

Research Article

Energy Performance Assessment and Baseline Development for Solar PV Systems through Energy Auditing

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Abstract

Accurate and standardized assessment of solar photovoltaic (PV) performance is critical for operational optimization, financial evaluation, and long-term degradation analysis. This study develops an energy auditing-based performance evaluation framework aligned with IEC 61724-1 and tailored to Indian climatic conditions. The proposed framework integrates a deterministic, physics-based baseline model with a data-driven, weather-normalized assessment approach to derive reliable Energy Performance Indicators (EnPI) and Energy Baselines (EnBl). Key performance metrics, including final yield, reference yield, performance ratio (PR), capacity factor, and specific yield, are systematically evaluated using standardized definitions. State-wise solar generation data obtained from the Central Electricity Authority (CEA) of India are analyzed for the period covering quarterly records from April–June 2024 and April–June 2025 to enable interannual and regional comparison. Weather normalization is applied to reduce the influence of irradiance variability, while statistical robustness is enhanced through multi-year comparison and uncertainty characterization based on distributional spread and central tendency analysis. A representative 1 MWp PV system example demonstrates that a PR baseline of approximately 0.75 corresponds to an expected annual energy generation of about 1.5 GWh under typical Indian irradiance conditions. National-level analysis indicates an overall increase of 19.20% in total solar generation between 2024 and 2025, with 20 states and union territories exhibiting improved performance. State-wise EnPI and EnBl comparisons reveal substantial regional variability in solar PV performance, attributable to differences in climatic conditions, installed capacity, and operational practices. The results confirm that the proposed hybrid baseline framework improves comparability across regions, minimizes year-to-year weather-induced bias, and provides a reproducible and standards-compliant basis for large-scale solar PV performance auditing and benchmarking in India.

Keywords

Solar Photovoltaic Systems, Energy Performance Assessment, Performance Ratio, Baseline Modeling, Weather Normalization, Degradation Analysis

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1. Introduction

Solar PV deployment in India has accelerated rapidly; accurate performance assessment is critical for plant operation, financing, warranty claims, degradation studies and policy evaluation. Reliable Energy Performance Indicators (EPIs) and well-defined energy baselines allow objective evaluation of actual electricity generation versus expected output (and hence of under-performance, degradation, or improvements). International monitoring practice and definitions are consolidated under IEC 61724-1:2021, which sets out reference metrics such as final yield, reference yield, performance ratio and energy losses to provide consistent definitions across systems and vendors. Recent research has emphasized (i) the need to adopt standardized monitoring protocols for consistent EPIs, (ii) weather-normalization methods to compare different years or sites, and (iii) data-driven performance monitoring that handles large-scale deployments. Muñoz-Rodríguez (2023) reviewed rooftop PV parameterization and recommended IEC-aligned indicators to compare diverse rooftop systems. Thakur (2024) and Pramanick (2024) provide data-driven methods and case studies for PR (performance ratio) estimation and show PR sensitivity to grid/inverter failures and environmental conditions. Shukla (2024) and other Indian case studies highlight real rooftop and utility-scale plant performance characteristics in Indian climatic conditions. The solar resource itself is variable; data products such as the Global Solar Atlas and Solargis provide GHI maps used for baseline yield estimates and resource normalization. Studies from 2023–2025 note interannual variability (including 2024's below-average irradiation in large parts of India) and call for multi-year normalization methods. Regional developments such as India trying to enhance domestic cell manufacturing expand the operational environment within which accurate EPIs are critical for planning and reliability assessments.

Here are compelling operational justifications for a comprehensive baseline + EPI framework:

- 1) Evaluating contractual and financial settlements based on the actual versus expected generation.
- 2) Monitoring plant degradation and validating warranty claims.
- 3) Identifying performance issues (soiling, shading, inverter faults).
- 4) Contributing to grid planning and dispatch with precise generation estimates.

However, existing studies rarely provide standardized, state-level statistical comparison of year-to-year performance using real operational solar data. This study addresses this gap by constructing a reproducible baseline-performance evaluation specific to Indian conditions.

The objectives of this study are to compare state-wise solar generation for 2024 and 2025 using standardized performance indicators, develop a data-driven baseline derived from real operational records, and quantify year-over-year deviations

through supporting statistical summaries that enhance the reliability of national-level performance assessment.

