

Archives available at journals.mriindia.com

International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 07 Issue 01, 2018

Performance Analysis of Solar Photovoltaic Systems Under Variable Environmental Conditions

Gyeong Zuberiwala

Department of Computer Science and Engineering, Borneo School of Business and Technology, Malaysia
 gyeong.zuberiwala@bsbt-my.org

Peer Review Information

Submission: 06 Feb 2018

Revision: 05 March 2018

Acceptance: 02 April 2018

Keywords

Solar Photovoltaic,
 Environmental Condition,
 Solar Irradianc, Module
 Temperature, Performance
 Ratio

Abstract

Solar photovoltaic (PV) output is highly sensitive to environmental conditions because irradiance, module temperature, wind, partial shading, and surface soiling alter the current-voltage operating point and the amount of useful energy that can be extracted. This methodology paper develops a compact and reproducible framework for evaluating PV performance under variable outdoor conditions using measured or representative meteorological inputs, a temperature-corrected electrical model, and normalized performance indicators. The procedure combines irradiance normalization, module-temperature estimation, maximum-power calculation, and explicit loss factors for shading and soiling. A 250 Wp crystalline-silicon module is used as an illustrative case to demonstrate the analysis over irradiance levels of 400-1000 W/m² and cell temperatures of 25-65 °C. The modeled results show the expected near-linear increase of maximum power with irradiance and a clear reduction in power as module temperature rises. At 1000 W/m², increasing cell temperature from 25 °C to 65 °C reduces predicted peak power from 250 W to approximately 205 W when a -0.45%/°C power-temperature coefficient is used. Additional mismatch or soiling losses further reduce output even when irradiance is high. The framework is suitable for laboratory studies, field monitoring, and comparative analysis because it links environmental measurements to energy-yield indicators in a transparent step-by-step manner. References are restricted to work published in or before 2018.

Introduction

Photovoltaic modules are rated at standard test conditions (STC), normally 1000 W/m² irradiance and a cell temperature of 25 °C, but actual operating conditions continuously depart from these values. Consequently, nameplate power alone is insufficient for predicting field behavior. De Soto, Klein, and Beckman (2006) demonstrated that PV array output can be translated from manufacturer data to other irradiance and temperature conditions using a parameterized electrical model. Their work provides an important basis for performance

modeling because it explicitly connects changes in environmental inputs to the I-V characteristics of a PV device.

Among environmental variables, irradiance primarily controls photocurrent and therefore available power, while temperature mainly changes voltage and efficiency. Skoplaki and Palyvos (2009a) reviewed temperature-power correlations and showed that increasing operating temperature generally decreases module electrical efficiency. A related survey by Skoplaki and Palyvos (2009b) emphasized that module temperature itself depends on

irradiance, ambient temperature, wind, mounting configuration, and heat-transfer conditions. Singh and Ravindra (2012) further explained the physical temperature dependence of open-circuit voltage, short-circuit current, fill factor, and conversion efficiency across photovoltaic materials.

Outdoor performance is additionally affected by nonuniform irradiance and optical losses. Patel and Agarwal (2008) showed that partial shading can produce multiple peaks in P-V characteristics and substantial mismatch loss. Mani and Pillai (2010) identified dust deposition as another location-dependent factor that lowers transmittance and energy yield. Therefore, a practical performance analysis should not isolate irradiance and temperature from shading or soiling when these conditions are present. The objective of this paper is to define a concise methodology that combines these influences and produces comparable indicators for assessing PV operation under variable environmental conditions.

Literature Review

PV performance literature has evolved from device-level electrical models toward long-term outdoor system assessment. The five-parameter approach improved by De Soto et al. (2006) is widely useful because it requires commonly available manufacturer data while accounting for irradiance and temperature. For nonuniform illumination, Patel and Agarwal (2008) established a simulation framework capable of representing bypass-diode action, array configuration, and multiple power maxima under partial shading. These studies support the use of a physics-informed but computationally manageable electrical model in the present methodology.

