CHAPTER 2

REVIEW OF LITERATURE

This chapter provides the literature on works related to the present work. ***Section 2.1*** *presents a glimpse of the spectral, electrical, and thermal modeling of photovoltaic (PV) modules in previous works by various researchers. Also, the section shows the spectrum's effect on the PV module's performance.* ***Section 2.2*** *reviews multiple publications on the impact of soiling on PV module performances. This section also examines the effect of varying environmental parameters on PV soiling.* ***Section 2.3*** *reviewed the studies based on the seasonal performance analysis of the PV modules.*

2.1 Modeling approaches for performance analysis of photovoltaic module

The performance of the photovoltaic module depends on various parameters includes solar spectrum and environmental parameters. Several modeling approaches have been developed for precise estimation of the PV modules. Some models emphasize on the electrical performance, while some on the thermal performance. Other modeling approaches are integration of solar spectrum with electrical and thermal model.

2.1.1 Spectral modeling

The spectral variation plays a vital role in the performance of the photovoltaic system. The influence of seasonal variation of the solar spectrum is important in optimum solar photovoltaic system design [76]. The spectrum of the sunlight changes with the change in the time throughout the day, month, or year [77, 78]. The spectrum is ‘red’ during sunrise and sunset and ‘blue’ during noon. The significance of the changing solar spectrum varies differently based on the photovoltaic technology considered [79]. The solar spectrum is sensitive to declination angle, latitude, hour angle, aerosol density, water vapor, and ozone thickness [77]. The spectral response of a PV cell relates to the location and time of the day. The variation in the spectral distribution depends on the meteorological conditions and the sun’s position. It is considered that not all atmospheric parameters are responsible for the spectral variation. Some main parameters are irradiance, air mass, aerosol, and turbidity. The atmospheric constituents available in the atmosphere are responsible for absorption and reflection of the incident spectrum falling on the earth's surface. The main meteorological parameters affecting the performance of the PV system include solar geometry, global irradiance, diffuse irradiance, ambient temperature, relative humidity, and wind speed [80]. Different PV systems act in different ways to the incident spectrum wavelength range based on their band energies. For example, the utilization of spectral irradiance for electricity generation and part of the spectrum that contributes to heat generation in crystalline silicon solar cells is shown in Figure 2.1. In a single junction, the spectral response is based on only one material, whereas in a multijunction, several cells of varied material with suitable band energies are stacked together to obtain a better spectral response. Different PV technologies are experimentally investigated under varying bands of the spectrum. Some authors have worked on monocrystalline silicon cells [81-84], multicrystalline silicon photovoltaic modules [81-87], some on single junction amorphous silicon PV modules [81-83, 86-88], double junction amorphous silicon solar cells [88], three-stacked amorphous silicon photovoltaic module [87], thin film CdTe, CIGS, perovskite [82], and triple junction PV modules [89].

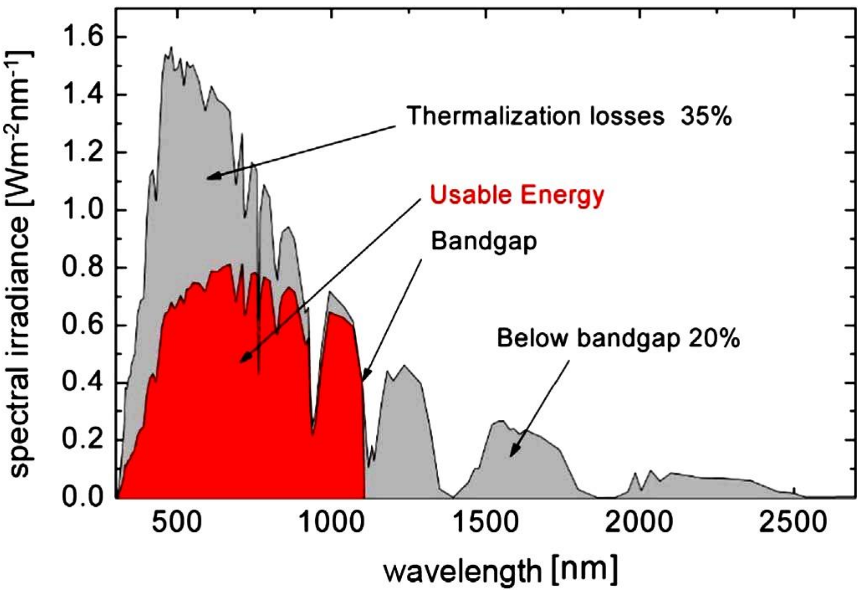
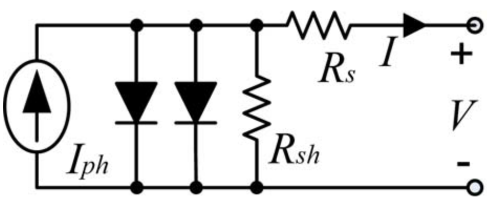


Figure 2.1 Distribution of solar spectrum used for electricity and heat generation in silicon solar cell [90, 91].

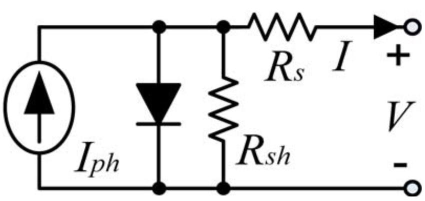
For PV modules with small band gap material (crystalline silicon), the efficiency lies from 4% to 5% between seasons, while for high band gap materials (amorphous Si) the efficiency varies from -10% to 15% between seasons [92]. However, the total installed capacity of the crystalline silicon solar cell was 93% in 2016 [93], which gives an interest in the consideration of crystalline silicon solar cells. There are various spectral models used for spectral modeling in clear-sky and cloudy conditions. Some of them are SMARTS2: Simple Model of the Atmospheric Radiative Transfer of Sunshine version 2 [94, 95], SPCTRAL2: Simple Solar Spectral Model for Direct and Diffuse Irradiance on Horizontal and Tilted Planes at the Earth's Surface for Cloudless Atmospheres [96, 97], SEDES2 [98], SBDART: Santa Barbara DISORT Atmospheric Radiative Transfer [99], and ASPIRE: All-sky Spectral IRadiancE [100].

