\text{cell,NOCT}} - T_{\text{amb,NOCT}}}{G_{\text{POA,NOCT}}} \cdot (G_{\text{POA,front}} + G_{\text{POA,back}}) \quad (68)$$

The only modification is the addition of irradiance on the back of bPV modules.

To consider the geometrical and weather parameters [103], a modified version of the Sandia thermal model was developed for investigating the temperature of bPV modules, as in [104]. These models evaluate the temperature of the module as a linear function of the solar irradiance and an exponential function of the wind speed. It considers the measured coefficients a and b to account for the mounting structure and material influence on the convective and radiative cooling:

$$T_{\text{mod}} = T_{\text{amb}} + (1 - \eta_{\text{STC}}) \cdot (G_{\text{POA,front}} + c \cdot G_{\text{POA,back}}) \cdot e^{a + b \cdot v} \quad (69)$$

where the coefficient, c , is the ratio between the power produced by the rear side of the module and the power generated by its front side, known as the “bifaciality factor”.

Keddouda et al. in the work [105] following the Sandia model, modified the mathematical exponential expression for the thermal model by recurring to detailed CFD simulations of polycrystalline silicon PV modules. This model was validated using an experimental setup at El Oued University, Algeria, over three days of experimental data collection. The experimental setup confirms the accuracy of this model, and it was reported that the proposed model is more accurate than the Ross model [73], and the Skoplaki model [62]. The wind speed is proposed to be measured 2 m above ground level or 0.5 m above the PV module.

$$T_{\text{mod}} = 0.905 \cdot T_{\text{amb}} + 0.0291 \cdot G_{\text{POA}} \cdot e^{-0.031v} \quad (70)$$

The Tamizhmani model is an empirical temperature model that was developed after two years of experimental campaign at Arizona State University, presenting the hot desert climate installation, and NREL’s Solar Radiation Laboratory (SRRL) on the top of South Mountain in Golden, Colorado. At SRRL, PV modules experience four different climate seasons. The neural network method was used to analyze PV modules of different technologies. It can be noted that the Tamizhmani Model depends on instantaneous weather parameters, as follows [90]:

$$T_{\text{cell}} = 0.943 \cdot T_{\text{amb}} + 0.028 \cdot G_{\text{POA}} - 1.528 \cdot v + 4.3 \quad (71)$$

This model also analyzed the effect of humidity on the PV module, and it can be neglected for dry climate conditions.

3.1.4. Time-Dependent Empirical/Semi-Empirical Models

Empirical/Semi-Empirical models are mostly stationary. Duffie–Beckman model [106] has been modified via Homer software [107] by investigating the standard operating condition rather than considering the heat transfer. In Homer software, the cell temperature has been calculated by supposing the PV module to be operating at the maximum power point MPP. It also considers the negative temperature coefficient of power [9], as follows:

$$T_{\text{cell}} = \frac{T_{\text{amb}} + (T_{\text{cell,NOCT}} - T_{\text{amb,NOCT}}) \cdot \left(\frac{G_{\text{POA,STC}}}{G_{\text{POA}}} \right) \cdot \left(1 - \frac{\eta(1 - \beta \cdot T_{\text{cell,STC}})}{\tau\alpha} \right)}{1 + (T_{\text{cell,NOCT}} - T_{\text{amb,NOCT}}) \cdot \left(\frac{G_{\text{POA,STC}}}{G_{\text{POA}}} \right) \cdot \frac{\eta\beta \cdot T_{\text{cell,STC}}}{\tau\alpha}} \quad (72)$$

where η and β are the solar module's efficiency at temperature T and temperature coefficient for power (%/°C), whereas $T_{\text{cell,STC}}$ is the STC temperature of the module (25 °C).

3.2. Spatial Distributed Thermal Models

PV module's temperature can be precisely evaluated by assessing the three types of heat transfer, radiation, convection, and conduction, occurring both within the various layers, and between the module and the surrounding environment. In this context, a crucial aspect to simulate the module's spatial temperature distribution under variable weather situations is the identification of the most suitable boundary and initial conditions. The PV module's temperature is affected by different parameters, including its optical and thermal characteristics, the spectral content of the solar energy collected, the relative humidity, the direction of the wind and its speed, and the installation conditions of PV modules.

In order to obtain an accurate evaluation of the spatial distribution of the PV temperature, the one-, two-, or three-dimensional heat equation should be solved. These models investigate the module temperature by considering heat exchanges inside the module, evaluating the conduction through different layers of the PV module, the radiative heat exchange, and heat exchanged through convection. Heat exchanges can occur both along the direction of the layers, considering different materials and geometry, and in the transverse direction in order to consider the spatial distribution of the cells and the interaction with the ambient in which the module is immersed. Different methods are used to estimate the thermal gradient within the module, such as spatially distributed thermal models can accurately predict temperature profiles under various operating conditions, including non-uniform irradiance and complex cooling configurations [108]. They are handy for identifying hotspots, optimizing module design, and evaluating the effectiveness of different cooling strategies. However, the increased accuracy comes at the cost of higher computational requirements and model complexity, as they are capable of accurately capturing localized effects in strongly coupled thermo-electrical models, specifically under partial shading and transient conditions. Setting up and running these numerical simulations requires specialized software and expertise, and the simulation time can be significant, especially for large and complex modules [109,110]. Distributed thermal models solve the heat diffusion equation (energy conservation) to evaluate the spatial temperature gradient within PV modules, as follows:

$$\rho c_p \frac{\partial T(x,y,z,t)}{\partial t} = k \nabla^2 T(x,y,z,t) + q(x,y,z,t) \quad (73)$$

where ρ is the density, c_p is the specific heat capacity of the different layer materials, k is the thermal conductivity, and q is the volumetric heat source in the x , y , and z directions. The spatial solution of the heat equation can be obtained by following different numerical techniques.

