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Solar Power Generational Analysis Using PVsyst and SAM: System Advisor Module Simulations and Seasonal Irradiation Analysis in Gujarat, India

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Abstract

Accurate modelling and analysis of solar power generation are crucial for optimizing the deployment of photovoltaic (PV) systems, particularly in rapidly developing solar markets like India. The Gujarat region, with its high solar potential, serves as a focal point for such studies. This literature review examines the application of two prominent PV simulation tools-PVsyst and the System Advisor Model (SAM)—to analyses solar power generation profiles in Gujarat, India, across the winter, summer, and monsoon seasons. Drawing on global and regional literature, the review examines effective solar irradiation patterns, the influence of seasonal variability, model accuracy, and the integration of high-fidelity and machine learning approaches. The review highlights the importance of data quality, system modelling sophistication, and capacity value assessment. It concludes with recommendations for best practices in generational forecasting and system design for PV deployment in Gujarat and similar high-irradiance regions.

Keywords: Solar power, PVsyst, System Advisor Module (SAM), Gujarat, India, solar irradiation, generational analysis, seasonal variation, capacity value, simulation

1. Introduction

The exponential growth of solar photovoltaic (PV) installations globally and in India necessitates the use of robust tools for modelling, forecasting, and optimizing solar power generation. Gujarat, recognized for its high solar insolation and ambitious renewable energy targets, presents a unique environment for the deployment and analysis of solar power systems. Accurate generational analysis is vital for system design, grid integration, and policy-making, particularly given the pronounced seasonal variations in solar resource availability in the region.

This literature review synthesizes current research on the use of PVsyst and the System Advisor Module (SAM) for solar power simulation, with a dedicated focus on the Gujarat region. It addresses the following research questions:

This review addresses the following research questions:

1) In what ways do PVsyst and SAM model both seasonal and annual solar power generation in Gujarat?
2) Which factors most significantly influence effective solar irradiation and system output during the winter, summer, and monsoon seasons?
3) How do the incorporation of high-fidelity, statistical, and machine learning models improve the accuracy of generational forecasts?

What are the implications for capacity planning, system design, and policy in the context of Indian solar development?

2. Background: Modeling Solar Power Generation

2.1. Overview of PV Simulation Tools: PVsyst and SAM

PVsyst and SAM are two widely used software platforms for simulating the energy yield and financial performance of solar PV systems. PVsyst, developed at the University of Geneva, offers detailed modeling of system components, shading, losses, and meteorological conditions. SAM, developed by the U.S. National Renewable Energy Laboratory (NREL), provides a flexible interface for performance and financial modelling, integrating weather data, system design, and economic parameters.

Both tools are capable of simulating system performance under variable climatic conditions, accounting for factors such as module orientation, tilt, shading, and temperature effects. They are underpinned by sophisticated algorithms that convert solar irradiation and meteorological data into hourly or sub-hourly PV output estimates, supporting both design-stage evaluations and operational forecasting.

2.2. Importance of High-Fidelity and Data-Driven Modeling

Accurate generational analysis depends not only on the physical modelling of PV systems but also on the quality of input data and the sophistication of the simulation approach. Recent advances have introduced high-fidelity models that account for geometric, thermal, and operational nuances, as well as machine learning techniques that can leverage large datasets for enhanced predictive accuracy.

For instance, Oettershagen (2017) introduced a high-fidelity solar power model for solar-electric UAVs, which, while focused on aerospace applications, underscores the importance of accounting for precise orientation, temperature, and angle-of-incidence effects in solar power simulations. Such approaches are increasingly relevant to terrestrial PV systems, where subtle interactions between environmental and system parameters can significantly influence output (Oettershagen, 2017).

3. Solar Resource Assessment in Gujarat, India

3.1. Regional Solar Irradiation Characteristics

Gujarat, located in western India, enjoys some of the highest solar insolation levels in the country. The state's mean annual global horizontal irradiance (GHI) typically ranges from 5.0 to 5.5 kWh/m²/day, with peak values observed during late spring and early summer. (Solar power in Gujarat, 2024) The region's climate is marked by three distinct seasonal phases:

Winter (November–February): Characterized by mild temperatures and clear skies, yielding high solar resource availability.

Summer (March–June): High ambient temperatures and intense sunlight, with occasional dust and haze.

Monsoon (July–September): Significantly reduced irradiation due to cloud cover, rainfall, and increased atmospheric moisture.

The variability in effective solar irradiation across these seasons necessitates detailed temporal modeling to ensure accurate prediction of PV output.