2.1.2 Extraction of solar cell parameters

The growth in energy crises and uncertainties in conventional energy sources have encouraged the development of self-dependent renewable energy sources. In the photovoltaic (PV) industry, efficiency and power output are considered to be the most important parameters since it defines the applicability of the PV panel for a specific purpose [101]. Practically, the output differs from the standard efficiency described by the manufacturer (labeled in the PV modules). The difference in the actual output is due to the variations in the solar radiation (in terms of magnitude and spectrum content) [102] as a function of the sun’s position, the cell temperature, the seasonal change, and the varying atmospheric parameters [101, 103]. The absorption and the scattering of air molecules and dust in the atmosphere are the major factors that contribute to the change in the integrated power of the spectrum [104]. Typically, the cell parameters provided by the PV manufacturer are under the standard test conditions (STC). These cell parameters are limited to the short-circuit current (I_{sc}), open-circuit voltage (V_{oc}), maximum current (I_{mp}), maximum voltage (V_{mp}), and maximum power (P_{max}). However, there are some significant unknown cell parameters such as photocurrent (I_{ph}), diode saturation current (I_o), ideality factor (n), series resistance (R_s), and shunt resistance (R_{sh}). Since the current-voltage (I-V) characteristics of a PV module is a non-linear implicit expression, and therefore models have been developed to determine these electrical parameters. These unknown cell parameters can be extracted from the three base points under STC. These points are the V_{oc} (open circuit condition), I_{sc} (short-circuit condition), and I_{mp} and V_{mp} (maximum power point condition) and can be obtained from the manufacturer datasheet [29, 105, 106]. A comparative review of different analytical of single-diode models and computational techniques of single-diode and double-diode models for different PV module technologies has been reported [107]. A current source is connected in parallel to a diode in a single-diode model, and its output is directly proportional to the amount of light that strikes the cell. Three parameters, I_{sc}, V_{oc} and n are all that needed for this model to fully describe the IV curve. Thus, this model simple and requires less computational time. While the PV cell is more precisely represented by the double-diode model, where one diode represents the diffusion current in the p-n junction and the other diode represents the space-charge recombination. At lower irradiance level, the double-diode model yields more accurate findings. This model can attain more precision, but it needs seven parameters including I_{ph}, I_{o1}, I_{o2}, R_s, R_{sh}, n_1 and n_2, where I_{o1} and I_{o2} are the diode saturation current of diode 1 and diode 2, respectively and n_1 and n_2 depicts the ideality factor of diode and diode, respectively [108]. The series resistance signifies the ohmic loss and loss due to impurity concentration along with junction depth. While shunt resistance is related to leakage current across the junction [109]. The electrical circuit of the double-diode and single-diode model is depicted in Figure 2.2.



(a)



(b)

Figure 2.2 The electrical circuit of solar cell with (a) double-diode and (b) single-diode models [110].

There are numbers of reported methods and techniques to solve this expression. Some authors have converted the implicit *I-V* equation to an explicit equation using Lambert W-function to numerically solve the single-diode *I-V* equation of the cell in order to extract the electrical parameters of the cell. They also implemented the Newton-Raphson method to solve the non-linear equation of the cell [102]. Moreover, the annual energy yield from the designed PV model was simulated using transient system simulation (TRNSYS) [111]. Ortiz-Conde et al. [112] determined the intrinsic and extrinsic parameters using the co-content function in terms of Lambert W-function under the cell's illuminated I-V characteristics. Yadir et al. [113] used analytical methods, concluding that the developed model correspondence with the model of Ortiz- Conde et al. [112]. Cuce et al. [114] experimentally and statistically determined the electrical cell parameters of m-Si and p-Si. The study was carried out at a solar intensity level range of 200-500 W/m^2 and a temperature range of 15-60°C. They defined a term called solar intensity coefficient, which is the ratio of current (A/m^2) and solar intensity (W) to correlate the solar radiation with the current parameters of the PV module. However, this study was conducted indoors in controlled environment. Pindado et al. [115] proposed an explicit equation from the manufacturer datasheet using power-voltage (*P-V*) curve. This model consists of two equations, first for the voltage values lower than the voltage at MPP and second for voltage values higher than the voltage at MPP.