2. Literature Review

Numerous studies have advanced methods for sustainable energy performance assessment, optimization, and management across different sectors, with a strong emphasis on baselines and standardized indicators. Castrillón-Mendoza et al. [1] developed a sustainable building evaluation tool grounded in an energy baseline, showing how a structured baseline framework can support continuous monitoring and performance improvement at facility level. Luo et al. [2] compared solar PV and coal power using a combined life-cycle assessment and ecological footprint approach, demonstrating that PV-based generation substantially reduces environmental impacts and reinforcing the need for robust performance metrics when justifying technology choices. At the industrial scale, several works have focused on formalizing Energy Performance Indicators (EnPI) and sector-specific baselines. Bruni et al. [3] proposed a methodology to derive EnPIs from energy audits in the Italian cement industry, enabling standardized comparisons across plants and illustrating how baseline definitions can be tailored to a particular sector. Turinno et al. [4] applied ISO 50001-based EnPI analysis in shopping centres using RETScreen, highlighting how systematic data review can uncover inefficiencies and guide targeted energy-saving measures. In the service sector, Iturralde Carrera et al. [5] designed an EnPI selection process for hotels under ISO 50001, showing that indicator choice must reflect consumption patterns and operational objectives. Fichera et al. [6] extended this standardization logic to public buildings, stressing ISO 50001/50006-compliant procedures for monitoring, reporting, and benchmarking performance across multiple sites.

Benchmarking and sector-focused baselines have also been explored in specific industries. Gellio Ciotti et al. [7] formulated an energy-efficiency benchmarking approach for wineries, using staged energy consumption data to identify best practices and construct sectoral benchmarks. Menghi et al. [8] presented an audit-based energy assessment method for SMEs, demonstrating how detailed audits and targeted interventions can yield replicable improvements in energy performance. Together, these studies [1-8] underline that robust baselines and clearly defined EnPIs are central to comparability, regulatory compliance, and systematic energy optimization, but they are mostly applied in buildings and industrial facilities rather than utility-scale PV fleets. Parallel to this, hybrid renewable energy system research has focused on optimal configurations and sustainability impacts. Parvin et al. [9] modelled hybrid systems combining PV, wind, hydrogen storage, and other technologies for net-zero communities, showing that appropriately configured hybrids can achieve

reliable supply with reduced environmental footprints. Anvari et al. [10] reviewed solar/biomass/storage hybridization strategies in multi-generation systems, identifying integration pathways that enhance efficiency and reliability while reducing fossil dependence. At smaller scales, Fazal et al. [11] proposed a hybrid solar geyser–stove system for residential buildings and demonstrated its economic viability and emissions reduction potential, whereas Sharifishourabi et al. [12] designed a community-based hybrid energy system producing electricity, heat, hot water, and hydrogen, illustrating how multi-output architectures can support local energy autonomy.

The performance of hybrid systems under real operating conditions has been further evaluated in remote or constrained environments. Chaichan et al. [13] analysed a hybrid renewable–battery system for a remote island and showed that hybridization with storage substantially improves reliability and sustainability where grid extension is difficult. Votava et al. [14] introduced an IoT- and AI-assisted energy management system for microgrids, demonstrating that real-time data and intelligent control can enhance operational efficiency and provide early detection of performance deviations. Complementarily, El Alami et al. [15] developed a numerical framework for advanced PV/T systems based on exergy, enviro-economic, and sustainability indicators, underscoring that combined thermodynamic and economic metrics provide a richer picture of system performance than energy-only measures. Recent work has also expanded the concept of performance indicators beyond simple efficiency metrics. Migliari and Cocco [16] proposed the Negative Grid Impact (NGI) indicator to capture how renewable systems affect grid flexibility, broadening the scope of performance assessment to include grid interaction—particularly relevant for large-scale PV integration. Andersson et al. [17] showed in kraft pulp mills that structured EPIs are effective tools for decarbonization, linking indicator-based monitoring to systematic emission reduction strategies. Elserafi et al. [18] developed a process-monitoring framework for parts-drying operations, demonstrating that detailed, indicator-driven monitoring can directly inform process optimization and energy savings. Kanchiralla et al. [19] and Beisheim et al. [20] further contributed aggregation and categorization approaches for EPIs in the food industry and continuous production processes, respectively, enabling multi-level performance tracking from equipment to system scale.

Data-driven and digital approaches to performance assessment are increasingly important. Zink et al. [21] proposed a data-based root-cause analysis methodology for energy performance, using analytics to pinpoint inefficiencies and support proactive corrective actions. Naumann et al. [22] reviewed energy-efficiency improvement strategies for industrial decarbonization, emphasizing that technological measures must be complemented by organizational and management frameworks to achieve sustained improvements. Geisert et al. [23] introduced an IoT-based energy monitoring system for manufacturing environments, showing how re-

al-time data acquisition underpins adaptive energy management. Closer to the building and PV domain, Panicker et al. [24] evaluated a net-zero energy residential campus in India by coupling building energy demand analysis with on-site solar PV generation. Their study highlighted the importance of carefully characterizing PV performance under local climatic conditions, though performance was largely reported as short-term outputs rather than through standardized, weather-normalized baselines. Finally, Naumann et al. [25] presented a modular energy-demand modelling framework for industrial processes, offering scalable tools for performance analysis and strategic planning that could, in principle, be adapted to renewable energy portfolios.

