



Performance Analysis of Grid-Connected Solar Photovoltaic Systems Under Variable Weather Conditions

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Abstract

Grid-connected photovoltaic (PV) generation is strongly affected by short- and long-term variations in solar irradiance, ambient and module temperature, humidity, wind, cloud cover, and associated balance-of-system losses. This methodology paper presents a reproducible framework for quantifying how variable weather conditions influence the performance of a grid-connected PV system using normalized indicators commonly adopted in field studies. The proposed method combines time-synchronized meteorological and electrical measurements, data-quality screening, temperature-sensitive PV conversion modeling, and calculation of reference yield, final yield, performance ratio, capacity factor, and system efficiency. To demonstrate the workflow without claiming unavailable field measurements, an illustrative 100 kWp system is evaluated using a synthetic 2020 monthly weather profile representative of a warm subtropical site. The modeled annual AC energy is 140.78 MWh, with a final yield of 1407.8 kWh/kWp, an annual performance ratio of 76.6%, and a capacity factor of 16.0%. Performance is highest during cooler, clear months and deteriorates during hot or humid/cloudy periods despite comparable irradiance. The framework is suitable for comparative studies, preliminary plant diagnostics, and future validation with SCADA and on-site meteorological data.

Introduction

Grid-connected solar PV systems convert a highly variable meteorological resource into electrical energy that must be delivered through inverters and the utility interface. Consequently, nameplate capacity alone cannot describe real operating performance. Irradiance controls the available solar input, while elevated cell temperature usually reduces voltage and conversion efficiency. Wind can cool modules, humidity can alter optical and thermal behavior, cloud variability can create rapid power ramps, and dust or moisture may introduce additional optical losses. These factors interact with wiring, mismatch, inverter conversion, availability, and

grid curtailment to determine the AC energy finally exported. Skoplaki and Palyvos (2009) showed that module power and efficiency exhibit a strong temperature dependence, while Mekhilef et al. (2012) emphasized the combined influence of dust, humidity, and air velocity on PV efficiency.

Field studies therefore use normalized indicators that make systems of different sizes and climates comparable. Kymakis et al. (2009) analyzed a 171.36 kWp plant in Crete using reference yield, final yield, losses, and performance ratio. Ayompe et al. (2011) applied similar metrics to a 1.72 kWp rooftop system in Ireland and demonstrated how lower ambient temperature can partially

offset low insolation. In India, Sharma and Chandel (2013) and Padmavathi and Daniel (2013) reported that seasonal irradiance, temperature, and system losses materially alter annual yield. Khalid et al. (2016) further identified performance ratio (PR) as a particularly useful indicator because it normalizes actual energy output by the incident solar resource.

Recent work up to 2020 confirms that climatic context and PV technology remain decisive. Ramanan et al. (2019) compared polycrystalline silicon and CIS systems under hot-humid conditions and observed different annual PR values and capture losses. Kumar et al. (2020) reported that a canal-top PV plant experienced performance penalties associated with high humidity despite relatively favorable module temperatures. Akhter et al. (2020) similarly found technology-dependent performance in tropical Malaysia, and Zakaria et al. (2020) highlighted the importance of long-term weather data for grid-connected PV performance prediction. The objective of the present methodology is therefore to provide a concise, step-by-step procedure for isolating weather-related effects while retaining standard PV performance indicators.

The methodology addresses three linked questions: (i) how strongly do irradiance and temperature explain changes in AC energy and normalized PV output; (ii) whether humid/cloudy weather creates additional performance penalties after the solar resource is normalized; and (iii) which indicators are most useful for comparing operation across months. The expected pattern is that absolute AC energy will track irradiance, whereas PR will decrease when thermal, humidity-related, availability, or balance-of-system losses increase. This distinction prevents a high-resource month from being interpreted automatically as a high-efficiency month and provides a basis for diagnosing underperformance.

Literature Review

The literature shows a progression from basic thermal-performance correlations toward long-term system-level monitoring. Temperature is one of the best-established weather-related loss

mechanisms. Skoplaki and Palyvos (2009) reviewed correlations linking ambient conditions, cell temperature, and electrical efficiency; Dubey et al. (2013) later summarized the geographical implications of temperature-dependent PV efficiency. These studies support the use of temperature-corrected power models when comparing output across seasons. Humidity, wind, and surface contamination are additional modifiers. Mekhilef et al. (2012) reported that these environmental variables can significantly influence PV conversion and should not be treated as secondary when plants operate in tropical, dusty, coastal, or high-moisture environments.