In some approaches researchers have applied analytical methods [116, 117], and numerical methods, namely, Newton-Rapshon method [102], Gauss-Seidel method [105]; and few other have used artificial neural network [118, 119] has been used to estimate the cell parameters. Chan et al. [116] analytically evaluated the electrical parameters of single-diode and double-diode solar cells. The percentage error was obtained to be less than 10% for all the parameters evaluated. Cubas et al. [117] used an analytical method to extract the electrical parameters of a 1-diode/2-resistor PV module. The boundary condition applied to this model is that the first derivative of the power with respect to the voltage output is considered to be zero. Villalva et al. [29] developed a model single-diode PV array to determine the electrical parameters of the I-V expression. Picciano et al. [120] solved the electrical parameters using empirical data. The approximate data obtained are processed under the iterative trial-and-error method. Phang et al. [121] and Blas et al. [122] developed a simple analytical methodology to extract parameters that defined PV behavior equations. Boutana et al. [123] have predicted the J-V behavior of the PV technologies multi-Si, CIGS, and CdTe, incorporating a comparison with the ones given in datasheet and the experimental results. They have compared different models developed by seven from the literature to explain the implicit and explicit modes of calculation. Bouzidi et al. [124] developed a model using a non-linear least-squares optimization algorithm based on the Newton method modified through the Levenberg parameter [125] to obtain the electrical parameters considering a series resistance and shunt conductance. Chenche et al. [107] compared the electrical parameters, coefficient of determination (R^2), and mean absolute percentage error (MAPE) value of monojunction and multijunction solar cells extracted by different researchers who have used different analytical and empirical methods to solve these parameters. They have concluded that the model proposed by Blas et al. [122] and Xiao et al. [126] are the best for monojunction and multijunction cells, respectively. Et-torabi et al. [105] implemented an iterative method (called Gauss-Seidel) using MATLAB on a single-diode model and an analytical method on a double-diode model to determine the cell parameters of monocrystalline silicon, multicrystalline silicon, and thin film PV modules. Models were also developed using MATLAB/Simulink. Stefan [127] developed a MATLAB/Simulink model using the *fsolve* function to numerical extract the electrical parameters of the PV module. They highlighted that out of the different optimization algorithms, Lavenberg-Marquardt algorithm is found provide the best results. Xiao et al. [126] developed Simulink model of CIG, monocrystalline silicon and multicrystalline silicon modules to obtain the parameters. They compared the obtained simulation parameter values with the constant parameter model (CPM), with visibly less deviation of simulation data compared to actual data. Li et al. [128] proposed a transient Multiphysics simulations in ANSYS CFX and MATLAB using compound parabolic concentrator (CPC) to obtain the six parameters under varying climatic conditions.

Various approaches have been adopted to accurately predict the performance of PV modules. The cell parameters, such as the ideality factor, linearly decrease with a rise in cell temperature, and the fill factor exponentially increases and linearly decreases with the intensity of light and cell temperature, respectively. Both series and shunt resistances have an inversely linear relationship with the cell temperature [114].

In one of the other methods, n is initially obtained from the diode characteristics of the I-V curve, and then the I_o is extracted using the n and open circuit condition. Next, the ideal I-V curve parameters were determined, substituting n and I_o values into the solar cell equation. The R_s and R_{sh} values were calculated using the value of the R^2. This value converges R_s and R_{sh} to optimum; if R^2 converges above 0.99, extraction of parameters is terminated, or else the procedure repeats [106]. Another method uses an optimization model, where the R_{sh} value is determined, and for each R_{sh} value, the other four unknown parameters are evaluated [110]. Studies have considered the fixed irradiance and temperature values to conduct a comparative study between the data provided by the manufacturer at different fixed conditions and the simulated results performed. The relative errors were determined on peak power voltage and peak power for copper indium diselenide (CIS), multicrystalline silicon, and monocrystalline silicon PV module technologies [129]. However, literature also showed work that does not use these three reference points but instead uses arbitrary points of the I-V curve. For example, an algorithm was introduced where the number of pairs of ideality factor and series resistance is used to extract the other three unknown cell parameters using a 3 by 3 linear system of equations. This method is independent of the usage of any assumptions on the parameters, calculations on slopes, and specific points of the I-V curve [130].

2.1.3 Thermal modeling of photovoltaic module

The cell temperature acts as an important parameter in the calculation of the efficiency of the PV module. The operating temperature of the PV module is a function of the PV cell technology, the physical properties of the PV cell, the environmental conditions, and the electrical loadings to the PV system [59, 60, 131-133]. The main environmental conditions that affect the temperature distribution in PV are solar irradiance, ambient temperature, and wind speed [134, 135]. Around 6-20% of the incident solar radiation is converted into electrical energy based on the type of solar cells and climatic conditions, whereas the remaining part acts as a source of heat generation in the cell [41]. Therefore, analysis of the thermal behavior of the PV under actual conditions is an essential concern. Thermal models have been developed to understand the effect of temperature on PV performance in terms of efficiency, power output, or energy generation. The relative change in V_{oc}, I_{sc}, FF, and P_{max} is reported to be -0.0025/°C, 0.002/°C, -0.0013/°C, and -0.002/°C, respectively, due to cell temperature for monocrystalline silicon solar cell [136]. The significance of temperature on PV performance has been widely studied experimentally and using a computational model [29, 42, 134, 135, 137-143]. Some of the adopted methods include explicit equations [144], simulations using various software such as MATLAB [145], numerical analysis using finite element heat transfer module with COMSOL Multiphysics [137-139, 146], using Galerkin finite element method to flow and energy equations with implicit convections [147], ANSYS [133, 135]. Also, some have developed thermal models using the energy balance of the PV module [59, 132, 134, 148]. Thermal models of PV systems with different dimensions have been proposed as 1D [101], 2D [60], and 3D [133, 137, 148]; the lower dimension model reduces the complexity of the model whereas to obtain higher accuracy from the model it is necessary to design a higher dimension model [149]. PV module is a multilayer, and heat exchanges occur between the layers and between the surfaces and the surrounding. The conduction heat exchange takes place between each layer of the PV module, while convection and radiative heat exchanges occur between the PV surfaces and the surrounding environment [139]. Figure 2.3 represents various physics within the structure and with the surroundings.