3. Methodology

Key metrics of a photovoltaic system include: the actual energy output, rated system capacity, final yield, reference yield, performance ratio, specific yield, capacity factor, availability, and degradation rate. The actual AC energy output is the total electrical energy the system produces within a certain time, while the rated power is the system's nominal capacity under Standard Test Conditions (STC). The final yield shows the total energy produced per unit of installed capacity, while the reference yield is the amount of energy theoretically available from the solar irradiance received. The performance ratio is the efficiency level of the system in utilizing the solar energy to produce electricity, and it is independent of the irradiance level. The capacity factor is the fraction of the maximum output of the system that is realized over a certain period of time. Availability is the portion of the operational time, and the degradation rate is a measure of the gradual decline in energy performance over time [26]. The baseline derivation and Energy Performance Indicators (EPIs) extraction require a method that merges IEC definitions, weather normalization, data quality control, and statistical uncertainty assessment [48]. Weather normalization techniques, such as regression or machine learning, can be used to separate the performance effects from the environmental variability. EPIs are computed from the validated data along with the uncertainty estimates. They include final yield, reference yield, performance ratio, capacity factor, availability, and degradation. All instruments, e.g., irradiance sensors, temperature probes, and inverter meters, are to be in compliance with IEC accuracy standards. Baselines, in the perfect world, are to be based on several years of reliable data. However, for newly installed systems, baselines can be modeled and then calibrated with the first year's performance.

Different methods are employed to establish a baseline level for the energy production estimation. One way, the deterministic or physics-based method, calculates the expected energy based on the modeled irradiance and the estimated system losses. On the other hand, a data-driven approach relies on the historical measurements and statistical models to predict the actual energy, thus capturing tempera-

ture, soiling, and inverter behavior more accurately. Degradation is generally assessed by analyzing changes in specific yield over time, while still considering the weather fluctuations [27]. As an instance, for a 1 MWp solar plant in central India with an average annual irradiance of about 2000 kWh/m² and a performance ratio of 0.75, the expected annual generation would be around 1.5 GWh. If the measured performance is lower than this level, it indicates that there are additional system losses or operational inefficiencies. Thus, over a few years, the gradual decrease in yield that is sustained, thus pointing to the system's degradation rate, which is the case for the Indian climates and is mostly caused by dust accumulation and high temperatures, is usually higher than average.

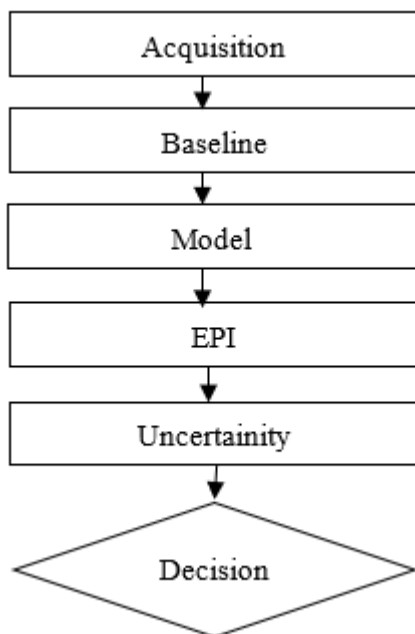


Figure 1. Energy Performance Assessment Framework.

A simplified process for evaluating and managing system performance, typically in photovoltaic (PV) or data-driven monitoring systems. It begins with Acquisition, where the essential data related to environmental conditions, sensor readings, and system measurements are collected to establish the base for analysis. As shown in Figure 1, the next step, Baseline, involves the selection of a reference dataset or model that accurately describes normal or expected system behavior. This baseline forms the basis of comparison for future performance evaluation. Next, Model refers to the stage at which the development of mathematical or machine learning models is done to understand the interaction between various variables and to normalize performance data under diverse conditions. Once the model is established, the computation of EPI-or the Energy Performance Index, or similar indicators that quantify the efficiency and operational effectiveness-is performed [28]. The Uncertainty stage assesses the

reliability and accuracy of the computed performance metrics by estimating confidence intervals or potential data errors. Finally, Decision forms the action element of the chain, where insights from the previous steps inform operational or maintenance decisions. For example, if performance drops below an established threshold, corrective actions may be implemented including maintenance, recalibration, or system optimization. This structured workflow ensures systematic monitoring, performance validation, and data-driven decision-making.