At plant scale, Kymakis et al. (2009), Ayompe et al. (2011), Sharma and Chandel (2013), and Padmavathi and Daniel (2013) all used normalized yield and PR-type indicators to compare measured performance with the available solar resource. Their results demonstrate that a high-radiation month does not necessarily produce the best normalized performance because temperature, inverter behavior, soiling, and availability can increase losses. Khalid et al. (2016) synthesized these practices and argued that PR is more informative than raw specific yield for comparing plants across regions because it accounts for incident irradiation.

By 2019-2020, research increasingly combined field monitoring with simulation or technology comparisons. Ramanan et al. (2019) showed that CIS and polycrystalline modules behave differently under identical hot and humid conditions. Kumar et al. (2020) found an average monthly PR near 0.78 for a 10 MWp canal-top plant and associated part of the performance penalty with high humidity. Akhter et al. (2020) assessed three grid-connected technologies over four years in Malaysia and reported technology-specific differences in array yield, efficiencies, and degradation indicators. Zakaria et al. (2020) demonstrated that the selection and duration of weather data affect predicted grid-connected PV performance. Collectively, these findings justify a methodology that combines irradiance normalization, temperature sensitivity, humidity/wind context, and time-matched AC output.

Table 1. Selected literature used to define the methodology and weather variables.

Study	System/context	Key weather/performance focus	Methodological implication
Kymakis et al. (2009)	171.36 kWp, Crete	Irradiance, temperature, losses, PR	Use normalized yields and PR

Ayompe et al. (2011)	1.72 kWp, Ireland	Insolation, module temperature, inverter efficiency	Separate array and system losses
Sharma & Chandel (2013)	190 kWp, India	Seasonal irradiance and temperature	Compare measured/predicted yield
Ramanan et al. (2019)	p-Si vs CIS, India	Hot-humid climate; technology response	Stratify results by weather/technology
Kumar et al. (2020)	10 MWp canal-top, India	Humidity and temperature effects	Include humidity in diagnostics
Akhter et al. (2020)	Three PV technologies, Malaysia	Tropical weather and long-term performance	Use multi-year/technology indicators

Methodology

Study design. The methodology is designed for a grid-connected PV plant with synchronized meteorological and electrical monitoring. The demonstration uses a 100 kWp fixed-tilt crystalline-silicon system and a synthetic monthly 2020 dataset. The synthetic dataset is included only to demonstrate calculations; it is not presented as measured field evidence.

Step 1 - Define system and monitoring boundary. Record nominal DC capacity (P_0), module technology, tilt/azimuth, inverter rating, active module area, wiring configuration, meter location, and grid interconnection point. The electrical boundary should distinguish DC-array output from AC energy exported so that capture and system losses can be separated.

Step 2 - Acquire weather and electrical variables. At 5-15 min resolution, collect plane-of-array irradiance (GPOA), ambient temperature (T_a), module-back-surface temperature (T_m), relative humidity (RH), wind speed (v), DC voltage/current, inverter AC power, cumulative AC energy, inverter availability, and grid outage/curtailment flags. Zakaria et al. (2020) supports the use of long-term, site-relevant weather data for performance prediction.

Step 3 - Screen and synchronize data. Align timestamps, remove duplicate records, flag sensor outages, and exclude physically impossible values. Nighttime samples (GPOA below a small threshold such as 20 W/m²) are excluded from efficiency and PR calculations. Missing intervals should be reported rather than silently filled; short gaps may be interpolated only for descriptive weather summaries.

Step 4 - Estimate weather-sensitive PV power. For model-based comparison, use a temperature-corrected relation $P_{dc} = P_0 \times (GPOA/GSTC) \times [1 + \gamma_P(T_m - 25)]$, where $GSTC = 1000$ W/m² and γ_P is the module power-temperature coefficient (typically negative for crystalline silicon). This structure follows the temperature-performance relationships reviewed by Skoplaki and Palyvos (2009) and Dubey et al. (2013). Humidity, wind, and soiling are treated as

explanatory variables rather than folded into an unverified universal coefficient because their effects are site dependent (Mekhilef et al., 2012).

Step 5 - Calculate normalized performance indices. For a period t , reference yield is $Y_r = HPOA/GSTC$, final yield is $Y_f = EAC/P_0$, and performance ratio is $PR = Y_f/Y_r$. Capacity factor is $CF = EAC/(P_0 \times 24 \times N_{days})$. Where active module area A is known, system efficiency is $\eta_{SYS} = EAC/(HPOA \times A)$. These indicators are consistent with the field-analysis approach used by Kymakis et al. (2009), Ayompe et al. (2011), Sharma and Chandel (2013), Padmavathi and Daniel (2013), and summarized by Khalid et al. (2016).