The Finite Difference Method (FDM) is the most common technique for estimating the spatial temperature distribution within PV modules because of its simplicity. The FDM divides the PV module into a 1-D/2-D/3-D grid, consisting of nodes and grid spacing Δx , Δy , and Δz . Taylor series expansions are used by finite difference methods to derive the derivatives in the form of differential equations for the nodes located at position (i, j, k) . These relations are substituted into the heat equation to evaluate the temperature distribution within the PV module. An example regarding the integration of FDM is in the work by Bevilacqua et al. [111], who proposed a thermal model solved by the finite difference method, including ambient factors.

The Finite Element Method (FEM) is another numerical method used to evaluate the spatial temperature distribution within a PV module when the complex boundary conditions, geometry, or module layout are given. The FEM divides the PV module into subdomains to compute the temperature distribution through the interpolation functions. The contributions of subdomains are integrated into the global system of equations that incorporates conduction, radiation, convection, and internal heat generation into a sparse matrix. This detailed computation makes the FEM a preferable choice in complex structures. The temperature distribution within each subdomain is given as follows:

$$T(x, y, z) = \sum_{j=1}^n N_j(x, y, z) T_j \quad (74)$$

where N_j is the shape function of the j subdomain, and the global system of equations for the entire domain is given as follows [112]:

$$\hat{C} \frac{d\vec{T}}{dt} + \hat{K} \vec{T} = \vec{Q} \quad (75)$$

being $\hat{C}$ is the heat capacity matrix, $\hat{K}$ is the conductivity matrix, and $\vec{Q}$ is the heat source vector. FEM solves the heat equation through different systems of equations to evaluate the temperature gradient within the PV module.

The finite volume method is based on the conservation of energy within a control volume, which is used to evaluate the temperature distribution within PV modules in both transient and steady states. The FVM divides the PV module into a set of control volumes. Heat flow into and out of the control volume is estimated through the approximation of thermal gradients at the volume faces. This allows us to analyze the conduction and convection when PV modules operate in unstable environmental conditions and the heat balance is maintained over the domain of the PV module, which is key to defining the losses and temperature gradient under non-uniform operating conditions. The FVM integrates the heat equation over each volume such that the following applies:

$$\int_V \rho c_p \frac{\partial T}{\partial t} dV = \int_{\partial V} k \nabla T \cdot \hat{n} dS + \int_V q dV \quad (76)$$

where ρ is the material density, c_p is the specific heat capacity, and k is the thermal conductivity. The FVM solves the heat equation through an iterative procedure and iterative techniques such as Multigrid, Gauss–Seidel, and Krylov methods. The FVM integrates the conservation equation over each control volume by applying Gauss's theorem to convert volume integrals to surface integrals, and then approximates these fluxes and storage terms to form algebraic equations, effectively solving for average temperature in each control volume, ensuring conservation of heat flow across faces using interpolation for conductivity, to be robust for complex geometries. For these reasons, the FVM is widely adopted in CFD.

Computational fluid dynamics approach solves mass, momentum, and energy equations of the PV module immersed in a fluid (air) in different ambient conditions and with

different boundary conditions [66]. CFD is a powerful numerical method that analyzes heat transfer problems (conduction, convection, radiation) and provides a detailed framework for the temperature distribution within and around PV cells/modules, crucial for predicting operating temperatures and efficiency, often involving simulating airflow, wind effects, and cooling systems, optimizing designs for better energy yield. These models couple fluid physics with heat transfer, analyzing factors like solar radiation, wind speed/direction, and mounting to improve thermal management and overall panel performance. Typically, conduction (through layers), convection (air/fluid flow), and radiation (solar input, emission) are solved simultaneously. Moreover, natural convection (buoyant flow) and forced convection (wind effects), is considered in order to analyze velocity fields and boundary layers. Finally, solar load and surface emissivity are considered, often using methods like discrete ordinates.

CFD models estimate spatial temperature distribution in order to identify hot spots and overall cell/module temperature, heat removal by air, varying with flow conditions, and link temperature to electrical efficiency as described in the next Section. CFD models can be used for testing different mounting structures, air gaps, or cooling channels. Typical steps in CFD simulations include geometry and meshing by including the PV panel layers and surrounding air/fluid domain, boundary conditions, and post-processing. By accurately simulating these complex interactions, CFD helps engineers design more efficient and durable PV systems. Examples of CFD models are presented in [113], in which CFD approaches have been integrated to obtain accurate solutions of spatial temperature distributions.

Table 5 reports the most relevant features of thermal models for estimating the temperature of PV modules: specifically, focusing on their main inputs, advantages, drawbacks, and accuracy performance.

Table 5. Summary of thermal models for PV modules.