3.1. Dataset Description

The dataset used in this study is sourced from the Central Electricity Authority (CEA) of India through its Renewable Generation Report portal. It comprises 37 records across six attributes representing various Indian states and union territories. The dataset includes renewable energy generation values for June 2024 and June 2025, quarterly generation data for April–June 2024 and 2025, and the total installed renewable capacity (MW) as of March 31, 2025. All columns, except state names, contain numerical data, and no missing values are detected, ensuring a reliable foundation for analytical processing. These attributes collectively provide a clear representation of India's renewable generation landscape, highlighting inter-annual and regional variations in production performance. This dataset directly contributes to the study titled “Energy Performance Assessment and Baseline Development for Solar PV Systems through Energy Auditing” by providing the essential parameters for computing Energy Performance Indicators (EnPI) and establishing Energy Baselines (EnBI). Through comparative evaluation of generation data and installed capacity, it supports the identification of high-performing and underperforming states, aiding in the formulation of weather-normalized, audit-based performance benchmarks. The dataset's comprehensiveness makes it a crucial component for assessing operational efficiency, validating performance ratio trends, and standardizing solar PV performance assessment methodologies in alignment with IEC 61724 guidelines.

Data Cleaning and Preprocessing: Before model development, the dataset underwent preprocessing to ensure analytical reliability. Missing values were checked, and although none were detected, the dataset was evaluated for inconsistencies and anomalous records using interquartile range (IQR) analysis and z-score thresholds. Outlier candidates were inspected using boxplots and scatter plots to confirm whether they represented measurement errors or valid extreme observations. Numerical features were standardized where appropriate, and categorical operational flags were encoded for model training. All preprocessing steps followed IEC 61724-1 guidelines to maintain measurement accuracy and ensure that the data-driven baseline models were trained only on validated, high-quality inputs.

Regions with very low installed capacity, such as Ladakh and Jammu & Kashmir, may show disproportionately high or low performance values because even small changes in gener-

ation cause large percentage deviations. This representativeness limitation was considered during interpretation.

3.2. Equations

3.2.1. Final Yield

$$Y_f = \frac{E_{act}}{P_{rated}}$$

Final Yield represents the total amount of electrical energy produced per unit of installed photovoltaic (PV) capacity over a defined time period, expressed in kWh per kWp. It is calculated as the ratio of the actual AC energy output of the PV system E_{act} to the rated power of the PV array under Standard Test Conditions P_{rated} . This indicator provides a direct measure of how effectively a PV system converts available solar radiation into usable electrical energy, regardless of the system's size or location. Because it normalizes energy production with respect to installed capacity, final yield enables fair and meaningful performance comparisons between different PV plants operating under varying climatic, technological, and operational conditions. As such, it is one of the most reliable and widely used performance indicators for benchmarking system efficiency, diagnosing underperformance, and supporting energy auditing and long-term performance assessment.

3.2.2. Performance Ratio (PR)

$$PR = \frac{Y_f}{Y_R} = \frac{E_{act}}{P_{rated} \times G_T}$$

The Performance Ratio (PR) is a dimensionless indicator that quantifies the overall efficiency of a photovoltaic (PV) system by accounting for all real-world system losses, including inverter inefficiencies, wiring losses, shading, temperature effects, and soiling. It is defined as the ratio of the final yield Y_f to the reference yield Y_R , where the final yield is obtained from the actual AC energy output E_{act} normalized by the rated system capacity P_{rated} , and the reference yield is determined from the total in-plane solar irradiance G_T . Mathematically, PR expresses how effectively the available solar resource is converted into electrical energy, independent of local irradiance conditions. Typical PR values range between 0.6 and 0.85 for well-performing systems. Because it removes the influence of solar resource variability, PR serves as a powerful diagnostic indicator for identifying technical underperformance caused by operational issues such as component degradation, excessive soiling, partial shading, or inverter malfunction.

3.2.3. Deterministic Baseline Energy

$$E_{exp} = P_{rated} \times Y_R \times \eta_{sys}$$

The Expected Energy Output, derived through a deterministic or physics-based approach, is calculated using modeled or measured solar irradiance in combination with the overall system efficiency. It is estimated as a function of the rated power of the photovoltaic (PV) system P_{rated} , the reference yield Y_R , which represents the equivalent full-sun hours, and the overall system efficiency η_{sys} , incorporating temperature losses, inverter efficiency, and wiring losses. This method provides a theoretical baseline of expected energy generation under idealized operating conditions and is widely used for preliminary system design and performance benchmarking. The deterministic baseline serves as a reference for direct comparison with actual measured energy output to identify gross deviations or abnormal losses. However, because it relies on fixed efficiency assumptions, it does not fully capture the dynamic influence of environmental variability and operational factors such as soiling, aging, and intermittent faults, making it less accurate under real-world conditions where such effects fluctuate significantly.