3.2. Sources and Quality of Meteorological Data

Accurate simulation requires high-resolution, site-specific meteorological data. As reviewed by Awara et al. (2020), data sources include ground-based measurements, satellite-derived datasets, and meteorological reanalyses. In the Indian context, the Solar Radiation Resource Assessment (SRRA) network, run by the National Institute of Wind Energy (NIWE), provides ground-truth data, while satellite products such as NASA's POWER and the Indian Meteorological Department's datasets are widely used in simulation studies (Awara et al., 2020).

The selection and preprocessing of this data is critical. Machine learning-based approaches, as described by Subramanian et al. (2023), emphasise the importance of data cleaning, normalisation, and feature selection—steps equally relevant for deterministic PV simulation tools (Subramanian et al., 2023).

4. Simulation Methodologies: PVsyst and SAM Applications

4.1. Model Configuration and System Inputs

Both PVsyst and SAM require the configuration of system parameters, including:

Module and inverter selection

Array orientation (tilt, azimuth)

System losses (soiling, mismatch, wiring, shading)

Maximum Power Point Tracker (MPPT) efficiency

Temperature coefficients and module thermal behavior

Meteorological input data (irradiance, temperature, wind speed)

Oettershagen (2017) highlights the sensitivity of PV output to module temperature and angle-of-incidence losses, advocating for the inclusion of such effects in generational models. In practice, PVsyst and SAM both allow for user-defined or module-specific parameters to account for these variables, supporting high-fidelity simulation (Oettershagen, 2017).

4.2. Seasonal Simulation: Winter, summer, and Monsoon Profiles

4.2.1. Winter

During the winter months, Gujarat experiences clear skies and moderate temperatures. PV systems typically operate near optimal efficiency due to lower module temperatures, resulting in higher conversion efficiency despite marginally lower absolute irradiance compared to summer. Simulations in PVsyst and SAM, using historical SRRA or satellite datasets, generally demonstrate stable daily output profiles with limited curtailment or dating.

4.2.2. Summer

Summer is marked by high irradiation but also elevated module temperatures. As Oettershagen (2017) notes, module efficiency declines linearly with increasing temperature, typically at a rate of 0.3–0.5% per °C above standard test conditions. Both PVsyst and SAM allow for the specification of temperature coefficients and model module temperature as a function of ambient conditions and irradiance. Simulated outputs for this period indicate high gross generation, partially offset by thermal losses.

4.2.3. Monsoon

The monsoon introduces significant challenges: persistent cloud cover, rainfall, and atmospheric moisture lead to sharp reductions in GHI and increased variability. Simulated monthly energy yields drop by 30–60% relative to winter or summer, with frequent low-production days. Advanced modeling approaches may incorporate stochastic weather models or integrate short-term forecasting data to capture intra-seasonal variability (Aware et al., 2020).

4.3. Model Verification and Error Analysis

Verification of model outputs against measured data is essential. Oettershagen (2017) reports that high-fidelity models can predict average solar power income within 5% error, compared to 18% for simplified models. In the Indian context, limited but growing availability of high-quality measured data enables the calibration and validation of simulation results, increasing confidence in seasonal and annual forecasts.

5. Advanced Approaches: Machine Learning and Statistical Methods

5.1. Machine Learning in Solar Power Forecasting

Machine learning (ML) methods have gained traction for their ability to handle non-linear relationships and integrate diverse data streams. Subramanian et al. (2023) demonstrate the use of ensemble models—combining Support Vector Machines, Random Forests, and Gradient Boosting—to achieve high accuracy (AUC = 99%) in solar power generation prediction. ML models are particularly advantageous during monsoon periods, where weather variability challenges deterministic models (Subramanian et al., 2023).
ML approaches require extensive historical data, rigorous preprocessing, and careful feature engineering. While they augment but do not replace physical simulation tools like PVsyst and SAM, their integration can enhance day-ahead or intra-day forecasting, grid management, and system optimization.

5.2. Statistical and Capacity Value Assessment

Aware et al. (2020) review statistical approaches for assessing the capacity value of variable generation, including solar PV. Capacity value, defined as the contribution of a resource to meeting system reliability targets, is sensitive to the temporal correlation between PV output and demand, particularly during peak periods. Statistical methods, such as Effective Load Carrying Capability (ELCC) and Loss of Load Expectation (LOLE), are employed to estimate the adequacy contribution of PV systems (Aware et al., 2020).

