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PERFORMANCE ASSESSMENT OF GRID-CONNECTED PV SYSTEMS UNDER SEMI-ARID CONDITIONS

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Abstract

Semi-arid climates—characterized by high solar irradiance (>2000 kWh/m²/year), elevated ambient temperatures (summer peaks often exceeding 45°C), low and erratic rainfall (250–500 mm/year), and frequent dust storms—present both the highest solar energy potential and the most challenging operating conditions for grid-connected photovoltaic (PV) systems. While these regions offer exceptional solar resources, the same environmental factors that enable high energy yield simultaneously accelerate module degradation, increase soiling losses, reduce performance ratios, and compromise long-term reliability. This study provides a comprehensive, multi-disciplinary analysis of performance assessment methodologies and empirical findings for grid-connected PV systems operating under semi-arid conditions. Through systematic synthesis of 25+ field studies from semi-arid regions (India, Morocco, Algeria, South Africa, Middle East), analysis of long-term monitoring data (1–10 years operational history), and comparative evaluation of multiple PV technologies (mono-crystalline, multi-crystalline/PERC, CdTe, a-Si, CIGS), we demonstrate that: (1) Performance ratios (PR) in semi-arid installations typically range from 65–85%, significantly lower than the 75–90% achieved in temperate climates, with median PR of 74.3% for utility-scale plants and 79.3% for well-maintained smaller installations; (2) Capacity factors (CF) range from 15–20%, reflecting the high insolation but offset by thermal and soiling losses; (3) Soiling is the dominant operational loss mechanism, contributing 0.5–1.5% daily performance loss during dry seasons and 15–25% annual energy loss without frequent cleaning; (4) Temperature-induced efficiency losses reduce output by 8–15% annually compared to Standard Test Conditions (STC), with crystalline silicon modules experiencing 0.4–0.5%/°C power reduction; (5) Annual degradation rates (PLR) in semi-arid climates are 1.5–2.5× higher than temperate regions, ranging from 0.8–1.5%/year for crystalline silicon compared to 0.5–0.8%/year in temperate climates; (6) Thin-film technologies (CdTe, a-Si) demonstrate superior temperature coefficients (−0.20 to −0.25%/°C vs. −0.35 to −0.45%/°C for c-Si) and maintain higher performance ratios under elevated temperatures, though CdTe requires careful end-of-life management. The research methodology integrates: (i) Systematic literature review of 25+ peer-reviewed performance assessment studies (2000–2020); (ii) Standardized performance indicator framework following IEC 61724 guidelines (reference yield YR, final yield YF, performance ratio PR, capacity factor CF, array losses LC, system losses LS, module efficiency ηpv, system efficiency ηsys); (iii) Statistical decomposition methods for degradation quantification (Classical Seasonal Decomposition, Holt-Winters, Seasonal-Trend decomposition using Loess [STL], Year-on-Year, Multi-Year-on-Year); (iv) Comparative analysis across multiple technologies and

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installation scales (rooftop 3–100 kWp, utility-scale 1–50 MWp); (v) PVSyst simulation validation for performance prediction and loss decomposition. Strong points include the largest synthesis of semi-arid PV performance data to date, rigorous adherence to IEC 61724 standards enabling cross-study comparison, and novel application of advanced statistical methods (STL, Multi-YoY) to degradation analysis; weak points include limited long-term (>10 year) datasets for emerging technologies (PERC, HJT, TOPCon), geographic concentration in North Africa and India with under-representation of semi-arid regions in Australia, South America, and Central Asia, and absence of standardized soiling measurement protocols across studies. Current trends include AI/ML-enhanced performance forecasting, drone-based infrared thermography for hotspot detection, automated robotic cleaning optimization, and digital twin integration for real-time performance monitoring and predictive maintenance. Historical context traces PV performance assessment from early IEC 61724 standards (1998, revised 2012) through the establishment of regional test centers (NREL, GEP Morocco, CENER India) to current smart monitoring and forecasting systems. The discussion integrates: (a) Technology comparison across semi-arid conditions—PERC demonstrates strong bifacial potential but higher temperature sensitivity, while HJT and CdTe offer better thermal stability; (b) Performance ratio decomposition—soiling contributes 5–15% loss, temperature 5–12%, inverter/transformer losses 3–8%, and DC wiring/connection losses 2–5%; (c) Degradation rate analysis—linear regression underestimates degradation compared to STL and Multi-YoY methods which account for seasonal variations; activation energy $E_a \approx 0.5$–0.7 eV for crystalline silicon modules in hot climates; (d) Simulation validation—PVSyst predictions typically overestimate actual performance by 5–15% in semi-arid conditions due to under-estimation of soiling and thermal effects; (e) Economic implications—each 1% reduction in PR increases LCOE by 1.5–2.5%. Results from representative case studies show: (a) Naàma 20 MW plant (Algeria): PR = 67.55%, CF = 17.10%, annual efficiency 4.10%, with linear regression $R^2 = 0.91$ for irradiation-impact and $R^2 = 0.28$ for temperature-impact on production; (b) Rajasthan 100 kWp plant (India): actual PR = 79.34% vs. simulated 83.72% (gap of 4.38 percentage points), 100kWp plant outperforming larger installations due to lower soiling accumulation and better maintenance access; (c) Moroccan Green Energy Park PERC string: NRMSE < 4.16% for developed models validating DM and BM analytical approaches; (d) Malaysian 36-month study (tropical variant): poly-Si PR = 86.74%, mono-Si PR = 56.30%, with forecasted degradation rates of 10.58% and 11.99% respectively; (e) Ghardaïa 16.28 kWp plant (Algerian Sahara): total energy production 171.42 MWh (8-month period), solar integration rate varying from 6.60% (January) to 22.96% (April). The conclusion recommends that (a) Semi-arid PV projects should use climate-adjusted performance expectations with PR targets of 70–80% rather than 80–85% used in temperate regions; (b) Soiling mitigation (automated cleaning, anti-soiling coatings) should be budgeted as operational necessity, not optional enhancement; (c) Technology selection should prioritize low temperature coefficients and robust thermal management (HJT, TOPCon, CdTe over conventional c-Si); (d) Performance monitoring should employ advanced statistical methods (STL, Multi-YoY) for accurate degradation detection; (e) PVSyst simulations require calibration with local soiling and temperature coefficients.

Suggestions include developing semi-arid specific performance benchmarks (IEC 61724 semi-arid annex), mandating soiling loss monitoring in all utility-scale projects, incentivizing low temperature coefficient technologies through feed-in tariff adjustments, establishing regional performance databases (MENA: RCREEE; India: NIWE) with open access, and standardizing degradation reporting protocols (NREL PVDAQ format). Future scope includes federated learning for cross-site performance prediction, self-cleaning nanostructured coatings, perovskite-silicon tandem validation in semi-arid field conditions, and digital twin integration with satellite soiling forecasting, and floating PV (FPV) performance assessment in semi-arid reservoirs.

Keywords:

Grid-connected photovoltaic systems; semi-arid climate; performance assessment; performance ratio; degradation rate; soiling losses; temperature coefficient; capacity factor; IEC 61724; PVSyst simulation; PERC technology; thin-film PV; statistical decomposition; STL method; Multi-Year-on-Year; energy yield forecasting; hot climate performance.

1. Introduction

1.1 The Semi-Arid Solar Paradox

Semi-arid regions—defined by the Koppen classification BSh/Bsk with annual precipitation of 250–500 mm—cover approximately 15% of the Earth's land surface and are home to over 1.2 billion people. These regions possess extraordinary solar resources: annual global horizontal irradiance (GHI) typically exceeds 2000 kWh/m²/year, with some locations reaching 2,500 kWh/m²/year. Consequently, semi-arid zones have become focal points for utility-scale solar energy deployment, with major projects commissioned across India (Rajasthan, Gujarat), Morocco (Noor Ouarzazate, Green Energy Park), Algeria (Naàma, Adrar, Ghardaïa), South Africa (Northern Cape), the Middle East (UAE, Saudi Arabia), and Australia (Queensland, Northern Territory).

Yet the same environmental conditions that provide abundant solar radiation simultaneously create severe operational challenges:

1. **Elevated operating temperatures**: PV modules in semi-arid climates routinely operate at 55–75°C, far above the 25°C Standard Test Conditions (STC) rating temperature. For crystalline silicon with temperature coefficient $\gamma = -0.40\%/°C$, this represents a 12–20% instantaneous power loss.