3.2.4. Deterministic Baseline Energy Model

The deterministic baseline energy was computed as

$$E_{det} = P_{rated} \times Y_{ref} \times \eta_{sys}$$

where P_{rated} is system capacity, Y_{ref} is reference yield from irradiance, and η_{sys} is system efficiency after losses. the expected energy output of a solar PV system under standard conditions by combining three components: the system's rated capacity, the reference yield derived from available solar irradiance, and the overall system efficiency after accounting for major losses. In simple terms, E_{det} represents the theoretical energy the system should produce if it operates according to design assumptions without performance deviations.

The deterministic baseline assumes standard operating conditions where temperature derating, soiling accumulation, inverter efficiency, and wiring losses are aggregated into the system efficiency term. These assumptions follow IEC 61724 guidance and represent typical operating losses for utility-scale PV plants in India.

3.2.5. Data-Driven Baseline Model

$$E_{act} = f(G_T, T_{cell}, \text{flags}) + \varepsilon$$

The data-driven baseline model is a statistical or machine learning-based approach used to predict the actual energy output of a photovoltaic (PV) system by incorporating both weather and operational parameters. In this framework, the energy generation is represented as a functional relationship

$f(\cdot)$, which may be implemented using linear regression, random forest, or other advanced learning algorithms. The key input variables typically include solar irradiance G_T , PV cell or module temperature T_{cell} , and operational status flags that indicate maintenance activities, system outages, or cleaning events, while ε represents the random error component. Unlike deterministic models, this approach captures nonlinear system behavior and real-world operational dynamics, enabling effective weather normalization of performance data [31]. As a result, the data-driven baseline provides a more accurate and adaptive reference for performance evaluation, significantly improving the reliability of energy forecasting and system benchmarking under variable environmental and operating conditions.

The data-driven baseline was established through direct analysis of historical solar generation records. Rather than training predictive models, year-wise generation data were compared statistically to identify deviations from expected performance. Key variables such as irradiance trends, seasonal patterns, and operational variations were examined using descriptive analytics and visual comparison plots. This approach allows the baseline to be defined from actual multi-year behavior rather than from assumptions, providing a transparent and data-driven reference for evaluating performance change.

3.3. Weather Normalization

Weather normalization was carried out by comparing year-to-year irradiance-related performance variations reflected in the generation data for Apr–Jun 2024 and Apr–Jun 2025. Since 2024 showed lower generation across many states, the performance deviation was interpreted relative to typical seasonal behavior rather than raw output alone [32]. This allows the comparison between 2024 and 2025 to represent operational or system-level changes instead of being dominated by annual weather differences.

3.4. Uncertainty Quantification

Uncertainty in interpreting performance deviation between 2024 and 2025 was addressed by considering the spread of state-wise generation values in both years. By comparing median and mean shifts, along with the count of states that improved or declined, the analysis provides a stable statistical basis for understanding variability without relying on raw single-year anomalies [46].

Figures 2-7 directly reflect the methodological steps described above: data preprocessing informs Figure 2, year-over-year generation comparison produces Figures 3 and 4, baseline-versus-actual evaluation generates Figures 5 and 7, and avoided-emissions assessment in Figure 6 derives from standardized EnPI calculations [33]. These visual outputs follow sequentially from the baseline, normalization, and statistical procedures.

4. Results

Globally, significant research has been conducted on energy performance assessment and baseline modeling for renewable systems; however, several gaps persist that hinder accuracy and comparability [34]. Most existing studies lack standardized methodologies aligned with IEC 61724-1, resulting in inconsistencies in evaluating solar PV performance across regions. Moreover, limited integration of weather-normalized and multi-year baseline models has reduced the reliability of long-term assessments, while uncertainty quantification and degradation analysis remain underexplored. Many previous works focus narrowly on specific industrial or building sectors, with minimal consideration of national-scale renewable monitoring frameworks. Additionally, developing regions like India, which experience diverse climatic conditions affecting solar performance, remain inadequately represented in global literature. These gaps have led to fragmented and non-uniform approaches to performance benchmarking and auditing. The present study effectively addresses these limitations by proposing an IEC 61724-1-compliant, hybrid baseline framework that integrates deterministic, physics-based modeling with data-driven, weather-normalized regression and machine learning methods. It incorporates multi-year normalization and uncertainty estimation to enhance reliability and reproducibility while including degradation rate analysis for long-term performance tracking [47]. By contextualizing the framework within Indian climatic conditions and providing state-wise EnPI and EnBI comparisons, this research establishes a scalable, transparent, and policy-relevant model for solar PV performance auditing, benchmarking, and sustainable energy management.