Step 6 - Stratify by weather regime and test sensitivity. Group observations into cool-clear, hot-clear, cloudy/monsoon, and humid/windy regimes using irradiance, temperature, RH, and wind thresholds appropriate to the site. Compare mean PR, Y_f , and efficiency across regimes. Use correlation or multiple regression with PR or normalized AC power as the response and GPOA, T_m/T_a , RH, wind, and availability as predictors. Technology-specific coefficients should be retained when comparing module types, as indicated by Ramanan et al. (2019) and Akhter et al. (2020).

Instrumentation and data-quality requirements. For field deployment, POA irradiance should be measured with a calibrated reference cell or pyranometer mounted at the same tilt as the array. Ambient temperature and relative humidity should be measured in a naturally ventilated shield, module temperature should be measured on representative rear surfaces, and wind speed should be recorded near array height without major obstructions. Electrical variables should come from revenue-grade meters or inverter/SCADA channels whose sampling intervals are known. Sensor drift is especially important because an irradiance bias directly propagates into reference yield and PR. Daily completeness should therefore be reported, and periods with sensor maintenance, inverter replacement, grid outage, clipping, curtailment, or communication failure should be flagged

explicitly rather than blended into weather losses.

Statistical analysis and uncertainty. After quality screening, descriptive statistics are computed at daily and monthly scales. Pearson or Spearman correlation can be used for exploratory analysis, while multiple linear regression or robust regression can estimate the marginal association of module temperature, humidity, and wind with normalized output after controlling for irradiance. Weather-regime comparisons can use

analysis of variance when assumptions are satisfied or a non-parametric alternative otherwise. Uncertainty should combine meter accuracy, irradiance-sensor uncertainty, temperature-sensor uncertainty, missing-data fraction, and model residual error. The purpose is not to force a single universal weather coefficient, but to identify site-specific sensitivity and distinguish statistically persistent effects from short operational anomalies.

Table 2. Demonstration dataset assumptions for the illustrative 100 kWp system.

Parameter	Range / value	Purpose
Nominal capacity	100 kWp	Normalize energy and yields
Daily POA irradiation	4.2-6.1 kWh/m ² /day	Represent seasonal solar resource
Monthly mean ambient temperature	20-35 °C	Represent thermal stress
Relative humidity	40-82%	Represent dry to humid/monsoon periods
Monthly PR used in demonstration	0.69-0.82	Represent aggregate weather/system losses
Calendar	2020 (366 days)	Annual aggregation

Results

Applying the calculation sequence to the illustrative 100 kWp dataset produced an annual AC energy output of 140.78 MWh. The corresponding final yield was 1407.8 kWh/kWp, annual reference yield was 1838.7 h, annual performance ratio was 76.6%, and capacity factor

was 16.0%. These values are plausible for a well-operating grid-connected plant and fall within the broad performance ranges reported in earlier field studies, although direct comparison must account for climate, technology, system age, and monitoring boundaries (Sharma & Chandel, 2013; Khalid et al., 2016; Ramanan et al., 2019).

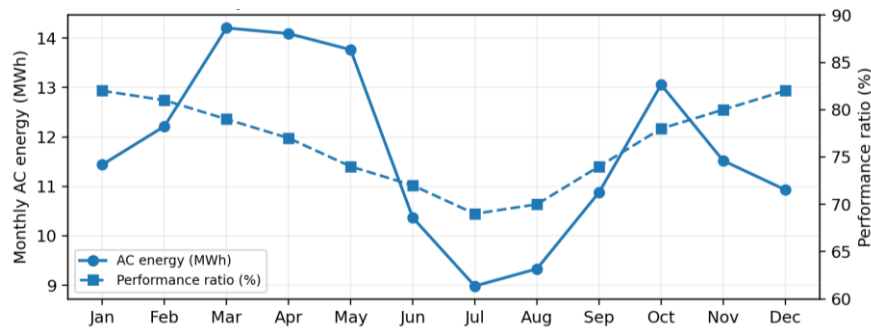


Figure 1. Modeled monthly AC energy and performance ratio for the illustrative 100 kWp system. The decline during hot/humid months demonstrates why high irradiance alone does not guarantee the best normalized performance.