Model Name	Governing Principle	Main Inputs	Advantages	Drawbacks	Uncertainty ($\pm\%$)
Lumped Parameter Models					
Nominal Operating Cell Temperature (NOCT) Model	Linear steady-state energy balance	Irradiance, ambient temperature	- Extremely simple - Minimal data requirement	- No wind dependence - Steady-state assumption	$\pm 5\text{--}10\%$
Ross Model	Linear empirical temperature relation	Irradiance, ambient temperature	- Simple empirical formulation - Easy implementation	- Ignores convective effects - Limited physical realism	$\pm 5\text{--}10\%$
Modified Ross Model	Ross model with wind correction	Irradiance, ambient temperature, wind speed	- Improved convective representation - Improvement vs. Ross model	Empirical formulation	$\pm 4\text{--}8\%$
Equivalent Cell Temperature Model	Simplified analytical energy balance	Irradiance, ambient temperature	- Improvement vs. NOCT model - Integration with electrical models	Limited wind and mounting effects	$\pm 4\text{--}7\%$

Mattei Model	Coupled energy balance with efficiency feedback	Irradiance, wind, and electrical efficiency	• Efficiency–temperature coupling • Improved accuracy of T distribution	• Requires calibration parameters	±3–5%
Duffie & Beckman Model	Analytical heat balance equation	Heat transfer coefficients, irradiance	• Physically derived formulation	• Simplified boundary assumptions	±3–5%
Sandia Thermal Model	Semi-empirical regression-based model	Irradiance, wind, mounting configuration	• Empirically validated • Includes mounting type	• Empirical coefficients required	±2–4%
Faiman Model	Empirical heat loss coefficient model	Irradiance, wind speed	• Explicit convective term	• Site-specific coefficients	±3–6%
Servant Model	Empirical heat transfer correlation	Irradiance, ambient temperature	• Simple implementation • Few data required	• Limited validation • Simplified heat loss terms	±4–7%
Skoplaki Model	Semi-empirical convective heat loss model	Irradiance, wind speed, mounting	• Improved wind effect modeling • Accurate heat loss estimation	• High parameter sensitivity	±3–5%
Keddouda Model	Empirical temperature estimation	Irradiance, ambient temperature	• Simple implementation • Minimal computational effort	• Limited generalization capability	±4–7%
Tamizhmani Model	Empirical multi-parameter regression	Irradiance, wind, and ambient temperature	• Multiple environmental effects • Improved evaluation accuracy	• Requires regression coefficients	±3–5%
Distributed Thermal Models					
Analytical/Semi-Analytical	Conservation of energy (heat equation)	Material properties, geometry, boundary conditions	• Physics-based formulation derived from energy conservation • Insight into temperature distributions • Lower computational cost than numerical models • Suitable for simplified geometries and steady-state analysis	• Limited applicability to complex module geometries • Simplified boundary condition assumptions • Difficult to include strong spatial non-uniformities • Limited handling of transient or multi-layer interactions	±2–3%
Numerical (Conservation of energy)	Solution by using different discretization methods (FDM, FEM, FVM)	Thermal conductivity (k), density (ρ), specific heat (c_p), geometry, irradiance, ambient temperature, convection coefficient	• Captures spatial temperature gradients • Suitable for multi-layer PV modules	• Cannot resolve air-flow physics • Wind effects approximated • Boundary condition sensitivity	±2–4%

Numerical CFD (Conservation of Mass, Momentum, and Energy)	(h), radiation parameters	Stable and well-established numerical schemes
	Full geometry, material properties, airflow velocity, turbulence model, radiation properties, irradiance, boundary conditions	- Resolves airflow and convective cooling directly - Accurate empirical heat transfer coefficients - Captures wind direction effects - Suitable for complex mounting configurations - High computational cost - Requires mesh generation and numerical stability analysis $\pm 1\text{--}2\%$ - Increased model complexity when including turbulence

4. Coupled Thermo-Electro Models

The accurate description of PV performance can be achieved by the integration among four models tailored for specific physical phenomena: a thermal model, an electrical model, an optical and radiation model, and a structural model. Figure 7 presents the flowchart including the integration among these Multiphysics models.

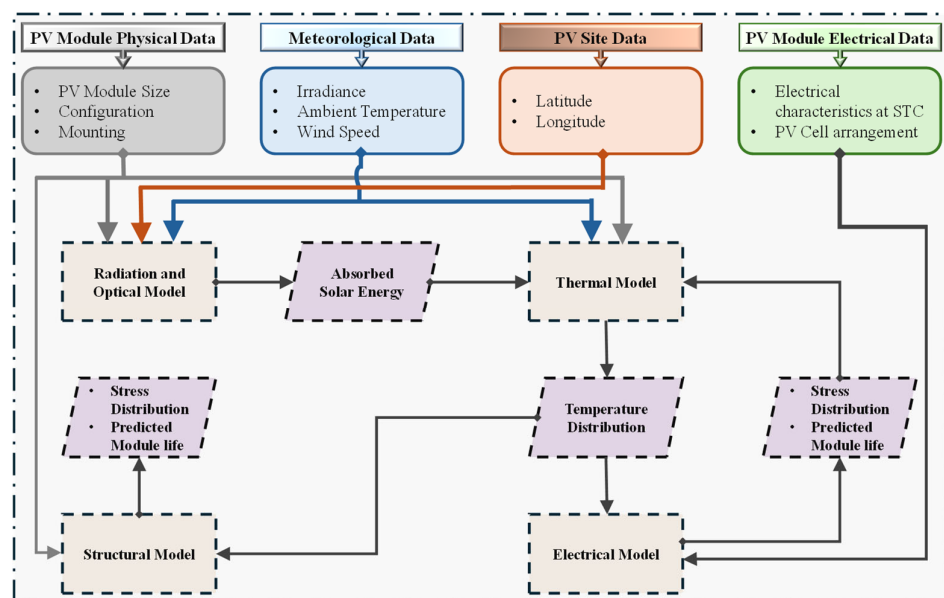


Figure 7. Multi-physics modeling of solar modules (adapted from [114]).