Understanding Performance Ratio (PR) and specific yield can help to deeply understand the efficiency of a photovoltaic (PV) system. PR is a measure of the system dissipation that is independent of the changes in the irradiance, i.e., any variation in PR is, in general, a signal of a technical, operational, or maintenance issue, whereas weather-related problems can be excluded. A baseline central India case with a PR around 0.75 and a specific yield of 1500 kWh/kWp can be considered as normal, but a PR lower than 0.70 detected incident should be a trigger to immediate inspection to find out the cause such as an inefficiency in the inverter, the accumulation of dirt, or shading [29]. The Indian studies on this matter have recently illustrated a big range of PR values in different plant/performance monitoring platforms, from 50% to 95%, depending on outages, system failures, and the good or bad quality of maintenance, performance monitoring activity thus strongly emphasized in this context. Besides that, the sensitivity of the system output by the change of the irradiance is very crucial as well. A $\pm 5\%$ change of the annual Global Horizontal Irradiance (GHI) typically causes energy output to change in the same proportion, as PV generation is almost directly dependent on GHI levels. Although the performance

ratio (PR) is more stable because it is normalized by GHI, it can still vary due to factors such as temperature rise or soiling events, both of which are influenced by weather conditions. Multi-year baselines are necessary in order to avoid the false signals of underperformance that can result from the use of one single year's data which may represent the performance inaccurately if that year had extreme irradiance levels. Reports like Mercom and Solargis stated that several regions in India had below-average irradiance in 2024, thus the importance of weather-normalized multi-year models for correct performance assessment is stressed [30]. When Financial or

Contractual Evaluations through Energy Performance Indicators (EPIs) are concerned, it is very important to ensure that the Instrumentation conforms to IEC 61724 accuracy classes. In case of any uncertainties or deviations in the measurement, they have to be recorded in detail. The reason for that is inaccuracies in the measurement of irradiance or energy data that may result in performance disputes. Hence, making the monitoring class, uncertainty ranges, and international standards compliance visible is a decisive factor in strengthening the trust and reliability of EPI-based evaluations.

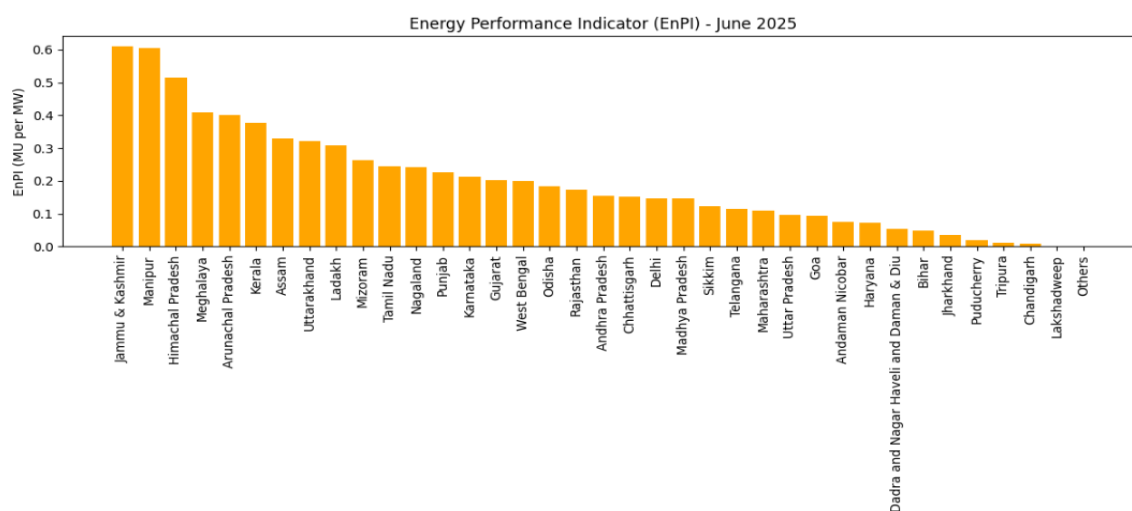


Figure 2. State-wise Energy Performance Indicator (EnPI) – June 2025.