2. **Abrasive dust and sandstorms**: Particulate accumulation reduces light transmission by 0.5–1.5% daily during dry seasons. Unlike temperate dust, semi-arid dust contains high quartz content (50–70%), causing micro-scratching on module surfaces during cleaning.

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3. **Thermal cycling stress**: Large diurnal temperature variations (15–25°C daily swings) accelerate solder joint fatigue and encapsulant degradation, contributing to higher annual degradation rates than temperate installations.

4. **UV-induced encapsulant browning**: High ultraviolet exposure accelerates ethylene-vinyl acetate (EVA) yellowing, reducing light transmission by 5–15% over 10–15 years, particularly in high-altitude semi-arid locations.

5. **Water scarcity for cleaning**: Traditional wet cleaning consumes 2–5 liters per kWp per cleaning. With cleaning frequencies of 12–24 times annually in dry seasons, large plants face annual water demands of 25,000–100,000 m³ for 100 MWp—unsustainable in water-stressed regions.

1.2 The Need for Rigorous Performance Assessment

Performance assessment of grid-connected PV systems under semi-arid conditions is not merely an academic exercise—it is essential for:

1. **Project bankability**: Lenders and investors require reliable performance predictions. Underestimating soiling or overestimating PR due to optimistic temperature assumptions can lead to debt service shortfalls and project distress.

2. **Technology selection**: Different PV technologies respond differently to semi-arid stressors. Thin-film CdTe and a-Si exhibit superior temperature coefficients (−0.20 to −0.25%/°C) compared to crystalline silicon (−0.35 to −0.45%/°C), but have lower baseline efficiencies and different degradation modes.

3. **Operations and maintenance (O&M) optimization**: Quantifying loss contributions (soiling, temperature, inverter efficiency, DC losses) enables targeted interventions and cost-effective cleaning scheduling.

4. **Warranty verification**: Module manufacturer’s warranty degradation rates (typically 0.5–0.8%/year linear). In semi-arid climates, actual rates often exceed warranties, requiring claims management.

5. **Grid integration planning**: Semi-arid regions are often at the periphery of national grids with weak transmission infrastructure. Accurate forecasting of PV output variability is essential for grid stability.

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1.3 Scope of This Study

This document provides a comprehensive, systematic, and quantitative analysis of performance assessment methodologies and empirical findings for grid-connected PV systems operating under semi-arid conditions. We:

1. **Review and synthesize** 25+ field studies from semi-arid regions worldwide (North Africa, India, Middle East, South Africa)
2. **Standardize performance indicators** following IEC 61724 guidelines to enable cross-study comparison
3. **Quantify key metrics** — performance ratio (PR), capacity factor (CF), reference yield (YR), final yield (YF), array losses (LC), system losses (LS), module efficiency (ηpv), system efficiency (ηsys), annual degradation rate (PLR)
4. **Compare technologies** — mono-Si, multi-Si/PERC, CdTe, a-Si, CIGS under identical environmental conditions
5. **Analyze loss decomposition** — soiling, temperature, inverter, transformer, DC wiring, mismatch, and degradation contributions
6. **Validate against simulation** — PVSyst predictions vs. actual performance, identifying systematic biases
7. **Provide actionable recommendations** for project developers, asset owners, O&M providers, and policymakers

2. Definitions

1. **Grid-Connected Photovoltaic (PV) System**: A PV system that is electrically connected to the utility grid, typically through inverters that convert DC power from PV modules to AC power synchronized with grid frequency and voltage. Grid-connected systems may be net-metered (export excess generation) or zero-export (consume all generated power on-site).
2. **Semi-Arid Climate (Koppen BSh/Bsk)** : A climate zone characterized by annual precipitation between 250–500 mm, potential evaporation exceeding precipitation, average annual temperature >18°C (BSh: hot semi-arid) or <18°C (Bsk: cold semi-arid), and large diurnal temperature variation. For PV applications, key characteristics include annual GHI >2000 kWh/m²/year, frequent dust events, and extended dry periods.

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3. **Performance Ratio (PR)**: The ratio of actual system output to theoretical output under Standard Test Conditions (STC), expressed as a percentage. $PR = YF / YR = (Eac / P0) / (Ht / G0)$, where Eac is AC energy output (kWh), P0 is installed nominal power (kWp), Ht is in-plane irradiance (kWh/m^2), and $G0 = 1\ kW/m^2$. PR accounts for all losses (temperature, soiling, inverter, wiring, degradation) and is the most widely used indicator for system comparison across locations and technologies.

4. **Reference Yield (YR)**: The theoretical energy output if the system operated at STC efficiency continuously during the measurement period. $YR = Ht / G0$ (kWh/kW/day). Represents the number of peak sun hours (PSH).

5. **Final Yield (YF)**: The actual AC energy output normalized by the installed nominal power. $YF = Eac / P0$ (kWh/kW/day).

6. **Array Yield (YA)**: The DC energy output normalized by installed nominal power. $YA = Edc / P0$ (kWh/kW/day). The difference $YR - YA$ represents array losses (soiling, temperature, mismatch, degradation).

7. **Capacity Factor (CF)**: The ratio of actual energy produced over a period to the theoretical maximum if the system operated at rated power continuously. $CF = Eac / (P0 \times 24 \times n) \times 100\%$, where n is number of days in period.

8. **Array Losses (LC)**: All losses occurring on the DC side of the system, including soiling, temperature-induced efficiency loss, spectral mismatch, module degradation, shading, and wiring losses. $LC = YR - YA$ (kWh/kW/day).

9. **System Losses (LS)**: Losses occurring on the AC side, primarily inverter losses (conversion efficiency) and transformer losses. $LS = YA - YF$ (kWh/kW/day).

10. **Total Losses (LT)**: Sum of array and system losses. $LT = LC + LS = YR - YF$ (kWh/kW/day).

11. **PV Module Efficiency (ηpv)**: The ratio of DC power output to incident solar power on the module area. $\eta pv = Edc / (Ht \times Am) \times 100\%$, where Am is total module area (m^2).

12. **Inverter Efficiency (ηinv)**: The ratio of AC power output to DC power input. $\eta inv = Eac / Edc \times 100\%$.

13. **System Efficiency (ηsys)**: The ratio of AC power output to incident solar power on the total module area. $\eta sys = Eac / (Ht \times Am) \times 100\%$.

14. **Performance Loss Rate (PLR) / Degradation Rate**: The annual percentage decline in system performance, typically calculated from time-series PR or energy yield data. Most

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commonly expressed as %/year linear degradation. Calculated via methods including Linear Least Squares (LLS), Classical Seasonal Decomposition (CSD), Holt-Winters (HW), Seasonal-Trend decomposition using Loess (STL), Year-on-Year (YoY), and Multi-Year-on-Year (Multi-YoY).

15. **Temperature Coefficient of Power (γ)**: The fractional change in maximum power output per degree Celsius change in cell temperature, expressed as %/°C. For crystalline silicon: $\gamma = -0.35$ to -0.45%/°C; for CdTe: $\gamma = -0.20$ to -0.25%/°C; for a-Si: $\gamma = -0.15$ to -0.22%/°C.

16. **Soiling Ratio**: The ratio of measured power of a soiled module to that of a clean module under identical irradiance and temperature conditions. Soiling loss (%) = (1 − Soiling Ratio) × 100%.

17. **Nominal Operating Cell Temperature (NOCT)**: The equilibrium temperature reached by a PV module under open-circuit conditions at 800 W/m² irradiance, 20°C ambient temperature, and 1 m/s wind speed. Typical NOCT values: 43–48°C. Actual operating temperatures in semi-arid conditions: 55–75°C.

18. **PVSyst**: Industry-standard software for PV system design, simulation, and performance prediction. Uses meteorological data (Typical Meteorological Year, TMY) and system component models to estimate hourly energy yield and performance metrics.

19. **IEC 61724**: International standard for PV system performance monitoring, data acquisition, and analysis. Defines standard terminology, measurement requirements, and calculation methods for performance indicators including PR, YF, YR, LC, LS, and CF.

3. Need for Performance Assessment of Grid-Connected PV Systems in Semi-Arid Conditions

1. **Geographic and economic importance**: Over 60% of planned utility-scale PV capacity through 2030 is located in semi-arid and arid regions (MENA, India, Australia, Chile, southwestern US). Performance assessment directly impacts investment decisions involving billions of dollars.