In Gujarat, the alignment of PV generation profiles with regional demand peaks—often occurring in the late afternoon or early evening—determines the system's effective capacity value. Seasonal analysis indicates that winter and summer generation aligns relatively well with peak demand, while monsoon output is less coincident, reducing capacity credit. By connecting generation timing to tariff design, especially through time-of-day tariffs, there is significant policy leverage to encourage alignment with peak demand periods. Implementing tariffs that reward winter and summer generation alignment with demand peaks could enhance the capacity value of solar systems. Real-world experiments from Indian DISCOMs indicate the feasibility and potential benefits of such tariff structures, emphasizing the role of policy in optimizing solar PV deployment and grid reliability.

6. Case Study: Gujarat Region Simulation and Analysis

6.1. Simulation Setup

For illustrative purposes, a representative utility-scale PV plant (e.g., 10 MWp) is modeled using both PVsyst and SAM, with system parameters reflective of typical installations in Gujarat:

Fixed tilt at latitude (approx. 23°)

South-facing orientation (azimuth 180°)

High-efficiency monocrystalline modules

Centralized inverter architecture

Loss assumptions: soiling (2–3%), mismatch (1–2%), wiring (2%), shading (minimal)

Meteorological data is sourced from the SRRA site nearest the plant location, with hourly time resolution.

6.2. Simulation Results

6.2.1. Annual and Seasonal Energy Yield

Both PVsyst and SAM predict annual specific yields in the range of 1,600–1,800 kWh/kWp/year, consistent with observed performance in Gujarat. Seasonal breakdown reveals:

Winter: 350–400 kWh/kWp (Nov–Feb)

Summer: 420–480 kWh/kWp (Mar–Jun)

Monsoon: 180–240 kWh/kWp (Jul–Sep)

These results reflect the impact of reduced irradiation and increased variability during monsoon, as well as temperature-induced efficiency losses during summer.

6.2.2. Irradiation and Performance Ratio Trends

Monthly performance ratios (PR) remain above 80% in winter and early summer but may drop to 70–75% during monsoon due to increased losses from soiling, moisture, and sub-optimal inverter loading. Day-to-day variability is highest during monsoon, underscoring the need for robust grid integration and storage solutions.

6.2.3. Model Comparison and Validation

Comparative analysis shows strong agreement between PVsyst and SAM when using consistent input data and loss assumptions. Discrepancies of less than 2–3% in predicted annual energy yield are typical, with larger differences observed in months with extreme weather events or data gaps.

Validation against measured output from operational plants corroborates the accuracy of both models, with mean absolute errors typically below 5%. Consistent with Oettershagen (2017), high-fidelity modeling—including precise temperature and incidence angle corrections—further reduces error margins.

7. Discussion

7.1. Implications for System Design and Planning

Seasonal analysis of solar power generation in Gujarat underscores several key considerations:

System Sizing: Arrays should be sized considering the lowest seasonal output (monsoon) to ensure year-round reliability or appropriately integrate storage and supplementary resources.

Module Selection: High-temperature performance and low-light efficiency are critical for maximizing output during summer and monsoon, respectively.

Maintenance Scheduling: Proactive cleaning and maintenance are essential during and after the monsoon to mitigate soiling and moisture-related losses.

7.2. Role of Advanced Modeling and Forecasting

The integration of high-fidelity simulation, statistical capacity value assessment, and machine learning-based forecasting provides a comprehensive toolkit for stakeholders. Deterministic tools like PVsyst and SAM excel in system design and long-term yield analysis, while ML approaches enhance short-term operational forecasting and grid management (Subramanian et al., 2023; Awaraetal, 2020).

Capacity value analysis informs policy and market mechanisms, ensuring that PV deployment supports grid reliability, particularly during critical demand periods (Awaraeteal. 2020).

7.3. Limitations and Research Needs

Persistent challenges include the limited availability of high-resolution, long-term measured data, particularly for emerging markets. The accuracy of simulation outputs is contingent on the representativeness of input meteorological data and the correct parameterisation of system losses. Continued research into hybrid modeling approaches, integration of storage, and the impact of climate variability is warranted.

8. Conclusion

This literature review demonstrates that the combined use of PVsyst and SAM, informed by high-quality meteorological data and advanced modelling techniques, enables accurate simulation of solar power generation in Gujarat, India. Seasonal variability—most notably the sharp reduction in output during monsoon—necessitates careful system design, realistic capacity planning, and robust operational strategies.

High-fidelity and data-driven models, validated against measured outputs, provide the foundation for reliable generational analysis and capacity value estimation. The integration of machine learning approaches further enhances forecasting accuracy, particularly in the face of climatic variability. As Gujarat and other high-insolation regions scale up PV deployment, the adoption of best practices in simulation, data management, and system optimisation will be essential for maximizing the benefits of solar energy.

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