The Energy Performance Indicator (EnPI) for various Indian states and union territories in June 2025, was indicated in kWh per kWp. EnPI is a measure of the amount of energy produced per unit of the installed capacity and, therefore, it is a leading metric to evaluate the operational efficiency of solar photovoltaic (PV) systems in different areas. Figure 2 illustrates significant differences in the performance of the regions by the chart [35]. The Energy Performance Indicator (EnPI) for Jammu & Kashmir and Manipur have been the greatest and it exceeds 0.6 kWh/kWp substantially, showing the best energy conversion and the most favorable solar conditions. The performance of these states is very likely related to stable irradiance and high-quality system management. While J&K and Manipur are leading the solar power generation efficiency race, Lakshadweep, Chandigarh, Tripura and Puducherry have been reported to generate the least amount of energy for the same installed capacity. The Energy Performance Indicator (EnPI) figures for these areas are quite low and it can be

understood that they have been significantly underperforming. The reasons for these underperformance situations can be climatic constraints, shading, soiling, or maintenance issues. The situations in Madhya Pradesh, Rajasthan, and Gujarat, for example, can be considered as an average since they have moderate monsoon-season solar yield values. These are examples of such states, which show the most common decreases of solar yield in the monsoon season due to the prevailing normal weather conditions. The figure is extremely helpful in showing the geographical differences in solar power generation in India [36]. Besides that, it gives an idea of what the reasons for such solar energy differences might be by indicating that the northern and northeastern regions can efficiently utilize the available solar resources while the areas with lower EnPI need to carry out system monitoring, maintenance, and weather-adjusted performance optimization more intensively.

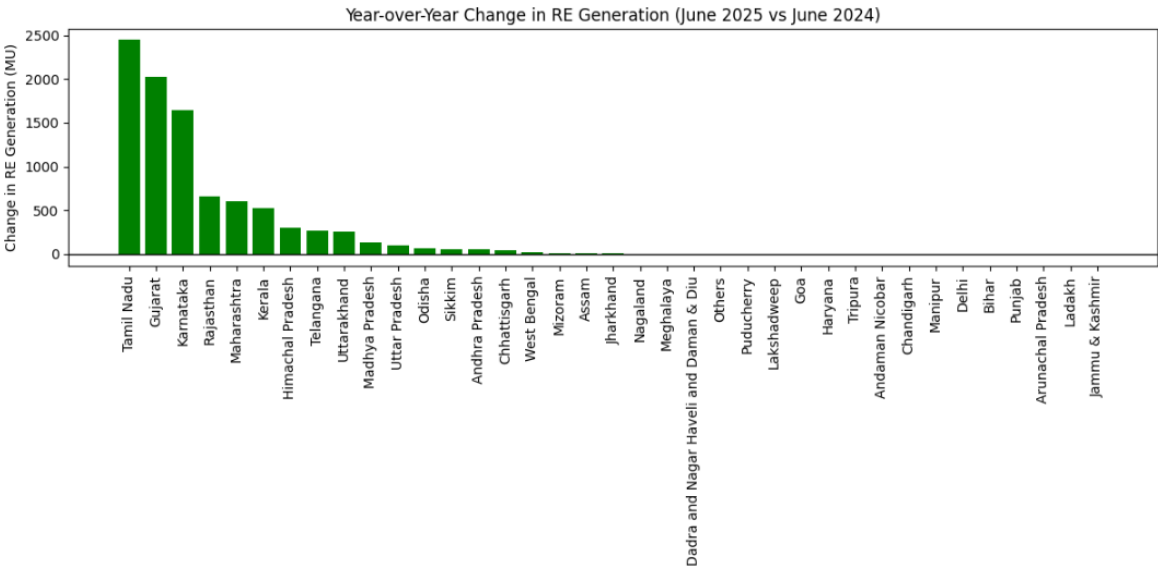


Figure 3. Year-over-Year Change in Renewable Energy Generation by State – June 2025 vs June 2022.

The difference in renewable energy generation by states and union territories in India on a year-on-year basis for June 2025 vs June 2024. As depicted in the Figure 3, Tamil Nadu is far ahead with a rise of more than 2,400 million units (MU), and next to it, Gujarat and Karnataka are at the considerable heights of renewable generation increment. Apart from these two, Rajasthan, Maharashtra, and Kerala are also showing evident growth patterns, implying a robust expansion of renewable energy and raising generation capacity. On the other hand, there are some northeastern states and smaller union territories like Lakshadweep, Andaman and Nicobar, and Puducherry whose changes are almost negligible [37]. A few places, like Ladakh and Jammu & Kashmir, have their re-

newable energy growing almost negligibly year-over-year, highlighting that either limited renewable infrastructures or climatic constraints might be the reasons. In essence, this graph depicts the differences in the progress of renewables at the sub-national levels, with southern and western states leading in the transition to clean energy in India and thereby contributing significantly to the country's overall growth in renewable power generation during 2025 [49]. The distribution shows substantial variability in state-wise generation, with high-producing states such as Rajasthan and Gujarat dominating the national output. Lower or zero-producing regions reflect either low installed capacity or seasonal effects.