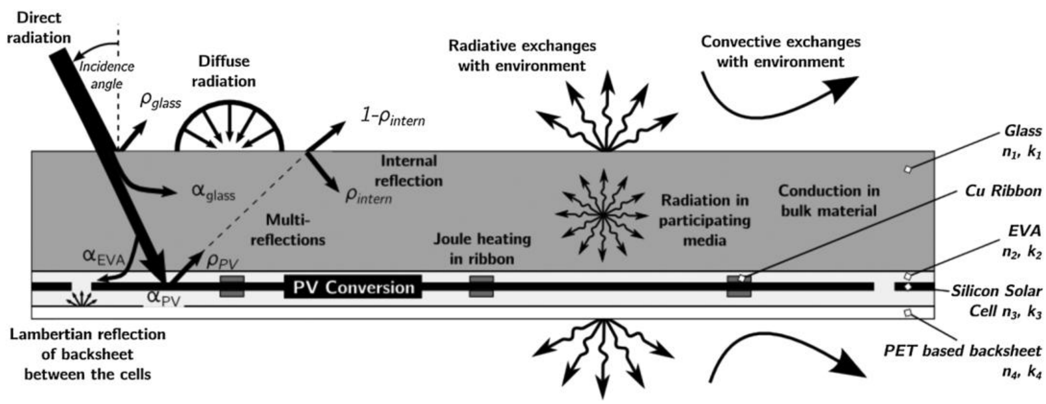


Figure 2.3 Heat exchanges and physical phenomena in a photovoltaic module [139].

A model has been developed based on finite differences for a double-glass multicrystalline PV module and experimentally validated to obtain root mean square error (RMSE) of 1.3°C for cell temperature. Here 22 different convection coefficient formulations were tested to find the best corresponding configuration [131]. Photovoltaic thermal (PV/T) system having monocrystalline PV panels with parallel-plate thermal collectors attached at the back has been modeled. The results highlighted that the power output and efficiency increase by 0.29 W and 0.05%, respectively, per 1°C decrease in cell temperature [146]. Barroso et al. [101] designed an electrical model using a particle swarm optimization algorithm and a 1D finite difference model for thermal modeling. The temperature and electrical efficiency of the PV panel under the influence of meteorological conditions were analyzed. Lee et al. [150] used finite element thermal analysis in order to understand the temperature distribution in different layers of the PV module (top glass cover, solar cells, bus bars, ethyl vinyl acetate (EVA), and Tedlar back sheet). Singh et al. [151] studied the performance of electrical parameters (V_{oc}, J_{sc}, FF, and η) subjected to change in the temperature ranging from 273K to 523 K. It was mentioned that an increase in temperature increases reverse saturation current I_o with which V_{oc} decreases. Therefore, FF decreases, and hence the efficiency decreases. On the other hand, the band gap of the material decreases with a rise in temperature, which increases the short-circuit current density (J_{sc}), efficiency enhancement. Therefore, these two conditions shown by the electrical parameters V_{oc} and J_{sc}, the solar cell efficiency decreases with increasing temperature since the rate of decrease ($-dV_{oc}/dT$) is much higher than due to J_{sc}. Kim et al. [152] evaluated the thermal characteristics of the PV module considering the varying ambient temperature throughout the day using the numerical analysis method. It was observed that the power of the PV module falls at a rate of around 0.5 %/°C and efficiency at 0.05 %/°C as ambient temperature rises. Mattei et al. [134] designed an electrical and temperature model with the employment of atmospheric variables, including solar irradiance, ambient temperature, and wind speed, using a simple energy balance method. Zondag et al. [149] also developed a 3D dynamic and 1D, 2D and 3D steady-state model to examine the thermal and electrical output of a PV-thermal collector. Aly et al. [60] developed a thermal model using the transient 2D finite difference method; the designed model had modified radiation, heat transfer, and thermal networks to increase the accuracy level. The designed model took into account the front glass cover, EVA binder, PV cells, and tedlar back sheet, where ARC (anti-reflective coating) and back contact did not take part in heat transfer. It was pointed out that negligence of heat transfer from the sides of the PV panel and heat generation in the front glass cover consideration does not make a remarkable difference. Their model was validated using a commercial FD-based numerical package ANSYS and experimental results. Barykina et al. [153] evaluated the thermal behavior of four different modules at five different sites having different climatic zone using the Faiman model. Bayrakci et al. [154] developed two models (temperature-dependent and temperature independent) using TRNSYS to investigate the influence of temperature variation on the PV system, considering the USA as the location for the study. Chander et al. [136] studied regarding the solar cell temperature controling the quality and performance of the multicrystalline silicon solar cell. Chander et al. [141] presented the influence of temperature on performance of PV mainly focusing the series and shunt connections of monocrystalline silicon. They experimentally illustrated using a solar simulator to generate constant light intensity 550 W/m^2 with cell temperature between 25-60°C. A temperature control unit consisting of a heater and temperature sensor, and monocrystalline silicon solar cell as a power source was used. The electrical parameters like V_{oc}, P_{max}, FF, and η are inversely proportional to the cell temperature, whereas I_{sc} slightly increases. This attributes to an increase in charge carrier generation with cell temperature [41]. The main parameters affecting the performance significantly are light intensity, tracking angle, and cell temperature. The typical operating temperature lies around 45°C ± 2°C in accordance with the nominal cell operating temperature. Tina et al. [142] designed an electrical-thermal model subjected to ambient temperature, wind speed, wind direction, relative humidity and electrical operating points to predict the energy production. For electrical modeling Least-square fitting has been used to calculate the equivalent model characteristics with the measured one. Du et al. [138] developed a time-dependent thermal model to examine the performance of PV modules with two configurations of glass-glass (GG) and glass-back sheet (GB). A heat transfer model was implemented using a COMSOL Multiphysics environment to investigate the thermal performance of the PV module. The heat transfer from the side boundaries, variations of heat capacities, and latent heat with temperature were neglected in the designed model. They have concluded that the GG configuration shows a better uniformity in the temperature distribution and heat dispersion compared to the GB configuration. However, the former has a slightly higher temperature. Dubey et al. [41] reviewed the significance of temperature on the PV module efficiency and power output linear relationship. They have presented different correlations for cell temperature defined by different authors and have checked its applicability to freely mounted PV arrays, PV/thermal collectors and building-integrated photovoltaics (BIPV) installations. Jones et al. [59] developed the energy balance model of PV cell under consideration of climate diversion. They noted the non-steady behavior of module temperature variation with respect to time. Weiss et al. [139] presented the radiative-heat transfer model to illustrate its significance on the module temperature. They have used SMARTS2 model for spectral modeling and COMSOL Multiphysics environment for thermal modeling. Kaplani et al. [155] determined the *f* coefficient that bridges the intensity of the global solar radiation on a PV plane and the PV temperature. They experimentally studied the effect of wind velocity, wind direction, and PV inclination angle on the temperature of the PV module. Their conclusion implied that on parallel wind flow on the PV module, the heat convection from the PV module reduces. Park et al. [156] examined the electrical and thermal model of the semi-transparent PV module, noting that the property of glass used in the PV module has a role to play in the temperature behavior and electrical performance of the PV module. Siddiqui et al. [133] developed a 3D thermal model considering the cooling and without cooling subjected to varying atmospheric conditions. Caluianu et al. [147] investigated the effect of free convection on the thermal behavior of the PV module. Armstrong et al. [35] designed a thermal model to estimate the temperature response model of the PV panel under the varying atmospheric conditions.