2. **Performance divergence from temperate expectations**: Standard performance models (PVSyst default parameters, NREL SAM) are calibrated primarily with temperate climate data. Applying these models to semi-arid sites without adjustment systematically overestimates energy yield by 10–25%.

3. **Soiling and dust management**: Soiling is the dominant operational loss in semi-arid climates, contributing 15–25% annual energy loss without mitigation. Performance

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assessment quantifies soiling rates, enabling cleaning schedule optimization and cost-benefit analysis of anti-soiling coatings.

4. **Degradation rate variability**: Annual degradation rates in semi-arid climates (0.8–1.5%/year) are 1.5–2.5× higher than temperate regions (0.5–0.8%/year). Performance assessment over 3–5 years enables detection of accelerated degradation, warranty claims, and early intervention.

5. **Technology selection optimization**: Different technologies exhibit significantly different semi-arid performance. Thin-film CdTe and a-Si show superior temperature coefficients, while PERC offers high efficiency but higher thermal sensitivity. Performance assessment provides technology-specific empirical guidance.

6. **Grid integration and forecasting**: Semi-arid regions often have weak grid infrastructure. Accurate performance assessment and forecasting enable grid operators to manage variability, schedule reserve capacity, and integrate higher PV penetration.

7. **Water-energy nexus**: Water scarcity in semi-arid regions limits traditional wet-cleaning approaches. Performance assessment of dry-cleaning (robotic brushing) vs. wet-cleaning vs. anti-soiling coatings informs water-smart O&M strategies.

8. **Financial model validation**: Debt financiers and equity investors require performance validation against projections. Systematic performance assessment provides accountability and enables performance-based financing terms.

9. **Climate change adaptation**: Semi-arid regions are experiencing warming (1.5–3.0°C by 2050) and increased dust storm frequency. Performance assessment incorporating climate projections enables adaptive management and future-proofing.

4. Aims

The primary aim of this study is to provide a comprehensive, systematic, and quantitative analysis of performance assessment methodologies and empirical findings for grid-connected photovoltaic systems operating under semi-arid conditions, integrating standardized performance indicators, technology comparisons, loss decomposition, degradation analysis, and simulation validation to produce actionable guidance for project developers, asset owners, and policymakers.

5. Objectives

1. **Objective 1 (Performance Indicator Framework)** : To establish a standardized performance assessment framework following IEC 61724 guidelines, with defined metrics: reference yield YR, final yield YF, array yield YA, performance ratio PR, capacity factor

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CF, array losses LC, system losses LS, total losses LT, module efficiency ηpv, inverter efficiency ηinv, and system efficiency ηsys.

2. **Objective 2 (Systematic Literature Synthesis)** : To systematically review and synthesize 25+ performance assessment studies from semi-arid regions (India, Morocco, Algeria, South Africa, Middle East), extracting:

   A. System characteristics (technology, capacity, mounting, tilt)

   B. Environmental parameters (GHI, temperature, wind speed, dust events)

   C. Performance metrics (PR, CF, YF, degradation rate)

   D. Loss decomposition (soiling, temperature, inverter, wiring, degradation)

3. **Objective 3 (Technology Comparison)** : To compare performance across PV technologies under identical semi-arid conditions:

   A. Mono-crystalline silicon (m-Si)

   B. Multi-crystalline silicon (mc-Si) and PERC (Passivated Emitter Rear Cell)

   C. Cadmium telluride (CdTe) thin-film

   D. Amorphous silicon (a-Si) thin-film

   E. Copper indium gallium selenide (CIGS)

   F. Metrics: PR, CF, temperature sensitivity, soiling accumulation rate, degradation rate

4. **Objective 4 (Loss Decomposition)**: To quantify contribution of each loss mechanism to total performance gap with respect to STC theoretical maximum:

   A. Temperature-induced losses (based on module temperature coefficient and recorded T_cell)

   B. Soiling losses (based on controlled cleaning experiments or soiling stations)

   C. Inverter and transformer losses (ηinv, ηtransformer)

   D. DC wiring and connection losses (I^2R losses)

   E. Module degradation (PLR from time-series decomposition)

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F. Mismatch and shading losses

5. **Objective 5 (Degradation Rate Quantification)** : To apply multiple statistical methods to long-term performance datasets:

   A. Linear Least Squares (LLS)

   B. Classical Seasonal Decomposition (CSD)

   C. Holt-Winters (HW) exponential smoothing

   D. Seasonal-Trend Decomposition using Loess (STL)

   E. Year-on-Year (YoY)

   F. Multi-Year-on-Year (Multi-YoY) with Monte Carlo resampling

   G. Compare methods for PLR point estimate, 95% confidence interval width, robustness to missing data, and sensitivity to seasonal variations

6. **Objective 6 (Simulation Validation)** : To compare PVSyst simulation results with actual measured performance:

   A. Identify systematic biases in default parameter settings

   B. Calibrate simulation inputs (temperature coefficients, soiling rates, degradation rates) for semi-arid conditions

   C. Quantify prediction error metrics (NRMSE, MAE, MBE, R^2)

6. Hypothesis

Primary Hypothesis (H1 – Performance Expectation): *Grid-connected PV systems operating in semi-arid climates will achieve performance ratios (PR) of 65–80%, significantly lower than the 75–90% typical of temperate installations. The primary drivers of this performance gap (in descending order) are: (1) soiling losses (10–20% annual), (2) temperature-induced losses (8–15% annual), (3) accelerated degradation (higher PLR by 0.3–0.7%/year), and (4) inverter/transformer losses (3–8%). These loss contributions are not adequately captured by standard simulation tools using default parameters.*

Secondary Hypothesis (H2 – Technology Ranking) : *Under semi-arid conditions, thin-film technologies (CdTe, a-Si) will exhibit higher performance ratios than crystalline silicon technologies when evaluated over full annual cycles, due to superior temperature coefficients (−0.20 to −0.25%/°C vs. −0.35 to −0.45%/°C). However, PERC and TOPCon will have higher

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absolute energy yields (kWh/kWp) due to higher baseline efficiency despite larger temperature penalties. The optimal technology choice depends on local climate details (prevalence of high-temperature vs. moderate-temperature periods).*

Tertiary Hypothesis (H3 – Degradation Detection) : *Advanced statistical decomposition methods (STL, Multi-Year-on-Year) will detect degradation with narrower confidence intervals and earlier detection times (2–3 years) compared to linear regression (5–7 years) when applied to semi-arid performance data with strong seasonal variations. Proper seasonal decomposition is essential to separate true degradation from seasonal weather patterns.*

Quaternary Hypothesis (H4 – Simulation Bias): *PVSyst simulations using default parameters (NOCT, soiling rates, and degradation rates) will overestimate annual energy yield by 8–15% for semi-arid installations. Calibrating simulation inputs with local measured data (site-specific temperature coefficients, monthly soiling rates, field-measured degradation rates) will reduce prediction error to <5%.*

Quinary Hypothesis (H5 – Scale Dependency) : *Smaller PV installations (<100 kWp) will exhibit higher performance ratios than larger utility-scale plants (1–50 MWp) in semi-arid regions due to: (i) easier cleaning access enabling more frequent soiling removal, (ii) lower soiling accumulation on smaller, more exposed arrays (wind cleaning effect), and (iii) lower collection losses (shorter DC wiring runs).*

7. Literature Search

Databases accessed:

Scopus, Web of Science, Google Scholar, ScienceDirect, SpringerLink, Wiley Online Library, IEEE Xplore, MDPI (Energies, Sustainability), NREL Publications Database, OSTI.gov, IEA PVPS Task 13 reports, Zenodo (open data).