Temperature has received particular attention because field module temperature can be tens of degrees above ambient temperature. Skoplaki and Palyvos (2009a) summarized linear efficiency and power-temperature relationships, whereas their companion survey (2009b) catalogued correlations that estimate operating temperature from environmental variables. Singh and Ravindra (2012) analyzed temperature effects at the semiconductor level and confirmed that open-circuit voltage and efficiency generally decline as temperature increases. More recently, Cotfas, Cotfas, and

Machidon (2018) experimentally measured different PV cell technologies between 25 °C and 87 °C and irradiance levels from 400 to 1000 W/m², showing that temperature coefficients may themselves vary with irradiance. Lopez-Garcia, Pavanello, and Sample (2018) likewise highlighted the importance of accurately characterized temperature coefficients for outdoor performance interpretation.

Eke and Demircan (2013) monitored a multicrystalline PV installation under real climatic conditions and reported close agreement between measured annual energy and module-based calculations, while also showing pronounced seasonal power differences associated with operating temperature. These results justify combining instantaneous electrical response with normalized energy-yield metrics. The literature also shows why environmental variables should be analyzed jointly rather than through isolated single-point efficiency values. High irradiance commonly coincides with elevated module temperature, so the increase in photocurrent can be partly offset by a reduction in voltage. Conversely, windy clear conditions may provide high irradiance while maintaining a lower module temperature, producing better normalized power. This interaction is a central reason for using temperature-corrected power and irradiance bins rather than comparing raw wattage alone. The review by Skoplaki and Palyvos (2009a) and the field evidence reported by Eke and Demircan (2013) both support this coupled interpretation.

Environmental contamination and nonuniform illumination create losses that cannot be represented adequately by a single temperature coefficient. Mani and Pillai (2010) noted that dust accumulation depends on climate, surface properties, rainfall, wind, and maintenance practice; therefore, a soiling factor should be measured or estimated for the particular location. Partial shading is even more nonlinear because bypass diodes and series-parallel array connections reshape the P-V curve. Patel and Agarwal (2008) showed that several local maxima may occur, which means a conventional maximum-power tracker or a simplified linear loss assumption can misrepresent available power. For this reason, the present methodology distinguishes between a simplified screening calculation and a detailed I-V/P-V modeling option.

Table 1. Selected literature supporting the proposed methodology

Study	Main variable	Method / contribution	Use in this paper
De Soto et al. (2006)	Irradiance, temperature	Five-parameter PV model	Electrical response translation

Patel & Agarwal (2008)	Partial shading	Array P-V simulation	Mismatch/shading loss
Skoplaki & Palyvos (2009a,b)	Module temperature	Temperature-performance correlations	Thermal correction
Mani & Pillai (2010)	Dust/soiling	Review of deposition effects	Optical loss factor
Eke & Demircan (2013)	Outdoor climate	Annual field monitoring	Yield validation concept

Methodology

The proposed methodology is designed for either measured field data or controlled simulation. The analysis unit may be one PV module, an array, or a grid-connected system, provided that the rated STC power and temperature coefficient are known. For demonstration, a crystalline-silicon module with $P_{STC} = 250$ W and a maximum-power temperature coefficient $\gamma_P = -0.0045$ per $^{\circ}\text{C}$ is used. The illustrative values are not presented as field measurements; they show how the method converts changing environmental conditions into comparable PV performance outputs.

1. Research design and test matrix

A repeated-measures design is recommended because the same PV device is observed across changing environmental states. The independent variables are plane-of-array irradiance, cell/module temperature, and, where applicable, wind speed, shading severity, and soiling level. The principal dependent variables are maximum DC power, normalized power, conversion efficiency, and energy yield. For controlled experiments, irradiance-temperature combinations should cover the expected outdoor range; for field studies, the natural observations can be grouped after measurement into defined irradiance and temperature bins. Replication within each bin improves the stability of average performance estimates.