Some of the assumed sets of hypotheses undertaken by different authors while performing the thermal analysis were:

- The part of solar irradiance which is not used in electricity production in PV modules is the source of heat [131, 137, 138, 148].
- The thermophysical properties of each layer of the PV module are homogeneous and isotropic [135, 137, 138, 148].
- The reflections and transmissions between the components, namely between PV cells and front glass, and the radiative transfer from PV cells to front glass are neglected [137, 138, 148].

- Solar irradiance is equally distributed over the PV surface [137, 138, 148].
- Conductive, convective, and radiative heat transfer takes place between the environment and the PV module [137, 138, 148].
- The radiation from the module to the environment is negligible [137, 138, 148].
- Heat transfer from the sides and edges of the PV module is neglected [131, 137].
- Heat transfer between the PV cell and EVA is neglected because of the extremely small area [137, 138, 148].
- The ambient temperature and wind speed surrounding the PV module are uniform [137, 138, 148].
- The module is considered to have five uniform layers because the difference in the width of the area between the cells is comparatively much smaller than the PV surface [137, 138, 148].
- The effect of dust or any other agent that is deposited on the surface is neglected [137, 138, 148].

For simplification, some heat transfers are neglected in the thermal model; for instance, convection heat transfer in both front and back surfaces and radiative heat transfer only at the front surface is considered [145]. Mettei et al. [134] coupled the electrical and thermal models to determine the PV output power against the solar irradiance, ambient temperature, and wind speed. The hypothesis considered were (i) the temperature difference between the PV cells and the front glass is neglected, (ii) the temperature is uniformly distributed in the module, and (iii) the radiative heat transfer is neglected. They reported an RMSE of 2.24°C. Kant et al. [148] reported a difference of 5-7% between the simulation and experimental data.

A detailed study on the effect of wind on developed thermal performance has been carried out by considering wind and without wind conditions. The calculated statistical errors R^2 and RMSE are 0.98 and 1.12°C for wind conditions and 0.96 and 1.7°C for those without wind conditions, respectively [157]. Skoplaki et al. [158] reviewed the implicit [159] and explicit correlation of the cell temperature with the irradiance, irradiance at nominal operating cell temperature (NOCT), ambient temperature, the temperature at NOCT, and wind speed from the literature. Skoplaki et al. [160] reviewed the correlation between the power output and efficiency of the PV module, operating cell temperature, and environmental parameters. Some of the defined correlations for the cell temperature of the PV module with respect to the environmental parameters are as follows:

King et al. [161] $$T_c = T_b + \frac{G}{G_r}\Delta T \quad (°C) \tag{2.1}$$

Chenni et al. [129] $$T_c = 0.943T_{amb} + 0.028G - 1.528W_s + 4.3 \quad (°C) \tag{2.2}$$

Skoplaki et al. [144] $$T_c = T_{amb} + \left(\frac{0.25}{5.7 + 3.8W_s}\right)G \quad (K) \tag{2.3}$$

Jha et al. [137] $$T_c = \frac{G}{G_{NOCT}}\left(NOCT - T_{amb\_NOCT}\right)\left(1 - \frac{\eta_c}{\tau\alpha}\right) + T_{amb} \tag{2.4}$$

Some researchers conducted experimental tests for thermal analysis, i.e., the effect of temperature on the electrical characteristics of semi-transparent PV module was evaluated. They observed a decrease in power generation of 0.48% per 1°C rise in temperature under the standard test condition except for temperature value and a decrease of 0.52% per 1°C rise in temperature under outdoor conditions (irradiance of 500 W/m^2) [156].

The heating effect of a PV module depends on the solar irradiance and the Joule heating effect [138]. However, the studies by [138, 162] showed that under the operating condition, solar irradiance is the main attribute of heating of a PV module, and minimal attribute of Joule heating effect is reported. A steady-state thermal model of a PV system cannot be justified due to the dynamic nature of the temperature response with fluctuating irradiance and changing atmospheric parameters [59, 132]. The dynamic model reduced the errors (RMSE and WMAE) by 50% compared to the steady-state model and conventional approaches (based on NOCT) [163]. The behavior of the thermo-electric model of a PV module can be characterized by the dynamic models when the actual weather data are input [163]. Thus, the numerical model helps in accurately predicting the PV output subject to the environmental conditions before installing the system in a particular location.

2.1.4 Integrated model for photovoltaic performance analysis

The integration of the electrical-thermal model has been developed by some researchers to obtain higher prediction level of the energy yield from the PV modules. Nagae et al. 2006 [87] evaluated the power output under the influence of solar spectrum and temperature variation for silicon-based PV modules such as p-Si, a-Si and three-stacked a-Si. Bliss et al. 2010 [164] carried out performance evaluation of amorphous solar cells under varying irradiance, temperature, and spectrum using solar simulator. A spectrum-dependent electrical-thermal model was developed, with limited values of air mass (AM) (AM1D to AM15D), ambient temperature (25°C to 45°C) and convective heat transfer coefficient only at the back surface (1200 W/m^2.K to 1600 W/m^2.K). This modeling was performed considering concentrating solar cell [24].