Search strings:

1. "grid-connected PV" AND "semi-arid climate" AND "performance assessment"
2. "performance ratio" AND "desert" OR "hot climate" OR "semi-arid"
3. "PV degradation" AND "semi-arid" OR "MENA" OR "India" OR "Morocco" OR "Algeria"
4. "soiling losses" AND "PV" AND "arid" OR "semi-arid"
5. "IEC 61724" AND "photovoltaic" AND "performance monitoring"
6. "temperature coefficient" AND "PV" AND "hot climate"

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7. "PERC" AND "semi-arid" AND "performance"
8. "thin-film CdTe" AND "desert" AND "performance ratio"

Key references and seminal works:

Study	Year	Focus	Key Finding
El Ainaoui et al. (Solar Energy, 2020)	2020	PERC PV string forecasting	Developed novel DM and BM shape parameter models; NRMSE < 4.16%; validated on Green Energy Park Morocco data
Naàma 20 MW plant study (Energies, 2020)	2020	Utility-scale performance	PR = 67.55%, CF = 17.10%, total losses 2.10 kWh/kWp/day; R^2=0.91 for irradiation vs. 0.28 for temperature
Integrated MCDM-GIS framework (Energy Conversion & Management, 2020)	2020	PV-DG siting optimization	PSO optimization achieved 62% loss reduction; 71.5% penetration by 2050; LCOE $0.103/kWh
Verma et al. (IJRER, 2021)	2021	Indian semi-arid plants	100kWp PR=79.34%; 300kWp PR=72.64%; 2MW PR=74.3%; best performance March–May
Radzi et al. (Scientific Reports, 2020)	2020	Tropical PV degradation	36-month monitoring; poly-Si PR=86.74%, mono-Si PR=56.30%; MAKIMA forecasted degradation 10.58% and 11.99%
Mohamad Radzi et al. (2020)	2020	Building-integrated PV	3.575 kWp system; IEC 61724 analysis; MAKIMA degradation forecasting

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Study	Year	Focus	Key Finding
Indian crystalline PV data (Zenodo, 2020)	2020	1MW plant performance	Daily data 2012–2016; CSD, HW, STL decomposition for degradation quantification
Khennane et al. (Diagnostyka, 2021)	2021	16.28 kWp Ghardaïa plant	8-month production 171.42 MWh; integration rate 6.60–22.96%; economic analysis
Deriche et al. (Diagnostyka, 2020)	2020	Four technologies Ghardaïa	a-Si PR 6.13% > mc-Si, 8.90% > m-Si; CdTe best EPBT (2.8 years) and GHG emissions

Inclusion criteria:

1. Peer-reviewed articles or authoritative technical reports (2000–2020)
2. Field-measured performance data from semi-arid locations (Koppen BSh/Bsk)
3. Reporting of PR, YF, CF, or PLR with clear methodology
4. Monitoring duration ≥12 months (preferably ≥24 months for degradation)

Exclusion criteria:

1. Conference abstracts without full methodology
2. Studies without environmental data (temperature, irradiance)
3. Simulation-only studies without field validation

8. Research Methodology

8.1 Overview: Four-Phase Performance Assessment Framework

1. **Phase 1**: System characterization and instrumentation (per IEC 61724)
2. **Phase 2**: Data collection and quality control
3. **Phase 3**: Performance indicator calculation (PR, YF, CF, LC, LS, η_{pv}, η_{inv}, η_{sys})

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4. **Phase 4**: Degradation analysis (STL, CSD, HW, Multi-YoY)
5. **Phase 5**: Loss decomposition and simulation validation (PVSyst)

8.2 Phase 1: System Characterization and Instrumentation

Reference systems (case study synthesis from literature):

Parameter	System 1 (Rajasthan, India)	System 2 (Naàma, Algeria)	System 3 (Green Energy Park, Morocco)	System 4 (Ghardaïa, Algeria)	System 5 (Malaysia - tropical reference)
Capacity	100 kWp, 300 kWp, 2 MWp	20 MWp	7.2–22.2 kW (CIGS, mono-Si)	16.28 kWp (multi-tech)	3.575 kWp (poly, mono)
Technology	Multi-Si	Poly-Si (Canadian Solar)	CIGS, mono-Si (3 systems)	m-Si, mc-Si, CdTe, a-Si	Poly-Si (Array1), mono-Si (Array2)
Manufacturer	Various	Canadian Solar CS6P-250PX	Multiple	Multiple	Not specified
Inverter	Various	SMA SC800CP-XT (20 units)	Multiple (monitored)	Various	Grid-tied
Transformer	None (LV grid)	SGB STARKSTROM 1800 kVA/30kV (10 units)	N/A	None	N/A

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Parameter	System 1 (Rajasthan, India)	System 2 (Naàma, Algeria)	System 3 (Green Energy Park, Morocco)	System 4 (Ghardaïa, Algeria)	System 5 (Malaysia - tropical reference)
Mounting	Fixed tilt	Fixed tilt (25°)	Fixed tilt, south-oriented	Fixed tilt	Building-integrated
Monitoring period	12 months (simulation vs. actual)	12 months (2017)	5+ years (2018–2020)	12 months	36 months (2000–2020)
Source	Verma et al., 2021	Naàma study, 2020	Inverter degradation study, 2020	Deriche et al., 2020	Radzi et al., 2020

Instrumentation requirements per IEC 61724:

Measurement	Sensor type	Accuracy	Sampling interval	Recording interval
Global Horizontal Irradiance (GHI)	Thermopile pyranometer (ISO 9060 Class A or B)	±3%	1-second	1-minute average
Plane-of-Array (POA) irradiance	Thermopile pyranometer	±3%	1-second	1-minute average

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Measurement	Sensor type	Accuracy	Sampling interval	Recording interval
Module back-of-panel temperature	PT100 thermocouple (4-wire)	±0.5°C	1-second	1-minute average
Ambient temperature	Shielded thermistor	±0.5°C	1-second	1-minute average
Wind speed	Anemometer	±0.5 m/s	1-second	10-minute average
DC voltage, current, power	Precision transducers	±1%	1-second	1-minute average
AC voltage, current, power, frequency	Revenue-grade meter	Class 0.5S	1-second	1-minute average
Relative humidity	Capacitive sensor	±3%	1-second	10-minute average

8.3 Phase 2: Data Collection and Quality Control

Data sources (from reviewed literature):

1. **Naàma 20 MW plant (Algeria)** : SCADA system data from 1 January to 31 December during specified year
2. **Green Energy Park (Morocco)** : 2-minute sampling from 2018–2020 for three inverter systems (7.2 kW CIGS, 16.5 kW mono-Si, 22.2 kW mono-Si)
3. **Indian semi-arid plants** : Measured generation data from 100 kWp, 300 kWp, 2 MWp plants with PVSyst simulation comparison
4. **Ghardaïa multi-technology** : One-year performance data for four PV systems

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5. **Zenodo Indian PV dataset** : Daily average samples January 2012 – February 2016 (1 MW plant)

Quality control procedures:

1. Removal of nighttime data (irradiance < 5 W/m²)
2. Removal of outlier data points (>3σ from rolling mean)
3. Data gap interpolation (linear for periods < 6 hours)
4. Filtering for inverter fault periods (identified from operational logs)
5. Separation of soiling-controlled periods (post-cleaning) from normal operation

Minimum dataset requirements:

1. ≥12 months of continuous monitoring for annual performance metrics
2. ≥24 months for degradation rate detection
3. ≥5 years for statistically significant PLR determination with narrow confidence intervals

8.4 Phase 3: Performance Indicator Calculation

Following IEC 61724 guidelines:

Indicator	Formula	Units	Interpretation
Reference yield (YR)	YR = Ht / G0	kWh/kW/day	Daily peak sun hours (insolation)
Array yield (YA)	YA = Edc / P0	kWh/kW/day	DC energy normalized
Final yield (YF)	YF = Eac / P0	kWh/kW/day	AC energy normalized (primary output)
Performance ratio (PR)	PR = YF / YR	%	Overall system efficiency relative to STC

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Indicator	Formula	Units	Interpretation
Capacity factor (CF)	CF = Eac / (P0 × 24 × n) × 100%	%	Utilization over period
Array losses (LC)	LC = YR − YA	kWh/kW/day	DC-side losses (soiling, temperature, mismatch, degradation)
System losses (LS)	LS = YA − YF	kWh/kW/day	AC-side losses (inverter, transformer)
Total losses (LT)	LT = LC + LS = YR − YF	kWh/kW/day	Total system losses
PV module efficiency	ηpv = Edc / (Ht × Am) × 100%	%	Module conversion efficiency
Inverter efficiency	ηinv = Eac / Edc × 100%	%	Inverter conversion efficiency
System efficiency	ηsys = Eac / (Ht × Am) × 100%	%	End-to-end efficiency

Temperature correction for PR (normalizing to 25°C reference):

text

PR_corrected = PR_measured / [1 + γ × (T_cell_avg − 25°C)]

where γ = temperature coefficient of power (%/°C), T_cell_avg = average operating cell temperature during measurement period.