4.1. Radiation and Optical Model

The inputs of this model are the physical data of the PV module (dimensions, connections among its cells, and installation conditions of the generators), the weather data of the installation site (plane-of-array irradiance, air temperature, windspeed, and its direction), and the location of the site (latitude and longitude). Starting from these inputs, the radiation and optical models estimate the energy absorbed by the PV module.

4.2. Thermal Model

This model aims to estimate the temperature distribution between the cells of the module from the knowledge of the energy absorbed by the module, of its physical data, and of the weather data for the installation site under analysis. The most complex and accurate models permit the achievement of a temperature profile for each cell of the modules, while simplified models might estimate an average temperature for each cell or an average value for each PV string or module.

4.3. Electrical Model

This model aims to describe the electrical performance of the PV module under real operating conditions. The knowledge of the I - V curve of the generator under reference conditions (Standard Test Conditions, STC) and of the cell technology (full cells or half cells) is required to estimate the PV power of the module as well as the temperature distribution among its cells. The most advanced models permit identifying the maximum power point by estimating the whole I - V curve, while simplified models aim to obtain the single maximum power only.

The electrical and thermal models are strictly connected, and an iterative procedure can be performed to achieve a better accuracy of the temperature distribution among the cells and, thus, a more accurate PV power estimation [114]. The next section explores the most relevant works in the literature regarding the coupling between the electrical and thermal models.

4.4. Coupled Models

These models accurately define the interaction between the thermal and electrical aspects of the PV modules [115].

Klemen et al. [116] presented a coupled model based on dynamic modeling. A double-diode model has been considered to estimate the electrical parameters as functions of the plan of array irradiance and operating temperature, while empirical equations were used to calculate the temperature distribution within the PV module with a lumped parameter RC thermal network model for each layer. The simulated results are verified against the experimental setup; however, the model utilizes a 1D average temperature of the module.

Wenbu et al. [117] developed a coupled model that considers a thermal model based on an equivalent thermal resistance of the module, as shown in the Figure 8 and a single-diode model for electrical performance. The presented model does not consider the spatial temperature distribution but a 1D thermal profile through different layers of the PV cell/module.

G. Tina [118] developed a coupled model based on a single-diode model, along with a 1D thermal model along the thickness of the modules, assuming a constant temperature among the layers, including convective and radiative heat flows.

The study concluded that, at lower irradiance levels, an additional diode may be needed for improved model accuracy. Additionally, their research also investigated and demonstrated the significant impact of variable wind speed on module temperature; however, it has poor accuracy and stability at low irradiance.

Luca et al. [119] presented a dynamic coupled model for weekly PV performance forecasting and validated it using an experimental setup at SolarTechLab at Politecnico di Milano. They adopted a single-diode model for the electrical aspect, while a dynamic 1D thermal model is used by incorporating heat flow between different layers. Each layer of the PV module was modeled using thermal resistance and capacitance. The research concluded that forecast errors can be minimized by using a dynamic model instead of relying

solely on *NOCT* standards. This model considered uniform temperature distribution and ignored the internal heat losses.

Diego et al. [120] presented a theoretical coupled model based on the energy balance equation, considering heat exchange through convection, radiation, and conduction for a PV module represented as a solid plate. A single-diode model was adopted for electrical modeling, while the thermal model was based on a lumped parameter RC model. The results appeared promising, but this configuration did not consider the temperature through layers or the spatial temperature distribution within the PV module.