2.2 Effect of soiling on the photovoltaic module

The phenomenon of dust deposition on the surface of the PV module, known as soiling, depends on atmospheric parameters and the PV materials. The deposition of dust particles onto the surface of the PV modules blocks the incident solar radiation from reaching the module surface, thereby reducing the generation of charge carriers and an overall reduction in the power output. Figure 2.4 shows the light transmission, reflection, and absorption phenomena that take place on the glass surface of the PV module. Dust is made of solid particles having minute size with diameters as less as 500 μm, including soil, salt, snow, industrial carbonaceous dust, leaves, pollen, bird droppings, bacteria, fungi, microfibers from fabrics, etc. [34, 57, 68, 165]. Dust can be a mix of organic and inorganic solids. The inorganic part may be composed of abrasive minerals like silica (sand), which can scratch the surface, and bird droppings, leaves, pollen grains, soot, etc., are considered organic dust [165]. Local environmental factors take into account the built environment, vegetation cover of the area, and weather conditions [68]. Various factors affect the deposition of dust on modules, such as wind speed and direction, relative humidity, rainfall, the orientation of modules and properties, and the concentration of dust particles and the surface of the module [34, 166, 167]. Soiling has a significant impact on change in the transmitted spectrum; therefore, the spectral effect of dust deposition should not be underestimated. There are several works on the effect of soiling on the performance of the PV module [168-173], on power output from the PV module [174-176], and on energy losses associated with dust deposition [177]. The spectral effect on different PV modules due to dust deposition has been investigated using the spectral transmittance of the glass sample [178]. The wavelength range of the spectrum has been estimated, which can predict the soiling loss associated with different types of PV module technologies [179]. The electrical losses of soiling are caused by the

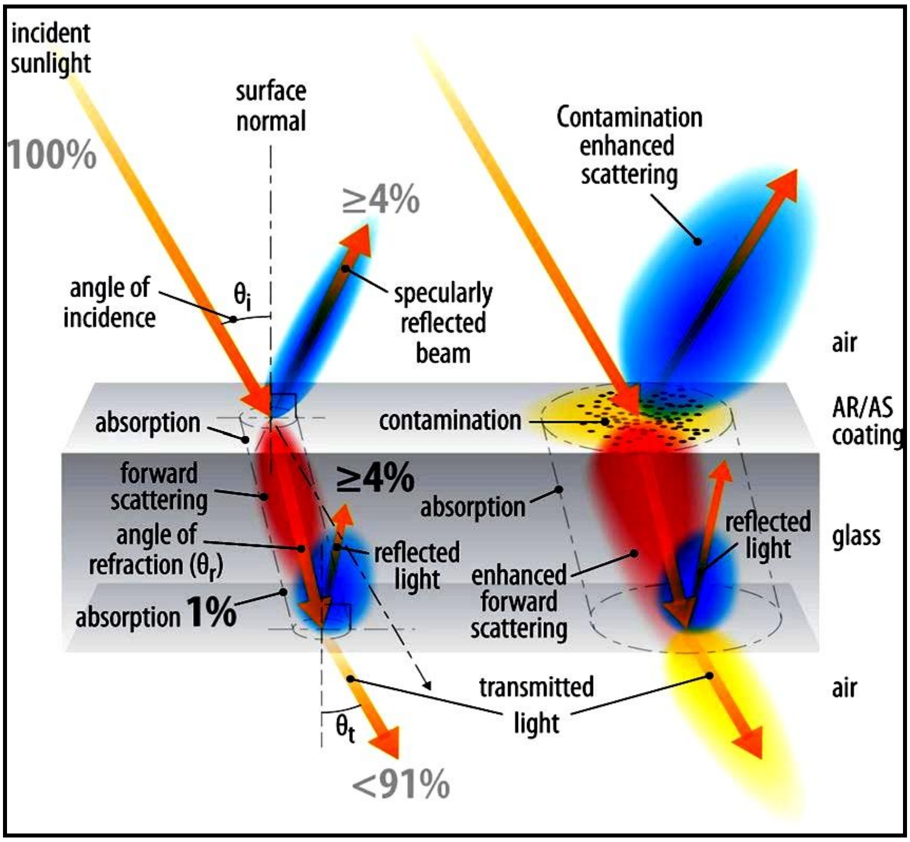


Figure 2.4 Variation in transmittance and reflectance of incident light on the front glass of PV due to soiling (courtesy: Al Hicks/NREL) [180].

reduction in transmittance, in some cases even higher than 50%, due to absorption and scattering phenomena [178, 181]. Many researchers have investigated the impact of soiling on PV technologies [48, 73, 182-184]. Shehri et al. [185] investigated the effect of dust accumulation on the transmittance of glass by exposing glass samples to the outdoor environment of Thuwal, Saudi Arabia, for one week. The maximum reduction reported on the first day was 2% with respect to the clean glass. Gholami et al. [186] experimented in Isfahan, Iran, and reported a decrease of 25% in the transmittance of the PV module's surface due to dust deposition over 70 days. Boyle et al. [187] observed a reduction in light transmission of 11% through the glass cover under natural dust deposition during 5 weeks in a rural and mixed industrial and residential area in Colorado, USA. In that case, the glass was covered with a roof preventing rainfall from cleaning the samples. El-Nashar [188] observed a 10-18% drop in the transmittance of the glass due to dust deposition on the evacuated tube collectors in a desalination plant installed in Abu Dhabi, UAE. In addition to reducing its broadband value, soiling has also a significant impact on the transmitted spectrum of the sunlight. The loss is indeed more enhanced in the blue region, and this may result in a variation of power output loss for different PV materials [178, 180]. Elminir et al. [45] found that with the increase in dust deposition density from 4.48 g/m^2 to 15.84 g/m^2, transmittance reduces from 12.38% to 52.54%. Guan et al. [189] conducted field test experiment in Chang'an District, Xi'an concluded that with increase in the dust deposition density, the relative transmittance decreases logarithmically and relative power output decreases linearly.