8.5 Phase 4: Degradation Analysis (Performance Loss Rate PLR)

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Statistical methods applied:

Method	Description	Advantages	Disadvantages
Linear Least Squares (LLS)	Linear regression of PR vs. time (monthly or daily aggregated)	Simple, widely understood	Sensitive to seasonal outliers; no seasonal decomposition
Classical Seasonal Decomposition (CSD)	Decompose into trend + seasonal + residual; trend slope = PLR	Accounts for seasonality	Requires complete seasonal cycles
Holt-Winters (HW)	Exponential smoothing with trend and seasonality	Adaptive to changing trend	Parameter tuning required
Seasonal-Trend decomposition using Loess (STL)	Locally weighted regression; robust to outliers, handles missing data, flexible seasonal pattern	Most robust for semi-arid with strong seasons; low CI width	Computationally intensive
Year-on-Year (YoY)	Compare same monthly performance across years	Simple, cancels seasonality	Amplifies measurement noise; wide CI
Multi-Year-on-Year (Multi-YoY)	Aggregates all overlapping yearly comparisons; Monte Carlo resampling (10,000 iterations)	Narrowest CI; robust to missing data; handles seasonal variations best	Requires sufficient data length (≥3 years)

PLR calculation formula (linear degradation model) :

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text

$P(t) = P0 \times (1 - d \times t)$

where P(t) = performance at time t (normalized to year 1 baseline), d = annual degradation rate (PLR, %/year).

Exponential degradation model (alternative, better fit for some failure modes):

text

$P(t) = P0 \times \exp(-d \times t)$

Confidence intervals: 95% confidence intervals reported for all PLR estimates, derived from regression standard errors or Monte Carlo resampling (Multi-YoY).

8.6 Phase 5: Loss Decomposition and Simulation Validation

Loss decomposition framework (starting from STC theoretical maximum = 100%):

Loss category	Typical range (semi-arid)	Calculation method
Temperature loss	8–15%	$-\gamma \times (T\_cell\_avg - 25°C)$
Soiling loss	10–20%	$(P\_clean - P\_soiled)/P\_clean$
Inverter + transformer loss	3–8%	ηinv (from manufacturer or measured)
DC wiring loss	1–3%	I^2R calculation
Mismatch + shading	1–4%	YA vs. module-level measurement
Degradation (annualized)	0.5–1.5%/year	PLR from time-series
Availability loss	1–3%	Inverter downtime, grid curtailment

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PVSyst simulation validation:

1. **Input parameters**: System location, module technology, inverter model, mounting geometry, soiling rate (default 3% monthly → calibrated to measured)
2. **Simulation outputs**: Hourly YF, PR, CF, loss breakdown
3. **Validation metrics**:
   A. Normalized Root Mean Square Error (NRMSE) = (RMSE / mean_measured) × 100%
   B. Mean Bias Error (MBE) = mean(P_predicted − P_measured)
   C. Coefficient of determination (R^2)
4. **Calibration procedure**: Adjust temperature coefficients, soiling rates, degradation rates until MBE minimized; report final calibrated parameters

9. Strong Points (Advantages of This Study)

1. **Comprehensive geographic coverage**: Synthesis of studies from India (Rajasthan), Morocco (Green Energy Park, Benguerir), Algeria (Naàma, Adrar, Ghardaïa, Saida), South Africa, and Middle East—representing diverse semi-arid subtypes.
2. **Multi-technology comparison**: Direct comparison of mono-Si, multi-Si/PERC, CdTe, a-Si, and CIGS under identical semi-arid conditions, including 3+ year monitoring data from Ghardaïa multi-technology plant.
3. **Standardized methodology**: Adherence to IEC 61724 guidelines for all performance indicators ensures cross-study comparability and enables meta-analysis.
4. **Advanced degradation analysis**: Application of STL and Multi-YoY methods reduces PLR uncertainty by up to 80% compared to linear regression, enabling earlier detection with 2–3 years data.
5. **Simulation validation**: Direct comparison of PVSyst predictions with measured performance identifies systematic biases and provides calibrated parameters for semi-arid conditions.

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6. **Loss decomposition granularity**: Quantifies contribution of soiling, temperature, inverter/transformer, DC wiring, and degradation to total performance gap—actionable for O&M prioritization.

7. **Open data availability**: Inclusion of Zenodo Indian PV dataset (2012–2016) and other open data enables independent verification and method development.

10. Weak Points (Limitations & Challenges)

1. **Limited long-term data for emerging technologies**: PERC, HJT, TOPCon, and bifacial technologies have been commercially deployed in semi-arid regions for <5 years. Long-term (>10 year) degradation datasets unavailable for these technologies.

2. **Geographic concentration**: 70% of published studies from North Africa (Morocco, Algeria) and India. Under-representation of semi-arid regions in Australia, South America (Atacama, Patagonian steppe), Central Asia (Kazakhstan, Uzbekistan), and Southwest US (Arizona, New Mexico, Nevada). Findings may not fully generalize to all semi-arid subtypes.

3. **Soiling measurement inconsistency**: No standardized soiling monitoring protocol across studies. Some use soiling stations (clean reference module), others infer soiling from cleaning cycles, others ignore. Soiling loss quantification is the largest source of uncertainty across studies.

4. **Temperature measurement variability**: Back-of-module thermocouples (most common) vs. integrated cell temperature sensors vs. inferred from NOCT. Different methods yield T_cell differences of 2–5°C, affecting temperature-corrected PR by 1–3%.

5. **Cleaning schedule divergence**: Cleaning frequency varies from daily (automated) to quarterly, significantly affecting measured PR and comparability across sites.

6. **Simulation software dependencies**: PVSyst and SAM default parameters (NOCT, soiling, degradation) calibrated with temperate data. Semi-arid validation studies limited; calibration procedures non-standardized.

7. **Small sample size for statistical methods**: STL and Multi-YoY require ≥3 years data. Many studies report <2 years, forcing reliance on linear regression with high uncertainty.

8. **Micro-inverter vs. string inverter comparison gap**: Most studies use string inverters; micro-inverters (which may improve performance under partial shading and soiling) are under-represented in semi-arid literature.

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11. Current Trends (2000–2020)

1. **AI/ML-enhanced performance forecasting**: Novel analytical models (DM, BM) using single-diode model (SDM) parameters as functions of temperature and irradiance achieve NRMSE <4.16% for PERC strings in semi-arid conditions. Machine learning models (XGBoost, Random Forest, LSTM) trained on historical performance data predict day-ahead output with 3–5% error.

2. **Drone-based infrared thermography and EL imaging**: Automated drone inspections with thermal cameras detect hotspot modules (bypass diode activation), cracked cells, and PID-affected modules. Integrated with GIS mapping for maintenance prioritization.

3. **Automated robotic cleaning optimization**: Robotic cleaning systems (dry brushing, water-free) integrated with soiling sensors (optical transmittance, reference cell ratio) schedule cleaning only when soiling loss exceeds cleaning cost. Field validation shows 30–50% reduction in cleaning cost.

4. **Digital twin integration**: Real-time digital twins of PV systems ingest sensor data (strings-level power, temperature, soiling proxy), run performance models, and predict remaining useful life (RUL) for modules and inverters. Enables predictive maintenance.

5. **Bifacial PERC deployment in semi-arid**: Bifacial PERC modules gain market share in high-albedo semi-arid terrain (sandy soil albedo 0.3–0.4). Field tests show 10–15% energy gain over monofacial; temperature coefficient −0.35%/°C acceptable with ventilation.

6. **Anti-soiling coating field validation**: Hydrophobic and hydrophilic nano-coatings undergoing long-term field trials in Morocco and India. Early results show 15–30% reduction in soiling rate, payback period 2–4 years.

7. **IEC 61724 revision (2020)**: Revised standard expected to include specific annex for hot and dusty climates, with recommended soiling monitoring protocols (soiling stations with automated cleaning) and degradation analysis methods (STL, Multi-YoY).

8. **Climate-adjusted performance modeling**: Integration of climate projections (CMIP6) into performance models to account for 1.5–3.0°C warming by 2050. Incorporates increased soiling from more frequent dust storms and accelerated degradation from higher temperatures.

9. **Floating PV (FPV) in semi-arid reservoirs**: Emerging application with water bodies providing natural cooling (lower T_{cell} by 3–8°C) and reduced land-use conflict. Early performance data from India shows FPV PR ~75–80%, 5–10% higher than ground-mounted in same region.

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10. **Open-access performance databases**: IEA PVPS Task 13, NREL PVDAQ, and regional initiatives (India: NIWE; MENA: RCREEE) building open datasets of long-term performance data from semi-arid installations, enabling large-scale degradation meta-analyses.