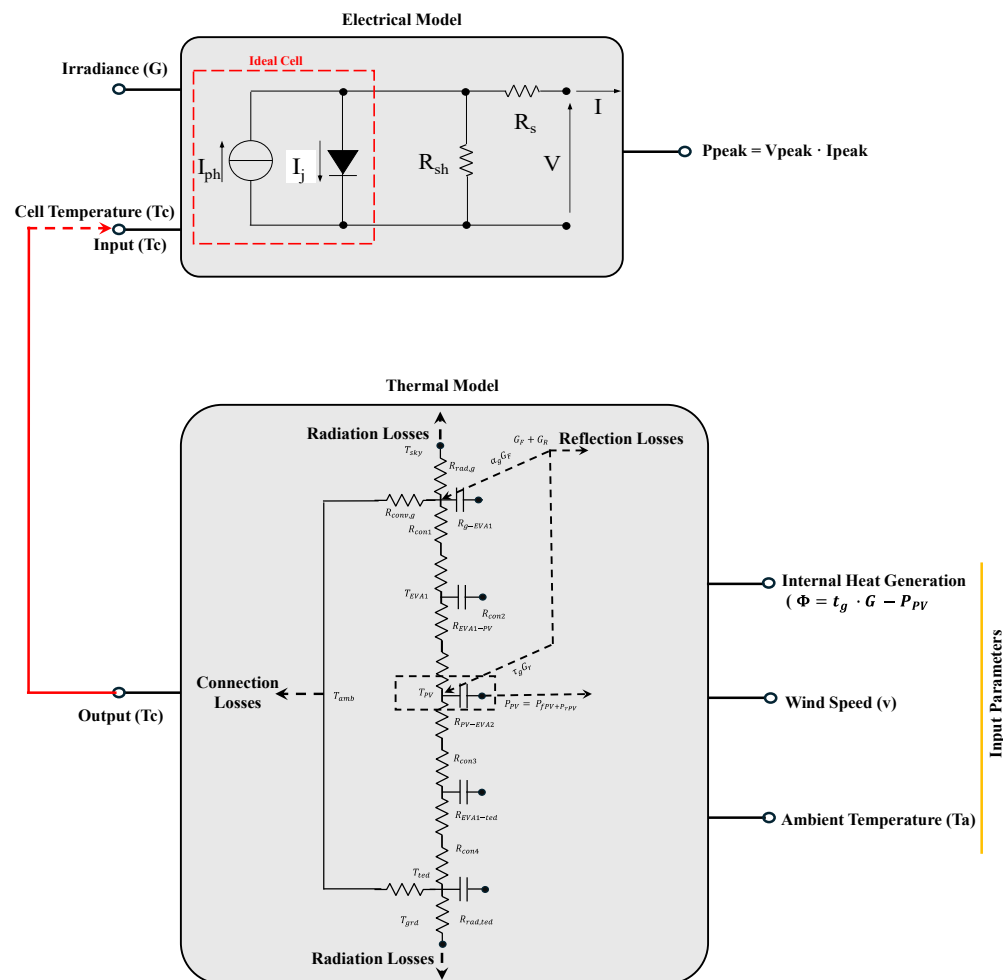


Figure 8. Schematic of the coupled model [117].

Barroso et al. [121] developed a theoretical model by examining boundary conditions from Siddiqui et al. [122], Armstrong and Hurley [123], and Notton et al. [10] and employing the finite difference method with a single-diode model for PV proposed by Siddiqui et al in the paper [122].

Nicolas et al. [124] presented a coupled model using the finite element method to assess the electrical power conversion efficiency of the PV modules under the influence of variable irradiance. They have also studied heat exchange by convection and conduction and its overall effect on the electrical performance of the PV module. It was mainly used for PV performance forecasting.

Aixue and Xiaofeng [125] developed a coupled model that takes into consideration the combined effect of thermal (solving the heat diffusion equation), electrical (solving

semiconductor drift-diffusion equations), and optical parameters on the performance of single-junction Gallium-Arsenide-based solar modules.

Guerriero et al. [126] developed a model that considers variable irradiance to decide the time-dependent temperature distribution within PV modules starting from the cell. In addition to radiation, free and forced convection have been considered by the authors and, by considering solar cells as electrical power sources converting irradiance, a lumped thermal feedback network has been extracted in the framework of the COMSOL environment. By adopting this procedure, both the self and mutual components of heating affect the temperature of the cells. The discretization helps to identify the cause of the hotspot and propose the maximum temperature the calls may reach, as well as the effect of partial shading. To analyze the electrical performance of the module during variable thermal conditions, a thermal feedback block is necessary, which is represented in Figure 9. The authors in [127] studied transient and steady-state operating conditions for the solar cell. A coupled finite-element-based thermal and single-diode-based electrical model was developed.

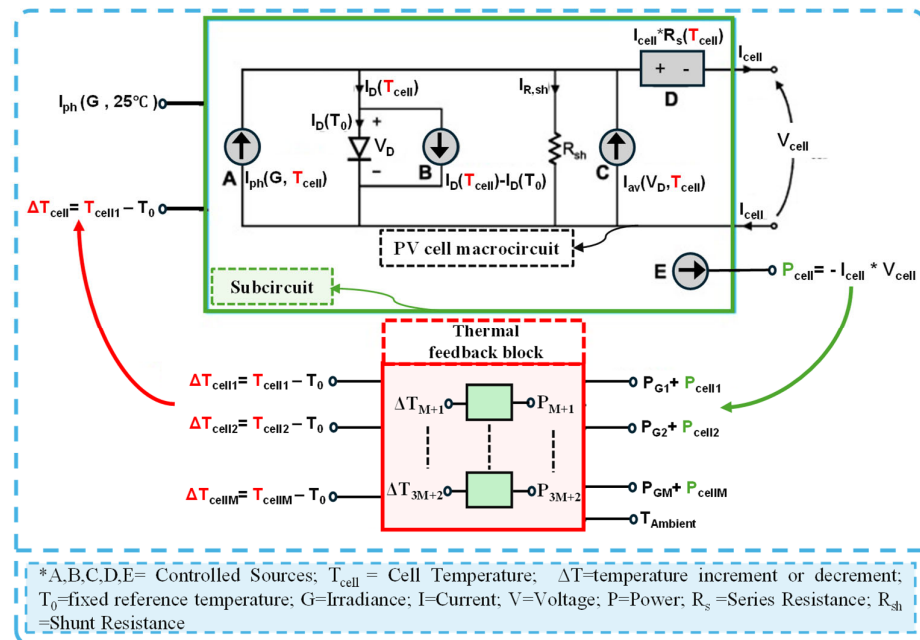


Figure 9. Coupled thermo-electric model at the cell level [126].

Wenbo et al. [128] developed a coupled model focused on bifacial PV modules. The study recommended the analysis of variable irradiance on the rear surface, multi-factor optimization, and row spacing influence.

Yaman and Arslan [129] developed a coupled model where the electrical model was based on a single-diode model, while the thermal model was based on lumped parameter RC equivalent circuits. They concluded that the most significant thermal resistance is radiative. Similarly, radiative convective thermal resistance is more sensitive to wind speed and ambient temperature.