Various atmospheric parameters such as relative humidity, rainfall, rain frequency, ambient temperature, dew point temperature, particulate matter, wind speed, wind direction, properties, and concentration of suspended particles affect the deposition of particles on the PV module's surface [34, 55, 166, 167, 186, 190]. Studies on the combined effect of atmospheric parameters on light transmittance were reported, including wind velocity and airborne dust concentration [191]; wind speed and humidity [192, 193]; and suspended particulate matter, rain, wind, and relative humidity [190]. The atmospheric parameters influencing soiling typically also have some seasonal trends that also reflect the loss profile. El Nashar et al. [194] investigated the seasonality of the transmittance loss of a glass tube for solar desalination in an arid, dry, and dusty location in the UAE. Csavina et al., 2014 [193] analyzed the effect of relative humidity and wind speed on the semi-arid locations: Green Valley, Arizona, USA, and Mexico (Juarez, Chihuahua). They pointed out that wind speed and relative humidity are not only the determinant factors of dust scattered but also the factors such as wind direction and wind gusts need to be considered. Figgis et al. 2016 [192] analyzed the dependence of wind speed and humidity on dust deposition. Analysis test for 10 days in Doha proved that wind speed is the main parameter for dust deposition whereas dust removal depends on wind speed and humidity. Tanesab et al. [195] studied the influence of the seasonal change of PV soiling in different locations in Indonesia. They concluded that sites with high relative humidity, a long dry season, and a low tilt angle are more susceptible to dust deposition. Micheli et al. [196] studied the contribution of the seasonal trends of rainfall and particulate matter on the soiling losses for locations in the U.S. Recently, Javed et al. [69] reported that in Qatar, the highest soiling deposition rates occur in the colder season, followed by summer. They were lowest in the rainy season.

Ideally, if the correlation between the soiling and the significant atmospheric parameters were known, this could be used to predict the soiling based on the atmospheric parameters of a location. A regression model is a useful statistical tool to determine the relationship between the independent variables (such as the atmospheric parameters) and the dependent variables (soiling in this case). The regression model is used to generate a linear function between the independent variables and the parameters connected to soiling loss [166, 167, 186, 187, 192, 197, 198]. Javed et al. [167] used the multi-variable linear regression (MLR) method to predict the daily soiling loss (in terms of clearness index) from atmospheric parameters such as wind speed, relative humidity, and particulate matter (PM10) in Doha, Qatar. However, suggestions were made to consider other atmospheric parameters for better accuracy in the prediction of the soiling loss [199]. A strong correlation between soiling to particulate matter concentrations and frequency of rainfall was found for different sites in the United States when the long-term average losses were estimated [200]. Jiang et al. 2015 [201] illustrated the effect of dust accumulation on the module under thermophoresis (temperature gradient) experimentally. The ratio of energy output tends to rise from 0.947 to 0.971 with the rise in temperature. Thus, dust accumulation has an impact on the reduction of the surface temperature. A linear relation was developed between the amount of dust accumulated and transmission loss using linear regression with an R^2 value of 0.69 [187]. MLR model has been used to predict the soiling loss in terms of power output reduction by the particle size at a certain irradiance level in Shekhawati, India [197]. Piedra et al. 2018 [181] have used the MLR model to predict the soiling loss in terms of power output reduction considering the particle size at a certain irradiance level.

A significant difference in the energy output of a PV plant compared to its estimated value can be observed if soiling is not taken into consideration [202]. Location-specific studies of soiling losses are therefore important to determine the power production at the highest accuracy, particularly for lower tilt angles ≤ 30° [203]. In a PV system, soiling losses contribute significantly to the reduction of the glass surface transmittance leading to a reduction in radiation from reaching the solar cells, which ultimately results in low output power. The negligence of the dust effect will generate a strong gap between the actual field and the estimated energy output of a PV power plant [202]. Location-specific study of soiling losses is important for accurately determining power production and for providing proper solutions for cleaning. These kinds of studies are essential to the effective saving of the installation cost of the PV system in a particular location. Therefore, potentially maximize the energy yield and the financial revenues for a PV plant.

2.3 Seasonal performance analysis of photovoltaic module

There are numerous reported works that have considered the seasonal trend while evaluating the energy output or power output of the PV module. Some studies on the evaluation of the energy output of different PV technologies, such as crystalline silicon, CIGS, amorphous silicon, CdTe [204], CPV [205], monocrystalline silicon [206], and amorphous silicon, hybrid, and crystalline silicon under season variation [207]. Ye et al. 2014 [208] discussed the effect of the solar spectrum on various thin-film PV modules considering Singapore's climatic condition. The seasonal variability in the thermal performance is analyzed in a study conducted at TUT Solar PV Power Research Test Plant in Tampere, Finland. It is observed that there is less than a 2% of deviation in the simulated module temperature compared to the measured module temperature during summer. Also, the model is reported to have an average accuracy of 1.63°C [132]. Jha et al. [137] developed a thermal model using finite element computation and experimentally validated it for different seasons of the year for the environmental condition of the Kharagpur, India. The operating temperature of the PV module obtained from the simulation/model is compared with the NOCT model. The results from the FE model are reported to have a better accuracy level compared to the NOCT model as different statistical errors MAE = 39.1%, MRE = 40.0%, and RMSE = 41.8% for FE model are calculated to be lower than the NOCT model. This is attributed to the reason that the FE model accounts for the daily dynamic solar radiation and heat exchanges, whereas the NOCT model considers only the specification provided by the manufacturer.