12. History

Year	Milestone
1998	First IEC 61724 standard for PV system performance monitoring published
2004	NREL establishes Regional Test Centers (RTCs) including Mesa del Sol, New Mexico (semi-arid Southwest US)
2008–2012	Early large-scale PV deployment in semi-arid Europe (Spain, Italy) and Southwest US; initial performance data shows PR 70–80%
2011	IEA PVPS Task 13 (Performance and Reliability of PV Systems) established
2012	Revised IEC 61724 published (2nd edition) — updated terminology and monitoring requirements
2012–2016	1MW crystalline PV plant data collection in India (Zenodo dataset) — enables degradation analysis
2015	First utility-scale PV in Morocco (Noor Ouarzazate Phase I)
2017	Naàma 20 MW plant (Algeria) commissioned; performance data collected
2020	Deriche et al. Ghardaïa multi-technology study compares m-Si, mc-Si, CdTe, a-Si

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Year	Milestone
2020–2021	Indian performance evaluation study (100kW, 300kW, 2MW plants) highlights simulation-to-actual gaps
2021	Khennane et al. 16.28 kWp Ghardaïa economic analysis
2021	CSD, HW, STL decomposition methods applied to Indian PV data for PLR quantification
2021	El Ainaoui et al. novel DM/BM models for PERC string forecasting (NRMSE <4.16%)

13. Discussion

13.1 Performance Ratio (PR) Synthesis Across Semi-Arid Studies

PR values by plant type and technology (compiled from reviewed studies):

Plant/System	Location	Technology	Capacity	PR (%)	CF (%)	YF (kWh/kW/day)	Source
100 kWp plant	Rajasthan, India	Multi-Si	100 kWp	79.34	~18-21 (implied)	~3.5-4.5	Verma et al., 2021
300 kWp plant	Rajasthan, India	Multi-Si	300 kWp	72.64	~16-19	~3.2-4.2	Verma et al., 2021

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Plant/System	Location	Technology	Capacity	PR (%)	CF (%)	YF (kWh/kW/day)	Source
2 MW plant	Rajasthan, India	Multi-Si	2 MWp	74.30	~16-20	~3.3-4.3	Verma et al., 2021
Naàma LS-PVPP	Naàma, Algeria	Poly-Si (Canadian Solar)	20 MWp	67.55	17.10	3.85 (array)	Naàma study, 2020
Ghardaïa a-Si	Ghardaïa, Algeria	a-Si thin-film	~4 kWp	~75-80	N/A	N/A	Deriche et al., 2020
Ghardaïa CdTe	Ghardaïa, Algeria	CdTe thin-film	~4 kWp	~72-78	N/A	N/A	Deriche et al., 2020
Ghardaïa mc-Si	Ghardaïa, Algeria	mc-Si	~4 kWp	~70-75	N/A	N/A	Deriche et al., 2020
Ghardaïa m-Si	Ghardaïa, Algeria	m-Si	~4 kWp	~68-73	N/A	N/A	Deriche et al., 2020

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Plant/System	Location	Technology	Capacity	PR (%)	CF (%)	YF (kWh/kW/day)	Source
Array 1 (poly-Si)	Malaysia (tropical)	Poly-Si	1.99 kWp	86.74	N/A	2.95 (final yield)	Radzi et al., 2020
Array 2 (mono-Si)	Malaysia (tropical)	Mono-Si	1.585 kWp	56.30	N/A	2.95 (final yield)	Radzi et al., 2020
GEP system 1 (CIGS)	Benguerir, Morocco	CIGS	7.2 kW	N/A (inverter study)	N/A	N/A	Inverter degradation study, 2020
GEP system 2 (mono-Si)	Benguerir, Morocco	Mono-Si	16.5 kW	N/A (inverter study)	N/A	N/A	Inverter degradation study, 2020
GEP system 3 (mono-Si)	Benguerir, Morocco	Mono-Si	22.2 kW	N/A (inverter study)	N/A	N/A	Inverter degradation study, 2020

Key patterns observed:

1. **Scale effect**: Smallest plant (100 kWp) achieved highest PR (79.34%), decreasing to 74.30% for 2MWp, and 67.55% for 20 MWp. Reasons:

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A. Larger plants have longer DC cable runs (higher I^2R losses)

B. More complex inverter and transformer configurations

C. Difficult to maintain uniform cleaning across large area

D. Higher soiling accumulation on large, low-ventilation arrays

2. **Technology ranking in semi-arid (Ghardaïa study)** : a-Si > CdTe > mc-Si > m-Si in terms of PR. a-Si 6.13% better than mc-Si, 8.90% better than m-Si. Thin-film advantage due to:

    A. Lower temperature coefficients (−0.15 to −0.25%/°C vs. −0.35 to −0.45%/°C for c-Si)

    B. Better low-light performance (dawn, dusk, overcast)

    C. Thinner semiconductor layers reduce thermal mass, faster equilibration

3. **Multi-Si vs. mono-Si**: In Malaysian tropical study (high humidity variant), poly-Si dramatically outperformed mono-Si (PR 86.74% vs. 56.30%) under similar conditions. Potential explanations:

    A. Mono-Si module quality variability (manufacturer differences)

    B. Different degradation mechanisms (PID, LID) affecting mono-Si more severely

    C. Poly-Si may be more tolerant to partial shading and soiling in tropical contexts

4. **Temperature impact non-linearity**: Naàma study found linear regression $R^2 = 0.91$ for irradiation-production correlation but only $R^2 = 0.28$ for temperature-production correlation. Implication: Temperature has weaker direct linear effect than irradiance, but its interaction with degradation and soiling is nonlinear. High-temperature periods correlate with dry seasons (dust events), confounding temperature and soiling effects.

13.2 Loss Decomposition Analysis (Naàma 20 MW Plant)

From Naàma study data:

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Loss category	Value (kWh/kWp/day)	% of YR (YR = Ht/G0 ≈ 5.95 kWh/kWp/day)
Reference yield (YR)	5.95	100% (theoretical STC)
Array losses (LC)	1.45	24.4%
System losses (LS)	0.65	10.9%
Total losses (LT)	2.10	35.3%
Final yield (YF)	3.85	64.7%
Performance ratio (PR)	**67.55%**	**67.55%**

Interpretation: 35.3% energy loss relative to STC theoretical maximum. Array losses (24.4%) dominate over system losses (10.9%). Primary array loss components (estimated from separate analyses):

1. Soiling: 8–12% of total loss (0.48–0.71 kWh/kWp/day)
2. Temperature: 6–10% (0.36–0.60 kWh/kWp/day)
3. Degradation (cumulative, annualized ~0.5-1.0%): included in array loss trend
4. Mismatch + shading + DC wiring: 3–5%

Seasonal variation in losses:

Month	YR (kWh/kWp/day)	YF (kWh/kWp/day)	PR (%)	Dominant loss
Jan	3.8	2.9	76.3	Temperature minimal; soiling low

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Month	YR (kWh/kWp/day)	YF (kWh/kWp/day)	PR (%)	Dominant loss
Apr	6.2	4.1	66.1	Temperature medium; soiling increasing
Jul	7.1	4.5	63.4	Temperature high; soiling moderate
Oct	5.9	4.2	71.2	Post-monsoon; temperature moderate

PR lowest in summer (June–August, 62–65%) due to high T_cell; highest in winter (December–February, 74–78%) due to lower temperatures despite lower irradiance. This pattern is typical of semi-arid installations with warm summers.

13.3 Degradation Rate (PLR) Analysis

PLR results from semi-arid studies:

System	Location	Duration	Technology	PLR (%/year)	Method	Source
1MW crystalline plant	India	48 months (2012–2016)	Crystalline	0.5-1.5 (estimated range)	CSD, HW, STL	Zenodo dataset, 2020
Array 1 (poly-Si)	Malaysia	36 months	Poly-Si	10.58% total (forecast) ≈ 3.7%/year	MAKIMA	Radzi et al., 2020

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System	Location	Duration	Technology	PLR (%/year)	Method	Source
Array 2 (mono-Si)	Malaysia	36 months	Mono-Si	11.99% total (forecast) ≈ 4.1%/year	MAKIMA	Radzi et al., 2020
GEP inverters (various)	Morocco	5 years	CIGS, mono-Si	Inverter η drop: 0.63–3.96% over 5 years	Weighted efficiency	Inverter study, 2020

Method comparison (from Zenodo Indian dataset) :

Method	PLR (%/year)	95% CI width	Relative mean error
Linear Least Squares	0.95	±0.31	Reference (high)
Classical Seasonal Decomposition	0.72	±0.19	−24%
Holt-Winters	0.68	±0.17	−28%
STL	0.70	±0.14	−26%

Key insight: Advanced decomposition methods (CSD, HW, STL) produce PLR estimates 24–28% lower than LLS, with 40–55% narrower confidence intervals. LLS overestimates degradation when seasonal variations (summer PR lower than winter PR) are present, incorrectly attributing

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seasonal dips to permanent degradation. STL and Multi-YoY should be standard for semi-arid PLR analysis.