D'Angola et al. [130] developed a theoretical thermal–electrical model to calculate the distribution of temperature among the cells of a module. The electrical model was based on a single-diode model, while the 1D steady state lumped parameter thermal models were developed by solving a system of algebraic equations. The research work was focused on outdoor testing of a laminated PV-T hybrid module prototype with and without a flow of coolant. The model developed accurately predicts the coolant outlet temperature when the coolant flow is applied. Similarly, Abdennour et al. [131] studied the electrical

(using a single-diode model) and thermal (through a 2D distributed heat conduction model) response of the PV modules, adopting cellular automata. Their study reveals that the electrical properties and temperature distribution within PV modules and cellular automata-based models can be the best alternatives to the CFDs or FEM-based models. The model was verified experimentally using electrical measurements and infrared (IR) thermal images, and a prediction error of less than 10% was observed, showing a good accuracy of the developed model.

W. Ahmad et al. [11] presented an innovative technique to develop a coupled thermo-electric model for the PV module. The thermal model was developed by considering the string level mismatch among the solar cells through a semi-analytical modeling by solving the 2D stationary heat equation, while the electrical model was based on a single-diode model. Dirichlet boundary conditions were considered to evaluate the temperature distribution within the PV module, and the average temperature of each string was the input to the electrical model.

X. Tian et al. [132] developed a coupled opto-electric-thermal model to estimate the performance of flexible photovoltaic modules. An optical model was used to estimate the solar irradiance, a thermal equivalent network based on the solution of the energy balance for multiple layers to estimate the operating temperature, and an electrical model based on a single-diode model for the output performance. Solar irradiance was assumed to be uniformly distributed. The results were validated with an indoor and outdoor experimental campaign, and the tilt angles were optimized with the operating temperature estimated theoretically.

G. Raina et al. [133] developed an opto-electric-thermal model based on a modified single diode (electrical) model and lumped parameter RC (thermal model) equivalent circuits for the bifacial PV modules, considering the impact of thermal mass and thermal exchange within the module.

H. Brahma and N. Sarmah [134] developed a coupled model to assess the seasonal performance of PV modules. The thermal model was based on the finite element method, while the electrical model was based on a single-diode model.

I. Kaaya et al. [135] developed a coupled opto-electric-thermal model to investigate the degradation rate in PV modules using a physics-based approach. A time-dependent single-diode model was used for the electrical performance, while the thermal model was based on a lumped parameter energy balance model. Their study investigated the evaluation of series resistance and transmittance at three locations. It was concluded that a hot and dry climate makes a greater contribution to the increase in series resistance rather than a hot and humid climate, where transmittance losses were higher.

M.H. Shahverdian et al. [136] developed an opto-thermal–electrical model for bifacial PV modules. Their research activity was mainly focused on the estimation of thermal resistances, namely, convective, conductive, and radiative, under variable environmental conditions to investigate their effect on PV power estimation. The optical model was based on a layer model, a 1D multi-layer model based on energy balances was followed for thermal analysis, while the electrical model was a simple semi-analytical formulation including the bifacial contribution.

Osama et al. [137] investigated the impact of electrical parameters on thermal performance. Existing models for thermal analysis were compared, and it was concluded that at high wind speed and under short-circuit conditions, Duffie and Beckman models underestimate the temperature, while *NOCT* model overestimates it. For climates with ambient temperatures between 5 and 15 °C, the Keddoudo model was recommended. For climates with ambient temperatures between 25 and 30 °C, both the Keddoudo and Sandia models can be considered [137].

R. Wu et al. [138] developed a thermal–electrical model for the floating PV modules to predict the performance and heat transfer mechanism between the module and water. A single-diode model was used to model electrical performance, and a lumped parameter RC circuit-based thermal model was obtained to understand the thermal behavior with and without water contact. The results were validated with experimental data, and a good understanding between the model and field data was noted.

Similarly, T. Ma et al. [139] developed an opto-electrical–thermal model for analyzing PV performance. Electrical properties of the module were calculated using an equivalent circuit model based on a single-diode model, optical analysis using a ray tracing model, while the thermal properties were investigated using a layered thermal resistance model. To consider multi-layer PV devices and different sizes, a Monte Carlo ray-tracing model [140] was followed along with the transfer matrix method [141]. The obtained model was tested with different operating conditions for the heterojunction technology-based (HJT) PV modules.

Table 6 presents the main specifications of coupled thermal–electrical models in terms of key findings, validation, performance and limits.

Table 6. Summary of the Coupled Models.

Article	Electrical Model	Thermal Model	Key Findings	Validation	Performance and Limits
Klemen et al. [116]	Double-Diode Model	Lumped Parameter RC Network	Improves performance estimation in outdoor operating conditions	Outdoor experimental setup using measured module temperature and <i>I</i> – <i>V</i> curves	• ± 1.75 °C <i>RMSE</i> (Thermal Model) • ± 20.3 W <i>RMSE</i> (Electrical Model) • Sequential temperature–electrical interaction
Wenbu et al. [117]	Irradiance and Temperature Dependent Single Diode Model	Equivalent Thermal Resistance	Radiative and convective resistances are key parameters to estimate PV performance, and conductive resistance can be neglected	Validated with experimental data for the four seasons.	• $\pm 19.2\%$ (Relative Error with respect to Monthly Energy yield) • Improved transient response modeling
G. Tina [118]	Single Diode Model	Energy Balance Equation	Highlights the effect of electrical operating point on module temperature	Validated through numerical and experimental results under varying weather conditions	• One of the first coupling approaches • Requires high-resolution meteorological data
Luca et al. [119]	Single Diode Model	RC Network	Thermal transient modeling across the different layers of the PV module to predict power	Validated against experimental rear surface module temperature, heat fluxes, and output power	• ± 4 W (Power Deviation) • Simplified heat transfer treatment • Moderate computational cost
Diego et al. [120]	Single-Diode Model Dependent on Solar Irradiance and Cell Temperature	Lumped Parameter RC Network	Accurate evaluation of energy yield under dynamic operating conditions	Validated through an experimental campaign over several days in Finland	• 1.98% <i>NRMSE</i> (Power Deviation) • system-level validation • Assumes uniform cell temperature
Barroso et al. [121]	Single-Diode Model	Finite Difference Method	Convection coefficients and sky temperature affect temperature distributions	The electrical model is validated against the manufacturer's STC values, and the thermal model is validated considering the <i>NOCT</i> and operating conditions	• Spatial thermal–electrical modeling • Complex parameter optimization conditions
Nicolas et al. [124]	Temperature-Dependent Efficiency Model	Finite Element Method	Assumptions made to mitigate missing input data cause the largest deviations from experimental results	Thermal results validated against <i>NOCT</i> ; long-term yields compared to 12 months of experimental data	• Coupled modeling with experimental comparison • Boundary condition sensitivity