Step 1: Define system and environmental inputs
Record module rated power, area, technology, voltage/current ratings, temperature coefficients, inverter efficiency if AC output is required, and array configuration. Environmental inputs should include plane-of-array irradiance G , ambient temperature T_a , module or cell temperature T_c when directly measured, and optional wind speed. When relevant, record shading fraction, dust/soiling condition, and data-quality flags. Irradiance and electrical quantities should use synchronized time steps, for example 1-15 min for field monitoring.

Step 2: Estimate or measure module temperature
Direct back-surface temperature measurements are preferred. If unavailable, module temperature can be estimated from an empirical

correlation that uses ambient temperature and irradiance, with wind included where data are available. This is consistent with the correlation-based approaches summarized by Skoplaki and Palyvos (2009b). The selected temperature model must remain fixed throughout the comparison so that changes in predicted power are attributable to environmental conditions rather than model switching.

Step 3: Calculate temperature- and irradiance-adjusted power

For a compact performance study, maximum DC power can be estimated by $P_{DC} = P_{STC} (G/G_{STC}) [1 + \gamma_P (T_c - T_{STC})]$, where $G_{STC} = 1000$ W/m² and $T_{STC} = 25$ $^{\circ}\text{C}$. For more detailed I-V studies, the De Soto et al. (2006) parameter model can be applied to update photocurrent, saturation current, series resistance, shunt resistance, and diode factor before solving the I-V curve and locating the maximum power point. This second option is especially useful when voltage/current behavior is itself an outcome of interest.

Step 4: Apply environmental loss factors

After the irradiance-temperature response is obtained, additional multiplicative loss factors are applied only when supported by observations. A soiling factor L_s can represent transmission loss due to accumulated dust, following the environmental-loss considerations discussed by Mani and Pillai (2010). Partial shading should ideally be represented through a module/array model with bypass diodes as in Patel and Agarwal (2008); for a simplified screening analysis, a mismatch factor L_{sh} may be applied with a clear statement that it cannot reproduce multiple local P-V maxima. The corrected DC power is $P_{DC,corr} = P_{DC} (1 - L_s)(1 - L_{sh})$.

Step 5: Determine energy and performance indicators

For time-series data, energy is obtained by integrating corrected power over the sampling interval. Recommended indicators include specific yield (kWh/kWp), normalized power P/P_{STC} , module efficiency $\eta = P/(G A)$, and performance ratio when reference irradiance and AC energy are available. The same indicator definitions and sampling rules should be used

across seasons or test cases. Kymakis et al. (2009) and Eke and Demircan (2013) demonstrate the value of normalized yield and performance-ratio concepts for outdoor system comparison.

Step 6: Quality control and comparison

Exclude night data, sensor faults, inverter-off periods that are unrelated to environmental response, and points outside physically plausible limits. Group valid observations by irradiance and temperature bins, then compare mean output, normalized output, and loss percentages. Sensitivity can be quantified by changing one variable at a time while holding others constant. This allows the analyst to separate irradiance-driven gains from thermal, shading, or soiling penalties.

Step 7: Statistical and sensitivity analysis

For measured datasets, calculate the mean, standard deviation, and coefficient of variation for power within each environmental bin. A multiple linear regression may be used as a descriptive check, with normalized power as the response and irradiance, module temperature, and wind speed as predictors, provided that residual behavior is examined and the model is not used to replace the physical PV model. Sensitivity coefficients can also be computed by varying irradiance by $\pm 10\%$, temperature by $\pm 10^\circ\text{C}$, and environmental loss factors by plausible ranges. Agreement between modeled and measured power can be summarized with mean bias error, mean absolute percentage error, and root-mean-square error. This step makes the methodology suitable for model validation as well as performance comparison.