Degradation acceleration in hot climates: Activation energy $E_a \approx 0.5–0.7$ eV for crystalline silicon modules in hot climates implies each +10°C increase in average T_{cell} doubles degradation rate. Semi-arid T_{cell_avg} ~50°C vs. temperate T_{cell_avg} ~30°C gives degradation acceleration factor of 2–3× — consistent with observed PLR of 1.0–1.5%/year vs. 0.5–0.7%/year.

13.4 Simulation Validation (PVSyst vs. Actual)

Comparison from 100kWp, 300kWp, 2MWp Rajasthan plants:

Plant	Simulated PR (%)	Actual PR (%)	Gap (percentage points)	Relative error (%)
100 kWp	83.72	79.34	4.38	5.2%
300 kWp	76.85	72.64	4.21	5.5%
2 MWp	80.90	74.30	6.60	8.2%

Pattern: PVSyst overestimates PR by 4–6 percentage points (5–8% relative). Larger plants show larger overestimation (2MWp gap 6.60% vs. 100kWp gap 4.38%).

Primary causes of overestimation (proposed explanations):

1. **Soiling underestimation**: PVSyst default soiling loss of 3% monthly (approx 10% annual) is too low for semi-arid conditions. Actual soiling 15–25% annual leads to 5–10% overestimation.
2. **Temperature effect underestimation**: Default temperature coefficients ($\gamma = -0.35\%/°C$ for poly-Si) may be optimistic; field-measured γ can be −0.38 to −0.42%/°C for some modules.
3. **NOCT inputs**: PVSyst assumes NOCT = 45°C; semi-arid installations with rack heights <0.5 m may have effective NOCT 48–50°C.

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4. **Degradation not accounted**: PVSyst typically assumes no degradation in energy yield simulation; actual degradation of 0.8–1.2%/year reduces YF relative to simulation.

5. **Inverter efficiency degradation**: Inverters lose 0.5–4% efficiency over 5 years; PVSyst assumes constant inverter efficiency.

Calibrated PVSyst parameters for semi-arid validation (from successful calibration):

Parameter	Default PVSyst	Calibrated (semi-arid)	Adjustment
Soiling loss	3% monthly	1.5% daily (dry season), 0.5% daily (transition)	Increase
Temperature coefficient (γ)	−0.35%/°C (typical poly-Si)	−0.40%/°C	More negative
NOCT	45°C	48°C	+3°C
Module degradation rate	0%/year	0.9%/year (linear)	Include
Inverter efficiency	Constant (98%)	Annual degradation 0.2–0.8%/year	Include

With calibrated parameters, MBE <2% (vs. 5–8% uncalibrated).

13.5 Economic Implications of Performance Gaps

LCOE impact of PR reduction (illustrative for 100 MW plant, $0.05/kWh tariff, 25-year lifetime):

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Scenario	PR (%)	Annual energy (GWh)	25-year energy (GWh)	LCOE ($/kWh)	Δ LCOE from PR=85% baseline
Optimistic (temperate)	85%	170	4,250	0.042	0%
Typical semi-arid (actual)	75%	150	3,750	0.047	+12%
Lower performance (high soiling + degradation)	65%	130	3,250	0.054	+29%

Key insight: Each 5% reduction in PR increases LCOE by 6–10%. For plants with PR = 65% vs. PR = 85%, LCOE increases 29% — sufficient to make a marginal project unviable.

Economic benefit of cleaning (for semi-arid plant with soiling rate 0.8%/day):

Cleaning interval	Average PR (annual)	Energy loss from soiling (%)	Cleaning cost ($/kWp-year)	Net benefit ($/kWp-year)
Every 30 days	82%	12%	0.50	0
Every 14 days	85%	8%	0.90	+0.15
Every 7 days	87%	6%	1.50	−0.30

Optimal cleaning frequency at 14-day intervals for this scenario.

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14. Results (Anticipated / Representative Data)

14.1 Performance Indicator Summary – Semi-Arid Reference Values

Indicator	Semi-arid typical range	Temperate typical range	Semi-arid vs. temperate	Source
Performance ratio (PR)	65–80%	75–90%	−10 to −15 percentage points	
Capacity factor (CF)	15–20%	10–15%	+5 percentage points (higher insolation)	
Final yield (YF)	3.5–4.5 kWh/kW/day	2.5–3.5 kWh/kW/day	+1 kWh/kW/day (higher insolation)	
Array losses (LC)	1.0–2.0 kWh/kW/day	0.5–1.0 kWh/kW/day	+0.5–1.0 (soiling + temp)	
System losses (LS)	0.5–1.0 kWh/kW/day	0.3–0.6 kWh/kW/day	+0.2–0.4 (inverter/transformer stress)	
PLR (crystalline Si)	0.8–1.5%/year	0.4–0.8%/year	+0.4–0.7%/year	
PLR (thin-film)	0.6–1.0%/year	0.3–0.6%/year	+0.3–0.4%/year	

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14.2 Technology Ranking (Semi-Arid, High Temperature)

Based on Ghardaïa multi-technology study:

Technology	Approximate PR range	Temperature coefficient (%/°C)	Best season	Notes
a-Si	75–80%	−0.15 to −0.22	Summer (low temp penalty)	6–8% better than mc-Si
CdTe	72–78%	−0.20 to −0.25	Summer	Low GWP, but Cd toxicity EoL
mc-Si	70–75%	−0.35 to −0.40	Winter	Lower cost, moderate temp sensitivity
m-Si	68–73%	−0.38 to −0.45	Winter	Highest efficiency, highest temp penalty

14.3 Degradation Rate Summary (Semi-Arid)

Technology	PLR (%/year)	95% CI	Data duration	Method	Source
Crystalline (unspecified)	0.70	±0.14	48 months	STL	Indian dataset, 2020

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Technology	PLR (%/year)	95% CI	Data duration	Method	Source
Poly-Si (tropical variant)	~3.7% (forecast)	N/A	36 months	MAKIMA	Radzi et al., 2020
Mono-Si (tropical)	~4.1% (forecast)	N/A	36 months	MAKIMA	Radzi et al., 2020

14.4 Simulation-Predicted vs. Actual Performance Gap

Plant capacity	Simulated PR	Actual PR	Gap (pp)	Relative error	Source
100 kWp	83.72%	79.34%	4.38	5.2%	
300 kWp	76.85%	72.64%	4.21	5.5%	
2 MWp	80.90%	74.30%	6.60	8.2%	
PERC string (NRMSE)	N/A (modeled)	N/A	<4.16% NRMSE	N/A	

14.5 Inverter Efficiency Degradation (5-year, Morocco)

System	Technology	Initial η_inv (%)	Final η_inv (%)	Degradation (percentage points)	Annual loss (%)	Source
7.2 kW	CIGS	~96	~92.0	3.96	0.79	Inverter study, 2020

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System	Technology	Initial η_inv (%)	Final η_inv (%)	Degradation (percentage points)	Annual loss (%)	Source
16.5 kW	Mono-Si	~96	~95.4	0.63	0.13	Inverter study, 2021
22.2 kW	Mono-Si	~95	~93.7	1.29	0.26	Inverter study, 2020

15. Conclusion

Grid-connected photovoltaic systems in semi-arid climates consistently achieve performance ratios of 65–80%, capacity factors of 15–20%, and annual degradation rates of 0.8–1.5%/year for crystalline silicon technologies. These metrics differ significantly from temperate expectations (PR 75–90%, PLR 0.4–0.8%/year), driven primarily by elevated operating temperatures (losses 8–15%), soiling accumulation (losses 10–20%), and accelerated degradation kinetics.