Aixue and Xiaofeng [125]	Non-Isothermal Carrier Transport Solves Maxwell's (Optical) and Poisson's Equations	Fully Coupled Opto-Electro-Thermal (OET) model; accounts for 5 heat sources	Joule losses accounting for over 70% of total heat loss.	Validated via energy/current conservation laws and comparison of temperature against empirical formulas	Limited long-term validation
Guerriero et al. [126]	Modified Single-Diode Model by Considering Temperature and Reverse Voltage Effects	Thermal Feedback Network	Cell-level discretization allows for accurate prediction of hot-spot under partial shading or mismatch	Comparison with Infra-Red (IR) camera maps and experimental data from a partially shaded 10-panel string	$\pm 3\text{--}5\text{ }^{\circ}\text{C}$ - Limited long-term validation
O.M. Maka [127]	Single-Diode Model	Finite Element Method	Includes dynamic efficiency	Comparison with commercial triple-junction cell (AZURSPACE) performance data (25–80 $^{\circ}\text{C}$).	12% Integrated Error b/w Steady State and Transient assumptions - Specific to Concentrated Solar Power (CSP) configuration
Wenbo et al. [128]	5-Parameter Equivalent Circuit Model	Unsteady-State Heat Transfer	Bifacial gain is higher on cloudy days due to high diffuse fractions	Validated against experimental data and existing literature	- Coupled bifacial/optical-thermal integration - Requires detailed irradiance distribution
Yaman and Arslan [129]	Single-Diode Model	Lumped Parameter RC Network	Radiative resistance accounts for 70–80% of total thermal resistance; wind speed is less dominant than radiation/ambient temperature	Validated with winter/summer experimental data	$\pm 1.34\text{ }^{\circ}\text{C}$ RMSE (Winter), $\pm 1.30\text{ }^{\circ}\text{C}$ RMSE (Summer) $\pm 5.09\text{ W}$ RMSE (Winter), $\pm 3.91\text{ W}$ RMSE (Summer) - No mismatch consideration
D'Angola et al. [130]	Single-Diode Model	Steady-State Lumped Parameter	Water cooling brings cell temperatures close to STC (25 $^{\circ}\text{C}$), significantly increasing electrical power compared to uncooled tests	Validated via outdoor tests in Torino, Italy; excellent agreement between calculated and measured outlet water temperatures	PVT coupled modeling
Abdenmour et al. [131]	Bishop Model	Distributed Heat Conduction Model	Accurate identification of overheating cells during partial shading	Laboratory testing via EESFC unit and IR thermal imaging	$\pm 4.5\text{--}11\%$ Relative Error (Power)
W. Ahmad et al. [11]	Single-Diode Model	Semi-Analytical Solution of the Heat Equation	Thermal mismatch causes a 5.43% power deviation, mainly because of voltage (4.84%), compared to uniform temperature assumptions	Comparison of simulated MPPs under NOCT conditions	$\pm 5.43\%$ Relative Power Deviation (w.r.t STC)
X. Tian et al. [132]	Single-Diode Model	Solution of the Energy Balance Thermal Networks	En-Flexible modules outperform in the morning/evening due to better incident angles	Indoor/outdoor test rigs at 30° and 90° tilts	$\pm 1\text{--}5\%$ MPP Deviation - Simplified irradiance distribution assumption

5. Concluding Remarks

This review has presented a detailed and structured overview of the modeling approaches used to describe the electrical, thermal, and coupled thermal–electrical behavior of photovoltaic (PV) modules. The analysis confirms that no single modeling technique can be universally adopted for all applications and weather conditions, as each class of models is characterized by specific assumptions, input requirements, and levels of accuracy.

Analytical and physical electrical models, specifically diode-based, provide a robust representation of PV cell and module behavior. These models are mainly tailored for detailed performance analyses and degradation studies, although their applicability may be limited by parameter identification complexity and computational burden. Semi-empirical models offer an effective compromise between accuracy and simplicity, making their

application adequate for large-scale simulations, energy yield estimation, and system-level analyses when limited input data are available. Empirical and data-driven approaches, including machine learning techniques, demonstrate high predictive capability in the case of complex and non-linear operating conditions; however, their lack of physical interpretability and dependence on large training datasets restrict their generalization outside the calibration domain.