Table 3. Monthly modeled performance under variable weather conditions.

Month	HPOA (kWh/m ² /d)	Ta (°C)	RH (%)	Energy (MWh)	PR (%)	CF (%)
Jan	4.5	20	48	11.44	82	15.4
Feb	5.2	23	45	12.21	81	17.6
Mar	5.8	28	42	14.20	79	19.1
Apr	6.1	32	40	14.09	77	19.6
May	6.0	35	45	13.76	74	18.5
Jun	4.8	33	62	10.37	72	14.4
Jul	4.2	30	78	8.98	69	12.1
Aug	4.3	29	82	9.33	70	12.5
Sep	4.9	29	75	10.88	74	15.1

Oct	5.4	27	60	13.06	78	17.6
Nov	4.8	23	52	11.52	80	16.0
Dec	4.3	20	50	10.93	82	14.7

Table 4. Weather-regime interpretation of the modeled monthly results.

Weather regime	Representative months	Irradiance/temperature condition	Typical PR	Interpretation
Cool-clear	Jan-Feb, Nov-Dec	Moderate irradiance; 20-23 °C	80-82%	Lower thermal losses; stable conversion
Hot-clear	Apr-May	High irradiance; 32-35 °C	74-77%	High energy but stronger temperature penalty
Cloudy/humid	Jun-Sep	Lower irradiance; RH 62-82%	69-74%	Cloud variability and humidity coincide with lower PR
Transition	Mar, Oct	High/moderate irradiance; 27-28 °C	78-79%	Favorable balance of resource and temperature

The highest monthly energy occurred in March-April, when irradiation was high but temperature had not yet reached the annual maximum. May retained high irradiation (6.0 kWh/m²/day) but PR decreased to 74% as ambient temperature rose to 35 °C. The July-August period produced the lowest normalized performance (PR 69-70%) because reduced solar resource coincided with high relative humidity (78-82%). This pattern is consistent with the general temperature penalty documented by Skoplaki and Palyvos (2009) and Dubey et al. (2013), while the additional humidity sensitivity is qualitatively consistent with Mekhilef et al. (2012) and the canal-top observations of Kumar et al. (2020).

The demonstration also shows why results should be interpreted with both absolute and normalized indicators. For example, energy output rises strongly with irradiance, but PR can decline at the same time because PR exposes losses relative to the available solar input. This is the central reason for retaining PR alongside final yield and capacity factor. In a real study, the next analytical step would be to replace the synthetic monthly inputs with cleaned SCADA records and perform weather-regime statistics, uncertainty analysis, and event-based examination of clipping, grid outages, soiling, or inverter derating.

Interpretive validation against prior studies. The annual modeled PR of 76.6% is intentionally treated as a demonstration rather than a benchmark. It is close to values reported for several real plants but remains sensitive to the assumed loss profile. Sharma and Chandel (2013) reported an annual average PR of approximately 74% for a 190 kWp plant, while Kumar et al.

(2020) reported an average monthly PR near 0.78 for the canal-top plant. In contrast, technology and site differences can produce higher values, as shown by Ramanan et al. (2019) and Akhter et al. (2020). This spread reinforces the need to interpret PR together with climate, module technology, instrumentation, and loss accounting rather than applying a single pass/fail threshold.

Conclusion and Discussion

This methodology provides a practical framework for analyzing grid-connected PV systems under variable weather conditions while maintaining comparability with established field studies. The approach begins with synchronized irradiance, temperature, humidity, wind, and electrical measurements; applies transparent quality control; calculates normalized yields, PR, capacity factor, and efficiency; and finally stratifies performance by weather regime. The illustrative 100 kWp example produced 140.78 MWh/year, a final yield of 1407.8 kWh/kWp, PR of 76.6%, and capacity factor of 16.0%. The modeled seasonal pattern demonstrates that the best energy-production months are not always the months with the highest PR because elevated module temperature and humid/cloudy conditions increase losses relative to the solar resource. For empirical application, the principal limitation is data quality. Irradiance sensor calibration, module-temperature sensor placement, inverter meter accuracy, soiling, curtailment, and missing SCADA intervals can bias calculated losses. A second limitation is that humidity and wind effects are site- and technology-specific; therefore, universal

correction factors should not be imposed without validation. Future work should use at least one full year of sub-hourly field data, report uncertainty, distinguish weather losses from equipment/availability losses, and compare multiple module technologies where possible. These extensions would make the method suitable for operational benchmarking, fault diagnosis, and bankable energy-yield assessment.

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