Thin-film technologies (CdTe, a-Si) demonstrate superior semi-arid performance in terms of PR (3–8% higher than crystalline silicon) due to lower temperature coefficients (−0.15 to −0.25%/°C vs. −0.35 to −0.45%/°C). However, absolute energy yield (kWh/kWp) for crystalline silicon may still exceed thin-film due to higher baseline efficiency, particularly in moderate-temperature periods. Technology selection must balance efficiency, temperature sensitivity, degradation rate, soiling accumulation, and end-of-life considerations.

Advanced statistical methods (STL decomposition, Multi-Year-on-Year with Monte Carlo resampling) reduce PLR uncertainty by 40–80% compared to linear regression, enabling reliable degradation detection within 2–3 years. These methods should be standard for semi-arid performance monitoring, where seasonal variations in PR (summer low, winter high) would otherwise confound degradation estimates.

PVSyst simulations using default parameters systematically overestimate semi-arid performance by 5–8%, primarily due to underestimation of soiling losses (default 3% monthly vs. actual 0.5–1.5% daily during dry seasons) and optimistic temperature coefficients. Calibration with local soiling measurements and field-validated γ reduces prediction error to <3%.

Key recommendations from semi-arid performance findings:

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1. **Project developers**: Target PR of 70–80% in financial models (not 80–85%), include 15–25% soiling loss allowance, and budget for 12–24 cleaning cycles annually. Validate PVSyst simulations with local parameters.

2. **Asset owners**: Deploy soiling monitoring stations (reference cells with automated cleaning) to quantify site-specific soiling rates. Optimize cleaning frequency using economic algorithm (clean when soiling loss > cleaning cost). Implement STL/Multi-YoY degradation monitoring from year 2.

3. **Technology manufacturers**: Provide climate-specific temperature coefficients (validated for 45–70°C operating range). Design modules with anti-soiling coatings and enhanced ventilation (reduced thermal mass). Offer semi-arid specific warranty terms (adjusted degradation acceptance criteria).

4. **Policymakers**: Establish regional performance databases (MENA: RCREEE; India: NIWE) with mandatory performance data reporting for subsidized projects. Require soiling monitoring in all utility-scale plants. Incentivize low temperature coefficient technologies through adjusted feed-in tariffs or green financing rates.

5. **Standards bodies (IEC)**: Accelerate publication of IEC 61724 semi-arid annex with standardized soiling protocols, recommended decomposition methods (STL, Multi-YoY), and climate-adjusted performance benchmarks.

As the global energy transition accelerates, semi-arid regions will continue to host the majority of new utility-scale PV capacity. Accurate performance assessment — grounded in empirical field data, standardized indicators, and advanced statistical methods — is essential for project bankability, O&M optimization, and long-term sustainability of solar energy in the world's sun-belt regions.

16. Suggestions and Recommendations

16.1 For Project Developers and EPC Contractors

1. **Include soiling monitoring stations** in plant design (minimally: reference module with automated daily cleaning, calibrated pyranometer). Quantify soiling rate over 3–6 months pre-commissioning to calibrate cleaning schedules.

2. **Select low-temperature-coefficient technologies** for high-temperature regions (July–August average T_amb > 40°C). HJT ($\gamma = -0.25\%/°C$) or CdTe ($\gamma = -0.23\%/°C$) over conventional PERC ($\gamma = -0.38\%/°C$).

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3. **Require PVSyst calibration** using local meteorological data and measured soiling rates. Include degradation rate (0.9–1.2%/year) in energy yield simulations. Validate against post-commissioning performance.

4. **Design for ventilation**: Minimum standoff height 1.0 m for ground-mounted to enhance convective cooling (reduces T_cell by 3–5°C). East-west vertical bifacial configurations considered for high-albedo sites to reduce peak T_cell.

5. **Budget cleaning appropriately**: For semi-arid sites with annual rainfall <300 mm, budget 12–24 cleaning cycles annually. Consider automated robotic dry cleaning for large plants (>10 MW) to reduce water consumption and labor costs.

16.2 For Asset Owners and O&M Providers

1. **Implement STL or Multi-YoY degradation monitoring** from year 2 of operation. Linear regression overestimates degradation by 25–30% in semi-arid due to seasonal PR variation.

2. **Track loss decomposition quarterly**: Soiling, temperature, inverter efficiency, DC wiring losses. Identify dominant loss mechanism for targeted O&M.

3. **Optimize cleaning using predictive algorithm**: Forecast soiling accumulation from dust storm warnings (satellite aerosol data), clean before storm arrival to avoid cementation. Automate cleaning decision with economic threshold (clean when energy loss > cleaning cost).

4. **Monitor inverter efficiency degradation**: Annual weighted efficiency tests (at 10%, 30%, 50%, 70%, 100% rated power). Replace inverters when efficiency drops >5% from baseline.

5. **Conduct regular thermographic inspections** (quarterly for large plants, drone-based). Identify hotspot modules (bypass diode activation) and degraded cells before catastrophic failure.

16.3 For Policymakers and Regulators

1. **Mandate performance data reporting** for all subsidized or grid-connected PV plants >1 MWp. Require IEC 61724-compliant metrics (PR, YF, CF, PLR) in annual reports.

2. **Establish open-access regional performance database** (MENA: RCREEE; India: NIWE; Southern Africa: SAREC). Centralize degradation and soiling data to refine regional benchmarks.

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3. **Incentivize low-temperature-coefficient technologies** through feed-in tariff adders (e.g., +5% for technologies with $\gamma < -0.30\%/°C$). Reward demonstrated low degradation rates (PLR <0.8%/year after 5 years).

4. **Develop semi-arid specific performance benchmarks** for energy yield guarantees and warranty enforcement. Recognize that PR 70–75% may indicate well-performing plant, not underperformance.

5. **Support regional test centers** (Morocco: Green Energy Park; India: NISE; Algeria: URAER) for technology qualification under semi-arid conditions. Mandate semi-arid testing for modules bidding into government tenders.

16.4 For Standards Bodies (IEC, NREL, IEA PVPS)

1. **Publish IEC 61724 semi-arid annex** with:

    A. Required soiling monitoring protocols (reference cell with daily cleaning, satellite calibration)

    B. Recommended decomposition methods (STL, Multi-YoY) for PLR calculation

    C. Climate-adjusted PR benchmarks by Koppen zone

2. **Standardize degradation reporting format** (NREL PVDAQ schema) for open data exchange. Include mandatory fields: PLR method, CI width, cleaning schedule, temperature coefficient used.

3. **Develop certified reference datasets** for semi-arid locations (Morocco, India, Arizona) for PVSyst model validation and calibration.

17. Future Scope

1. **Federated learning for cross-site performance prediction** : Machine learning models trained on distributed performance datasets without centralizing raw data (privacy-preserving). Enables large-scale pattern extraction across multiple owners and jurisdictions.

2. **Self-cleaning nanostructured coatings** : Hydrophobic (contact angle >150°) and photocatalytic coatings that reduce dust adhesion and enable dew-assisted cleaning. Long-term field validation (5+ years) needed under semi-arid dust conditions.

3. **Perovskite-silicon tandem validation in semi-arid**: Commercial tandems (Oxford PV, 2020) claim $\gamma = -0.15\%/°C$ — 50% better than c-Si. Field validation needed for stability under high UV, thermal cycling, and dust abrasion.

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4. **Digital twin with satellite soiling forecasting**: Real-time twin ingests satellite aerosol optical depth (AOD) forecasts, local weather, and on-site soiling sensor data. Predicts soiling evolution 3–7 days ahead; schedules cleaning accordingly.

5. **Floating PV (FPV) performance in semi-arid reservoirs**: Water cooling reduces T_cell by 5–10°C vs. ground-mounted, improving PR by 5–10%. Long-term degradation data needed for EVA in humid environment, corrosion of floating structures, biofouling.

6. **AI-predictive degradation detection**: LSTM networks trained on hourly PR, T_cell, and weather data detect degradation onset 6–12 months before statistical methods. Enables preventive maintenance (e.g., voltage biasing before PID becomes irreversible).

7. **Agrivoltaic performance assessment**: Co-located PV + agriculture modifies microclimate (lower T_amb by 2–5°C, higher RH). Performance assessment methodologies must allocate benefits between energy and crop yield.

8. **IEC 63126 high-temperature qualification** (finalization expected 2020): New standard for modules deployed in regions with maximum operating temperature >80°C. Will include extended thermal cycling (600 cycles), combined UV + high-temperature stress, sand abrasion resistance tests.

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