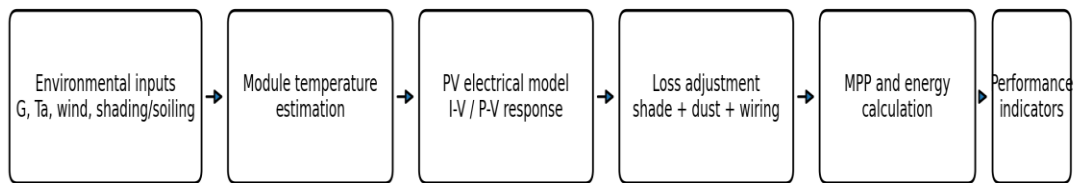


Figure 1. Step-by-step workflow used to translate environmental inputs into PV performance indicators.

Results

Table 2 presents illustrative outputs from the compact power model. The calculations demonstrate three expected behaviors. First, decreasing irradiance reduces power approximately in proportion to G when temperature and other losses are unchanged. Second, increasing cell temperature reduces

maximum power even under strong sunlight. Third, partial shading or soiling can make a high-irradiance condition perform worse than a cleaner, more uniformly illuminated condition. These trends are consistent with the experimental and modeling literature reviewed above.

Table 2. Illustrative modeled PV performance under representative environmental conditions

Condition	G (W/m ²)	T _c (°C)	Extra loss	P _{DC,corr} (W)	P/P _{STC} (%)
STC reference	1000	25	0%	250.0	100.0
Clear, warm	900	35	0%	214.9	86.0
Clear, hot	1000	65	0%	205.0	82.0
Moderate irradiance	600	45	0%	136.5	54.6
Dusty, high irradiance	900	45	8%	188.4	75.3
Partial shade	700	45	18%	130.6	52.2
Cloudy, cool	400	30	0%	97.8	39.1

At fixed irradiance of 1000 W/m², raising cell temperature from 25 °C to 65 °C lowers predicted power by 18%, from 250 W to 205 W. This result follows directly from the assumed $-0.45\%/^\circ\text{C}$ temperature coefficient and agrees qualitatively with the temperature sensitivity described by Skoplaki and Palyvos (2009a), Singh and Ravindra (2012), and Cotfas et al. (2018). The 900 W/m², 45 °C dusty case produces about 188.4 W after an 8% soiling penalty, illustrating

why optical cleanliness must be considered separately from temperature correction. Under the partial-shading screening case, an 18% mismatch loss further suppresses output; in a detailed array study, the full P-V curve should be simulated because local maxima may appear (Patel & Agarwal, 2008).

For a real field campaign, the same calculations would be repeated for every measurement interval and aggregated to daily or monthly

energy yield. Comparing normalized output within irradiance bins is particularly useful because it prevents a high-energy day from appearing more efficient simply because it received more sunlight. Seasonal comparisons should also separate temperature effects from availability, inverter clipping, wiring, and grid losses. This separation is consistent with system-level performance studies such as Kymakis et al. (2009) and Eke and Demircan (2013).

The scenario results also illustrate an important interpretation issue: the condition with the highest irradiance is not automatically the condition with the highest normalized efficiency. The clear-hot case receives full 1000 W/m² irradiance but delivers only 82% of STC power because of thermal derating. By contrast, the clear-warm case receives 900 W/m² and retains approximately 86% of STC power. When power is normalized by incident irradiance, the warmer module exhibits a larger thermal penalty. This distinction is essential when comparing climates, mounting configurations, or ventilation strategies.

The simplified loss factors for dust and shade are intentionally conservative analytical placeholders. In an experimental implementation, soiling loss should preferably be determined from paired clean/soiled measurements or a calibrated soiling sensor, whereas shading should be characterized by geometry, irradiance mapping, and bypass-diode behavior. If measured P-V curves exhibit multiple peaks, the detailed array model should replace the simple multiplicative shading factor. Thus, the proposed framework provides two levels of analysis without confusing screening estimates with full electrical simulation.