Eke et al. [92] reviewed the influence of seasonal solar spectrum variation on PV modules under outdoor conditions. Different spectrum indicators such as Spectral Mismatch Factor (MMF), Useful Fraction (UF), and Average Photon Energy (APE) that are used in spectral characterization are discussed. The influence of spectrum varies with the type of PV module consideration. Energy yield prediction gives the expected energy outcome of a specific PV at a particular location. Energy rating, on the other hand, provides the performance of the different PV modules at realistic under standardized conditions. The data set based on the climatic zones of the location of interest it is possible to check the relevance of various PV technologies for that particular location. So data set of European countries has been designed for the energy rating of the PV modules [209]. Alonso-Abella et al. [210] investigated the impact of solar spectrum distribution on a monthly and an annual basis in energy generation from a PV technology in a specific site is crucial for PV consumers. However, their study has not considered the impact governed by cell temperature and incident irradiance level. The spectral-mismatch loss, which includes sub-bandgap and thermalization loss, accounts for more than 50% of the overall heat generation and results in the dissipation of more than 60% of incident sunlight. The energy loss in the solar cell and from cell to module is reported to be 71.1% and 14.6%, respectively, for studies conducted on a typical sunny day [211]. Louwen et al. [212] investigated the seasonal and annual performance of different PV technologies, namely, monocrystalline, polycrystalline, amorphous, CdTe, copper indium (gallium) selenide, and silicon heterojunction have been analyzed under varying operating conditions such as irradiance, operating temperature, spectral composition in terms of average photon energy, and angle of incidence. The study considered the environmental conditions of North-Western European locations. They concluded that varying operating temperature of PV module leads to a significant change in the seasonal performance of all the considered PV modules. However, the magnitude of the effect will depend on the temperature coefficient of the PV module. The performance during summer decreases compared to winter; this is attributed to high operating temperatures. As the power output of the PV module drops with the rise in temperature, this is because electrical properties depend on the thermal properties of the solar cell [137]. Despite the fact that the energy yield during winter is lower compared to summer because of low solar insolation. The impact of average photon energy is also observed on the seasonal performance of the PV module, mainly for the amorphous silicon PV module. Similarly, the seasonal performance of solar power plant (20 kW_p) was experimentally investigated under the climatic conditions of the Indian Institute of Science, Bangalore, India. For different seasons, a decrease in module efficiency with the rise in operating temperature is reported. For operating temperatures greater than 45°C, 35°C, and 38°C during summer, monsoon, and post-monsoon, the module efficiency reduces by 0.08%, 0.04%, and 0.06% per degree rise in temperature. During winter, the drop in efficiency with respect to temperature was very low, and maximum efficiency was obtained at an operating temperature of 55°C. The reason for this is lower ambient temperature. They also considered the capacity utilization factor (CUF) and performance ratio (PR) as the determining factors. The average PR varies inversely with operating temperature. The higher value of maximum PR was obtained during winter and post-monsoon compared to summer and monsoon. The attributing factors are the lower ambient and operating temperatures in winter and higher solar insolation during post-monsoon. However, average PR is higher in monsoon and post-monsoon since monsoon experiences random rainfall which encourages the cooling of PV surfaces, and post-monsoon season have a higher number of day with clear sky condition [213].

Recently, Gholami et al. [214] reviewed the existing electrical, thermal, and optical models of PV systems and provided the trend of these studies carried out since 2000 to date, as shown in Figure 2.5. They recommended that even with a number of considerable research on this specific area, there still exists an opportunity for modeling the electrical behavior of the PV. Also, most of the models have good prediction levels for the conditions under the STC. However, if the models are to work consistently well and cover a wide range of actual operating conditions, more

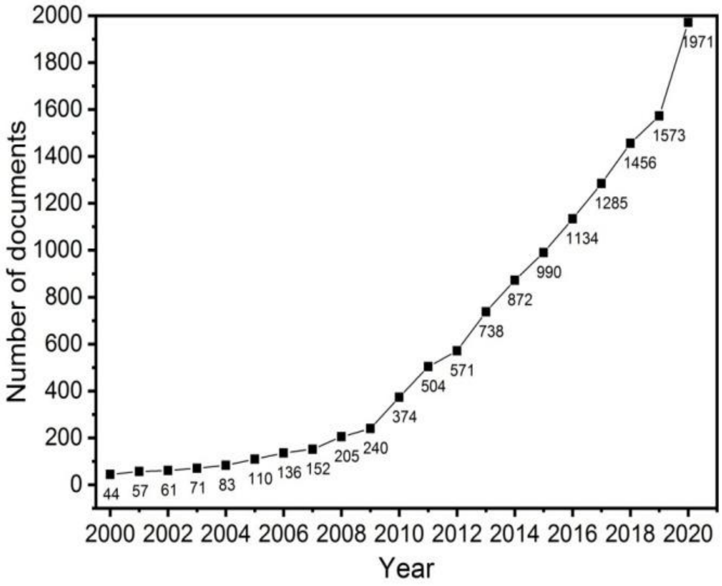


Figure 2.5 Trend on the number of studies related to different electrical, thermal, or optical modeling of PV [214].

enhanced improvements are required. Most of the PV models neglect the spectrum involvement and only consider solar broadband irradiance as the source. However, the spectral distribution plays a significant role in PV output, also the transient nature of the spectrum throughout the day with changes in the air mass value [89, 215, 216]. It was also reported that the error could rise up to 17% under the negligence of the varying environmental conditions, but considering the impact of soiling on the developed model has the potential to improve the prediction level up to 35% [214]. Therefore, based on the challenges and recommendations in the literature, the present study aims to develop a spectrum-integrated opto-electric-thermal model of PV module considering the actual varying environmental conditions with good prediction level.