From a thermal perspective, lumped parameter and thermal network models remain widely used due to their simplicity and low computational cost, particularly for steady-state and system-level evaluations. Nevertheless, these approaches are inherently limited in their ability to capture spatial temperature gradients, which are critical for quantifying mismatch losses and identifying hotspot formation and localized degradation. The adoption of these models might result in an inaccurate estimation of PV performance. On the contrary, spatially distributed thermal models are based on numerical solutions of heat transfer equations, providing significantly higher accuracy while estimating the temperature distribution at the cell level. The drawback of these models consists of a high computational effort due to their complexity.

The review highlights that coupled thermal–electrical models represent the most comprehensive framework for accurately predicting PV module performance under real operating conditions. By explicitly accounting for the bidirectional interaction between temperature and electrical behavior, these models enable more realistic assessments of power output, efficiency losses, and reliability. However, current coupled approaches often rely on simplifying assumptions, such as uniform irradiance or reduced spatial resolution, and experimental validation remains limited in many studies. Table 7 offers a comprehensive overview of the main features of the models under investigation in this work.

In summary, the distributed thermal models coupled with analytical electrical models are preferred choices for the cell-level analyses, as these models evaluate the local temperature gradients and non-uniform current flows. On the other hand, lumped parameter thermal models coupled with semi empirical electrical models are the preferred choices for the system level yield predictions, as these models have low computational cost with the accuracy required for long-term power predictions.

Table 7. Summary of the Different Electrical, Thermal, and Coupled Modeling Approaches.

Model	Uncertainty ($\pm$ %)	Computational Cost/Complexity	Spatial Resolution	Input Parameters	Best Applications
Analytical Electrical Models	± 3 –8%	Very low	Cell Level	I_{SC} , V_{OC} , I_{MPP} , V_{MPP} , G_{POA} , T_{cell}	System design, energy yield estimation
Semi-Analytical Electrical Models	± 2 –5%	Low to moderate	Module Level	Data Sheet as well as operating conditions (temperature and solar irradiance)	Module and inverter level studies
Empirical Electrical Models	± 1 –4% within the fitted range	Low	Module/System Level	Historical data, including I – V curves and ambient conditions, fitting parameters	Performance evaluation, experimental validation
Lumped-Parameter Thermal Models	± 3 –10%	Very Low	Average module temperature or single-point temperature	Operating ambient conditions, heat transfer coefficients	Long-term simulations, system-level analysis
Distributed Thermal Models	± 1 –3%	High to very high	Cell/Sub-Cell Level	Material properties, geometry, and boundary conditions	Hot-spot analysis, reliability, and degradation studies
Weakly Coupled Thermo-Electrical Models	± 3 –7%	Moderate	Cell/String Level	Electrical model and thermal outputs	Partial shading analysis, mismatch studies
Strongly Coupled Thermo-Electrical Models	± 1 –4%	High to very high	Cell/Sub-Cell Level	Fully coupled thermal and electrical parameters	Fundamental research, failure, and stress analysis

Future research efforts should focus on improving the physical consistency and scalability of coupled models, particularly by integrating more accurate spatial thermal analysis with advanced electrical modeling at the cell and string levels. Long-term experimental campaigns, multi-sensor temperature measurements, and standardized validation procedures are essential to guarantee the robustness of the models. Additionally, hybrid approaches combining physics-based models with data-driven techniques may offer a promising pathway to balance accuracy, interpretability, and computational efficiency. Overall, the systematic insights provided in this review can support researchers and practitioners in selecting and developing appropriate modeling strategies for performance prediction, optimization, and reliability assessment of photovoltaic systems operating under increasingly complex environmental conditions.

Author Contributions: Conceptualization, A.D. and G.M.; methodology, A.D. and G.M.; formal analysis, A.D. and G.M.; investigation, A.D. and G.M.; resources, W.A.; data curation, A.D. and G.M.; writing—original draft preparation, W.A.; writing—review and editing, A.D. and G.M.; visualization, W.A.; supervision, A.C., A.D., G.M., F.S. and N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

Abbreviations used in this review article are as follows:

ANN	Artificial Neural Network
AM	Air Mass
BP	Back Propagation
bPV	Bifacial Photovoltaics
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
CEC	California Energy Commission
c-Si	Crystalline Silicon
DDM	Double-Diode Model
ECT	Equivalent Cell Temperature
FDM	Finite Difference Method
FEM	Finite Element Method
FVM	Finite Volume Method
GPR	Gaussian Process Regression
G _{POA}	Plane of Array Irradiance
HJT	Heterojunction
IR	Infrared
I–V	Current–Voltage
I _{MPP}	Current at Maximum Power Point
I _{ph}	Photogenerated Current
I ₀	Saturation Current
LPM	Lumped Parameter Model
NOCT	Nominal Operating Cell Temperature
NREL	National Renewable Energy Laboratory
MPP	Maximum Power Point
mPV	Mono-Facial Photovoltaic
PVUSA	Photovoltaics for Utility Scale Applications
PV	Photovoltaic
P _{max}	Maximum Power

RF	Random Forest
RNN	Recurrent Neural Network
R_s	Series Resistance
R_{sh}	Shunt Resistance
SDM	Single-Diode Model
SNL	Sandia National Laboratories
SRRL	Solar Radiation Laboratory
STC	Standard Test Conditions
SVR	Support Vector Regression
T_{amb}	Ambient Temperature
T_{ref}	Reference Temperature
T_{coeff}	Temperature Coefficient
T_{mod}	Module Temperature
TN	Thermal Network
I_{sc}	Short-Circuit Current
T_{cell}	Cell Temperature
TDM	Triple-Diode Model
V_{oc}	Open-Circuit Voltage
v	Wind Speed
V_{MPP}	Voltage at Maximum Power Point
V_t	Thermal Voltage

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