Conclusion and Discussion

This paper presents a practical methodology for analyzing the performance of solar PV systems under variable environmental conditions. The framework begins with synchronized irradiance and temperature measurements, estimates module temperature when necessary, calculates the electrical response, applies documented shading or soiling losses, and converts the results into normalized performance indicators. The method is intentionally scalable: a simple temperature-corrected power equation is sufficient for screening and teaching applications, while the De Soto five-parameter formulation can be used when accurate I-V prediction is required. The illustrative results confirm that irradiance is the dominant driver of available power but that high temperature can materially offset the benefit of strong sunlight. Nonuniform shading and dust introduce additional losses that cannot

be inferred from irradiance alone. For rigorous experiments, the main limitations are sensor uncertainty, uncertain cell-temperature estimation, changing spectral conditions, and simplified treatment of mismatch. Future application should therefore use calibrated plane-of-array irradiance sensors, direct module-temperature measurements where feasible, technology-specific temperature coefficients, and bypass-diode-aware models for partial shading. Within these constraints, the proposed step-by-step procedure provides a transparent basis for comparing modules, climates, seasons, and operating conditions using literature available through 2018.

References

- Cotfas, D. T., Cotfas, P. A., & Machidon, O. M. (2018). Study of temperature coefficients for parameters of photovoltaic cells. *International Journal of Photoenergy*, 2018, 5945602. <https://doi.org/10.1155/2018/5945602>
- De Soto, W., Klein, S. A., & Beckman, W. A. (2006). Improvement and validation of a model for photovoltaic array performance. *Solar Energy*, 80(1), 78-88. <https://doi.org/10.1016/j.solener.2005.06.010>
- Eke, R., & Demircan, H. (2013). Performance analysis of a multi crystalline Si photovoltaic module under Mugla climatic conditions in Turkey. *Energy Conversion and Management*, 65, 580-586. <https://doi.org/10.1016/j.enconman.2012.09.007>
- Kymakis, E., Kalykakis, S., & Papazoglou, T. M. (2009). Performance analysis of a grid connected photovoltaic park on the island of Crete. *Energy Conversion and Management*, 50(3), 433-438. <https://doi.org/10.1016/j.enconman.2008.12.009>
- Lopez-Garcia, J., Pavanello, D., & Sample, T. (2018). Analysis of temperature coefficients of bifacial crystalline silicon PV modules. *IEEE Journal of Photovoltaics*, 8(4), 960-968. <https://doi.org/10.1109/JPHOTOV.2018.2834625>
- Mani, M., & Pillai, R. (2010). Impact of dust on solar photovoltaic (PV) performance: Research status, challenges and recommendations. *Renewable and Sustainable Energy Reviews*, 14(9), 3124-3131. <https://doi.org/10.1016/j.rser.2010.07.065>
- Patel, H., & Agarwal, V. (2008). MATLAB-based modeling to study the effects of partial shading on

PV array characteristics. IEEE Transactions on Energy Conversion, 23(1), 302-310. <https://doi.org/10.1109/TEC.2007.914308>

Singh, P., & Ravindra, N. M. (2012). Temperature dependence of solar cell performance-an analysis. Solar Energy Materials and Solar Cells, 101, 36-45. <https://doi.org/10.1016/j.solmat.2012.02.019>

Skoplaki, E., & Palyvos, J. A. (2009a). On the temperature dependence of photovoltaic module

electrical performance: A review of efficiency/power correlations. Solar Energy, 83(5), 614-624. <https://doi.org/10.1016/j.solener.2008.10.008>

Skoplaki, E., & Palyvos, J. A. (2009b). Operating temperature of photovoltaic modules: A survey of pertinent correlations. Renewable Energy, 34(1), 23-29. <https://doi.org/10.1016/j.renene.2008.04.009>