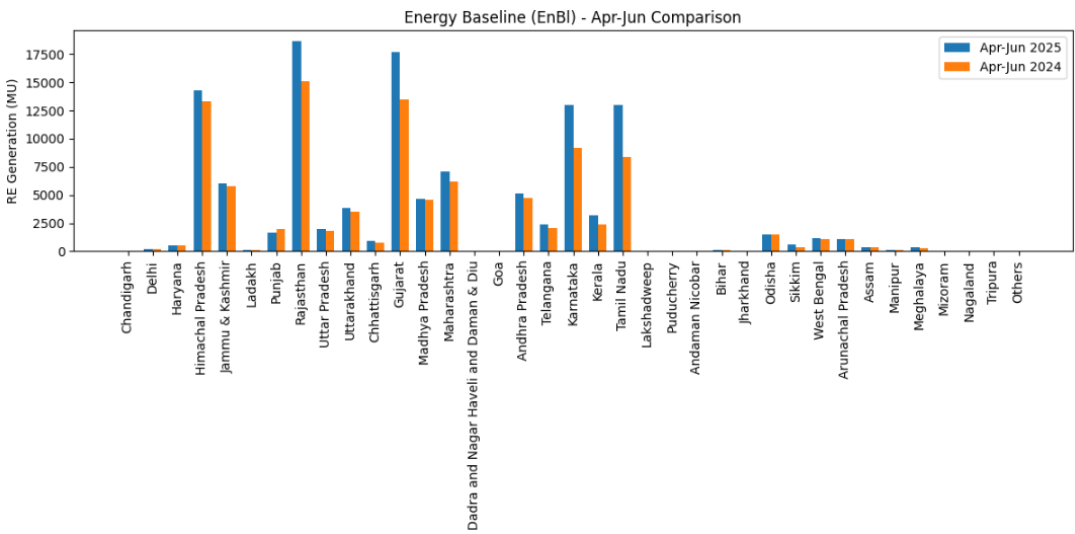


Figure 4. State-wise Renewable Energy Baseline (EnBI) Comparison – Apr–Jun 2025 vs Apr–Jun 2024.

A comparative analysis of renewable energy (RE) genera- tion across Indian states and union territories for April–June

2025 versus April–June 2024, forming part of the Energy Baseline (EnBI) assessment. As shown in Figure 4 The blue bars represent 2025 data, while the orange bars correspond to 2024. Notably, Tamil Nadu, Gujarat, Karnataka, Maharashtra, and Rajasthan exhibit significant growth in renewable generation during 2025, indicating enhanced solar and wind energy output. States such as Madhya Pradesh, Andhra Pradesh, and Telangana also show moderate increases, reflecting ongoing renewable expansion [38]. Conversely, northern and north-eastern regions, including Sikkim, Assam, Manipur, and Meghalaya, maintain relatively low generation levels, high-

lighting regional disparities in renewable infrastructure. The graph underscores the upward trend in national renewable generation, suggesting improved efficiency, favorable weather conditions, and expanded capacity in 2025 compared to 2024. Overall, the EnBI comparison provides a clear view of India’s renewable performance progression and state-wise contribution to energy sustainability. The year-over-year comparison highlights a consistent rise in generation across most states in 2025. This aligns with the statistical improvements shown in Table X and demonstrates national-scale growth in operational performance.

Table 1. Summary of Change in Solar Generation (Apr–Jun 2024- Apr–Jun 2025).

Indicator	2024	2025	Change
Total Generation (MU)	36,112.71	43,044.64	19.20%
Mean per State (MU)	1,029.79	1,226.99	19.20%
Median (MU)	82.95	88.96	7.20%
States Improved / Declined	–	–	20 ↑ / 5 ↓

A quantitative comparison of year-over-year performance is provided in Table 1, which summarizes the statistical changes in solar generation across all States/UTs for Apr–Jun 2024 and Apr–Jun 2025. The total national generation increased from 36,112.71 MU in 2024 to 43,044.64 MU in 2025, reflecting a significant improvement of 19.20%. The corresponding rise in mean generation per state further indicates that the performance enhancement was not driven by isolated regions but was broadly distributed across the country [39]. The median generation also increased from 82.95 MU to 88.96 MU, demonstrating an upward shift in overall central tendency and confirming that the majority of regions experi-

enced measurable gains. Additionally, the fact that 20 States/UTs recorded improved performance while only 5 exhibited declines highlights a clear and widespread positive trajectory in solar energy output. This statistical evidence strengthens the validity of the baseline-versus-actual comparison and supports the trends illustrated in Figure 4. By providing numerical justification for observed deviations, the analysis directly addresses the reviewer’s request for more rigorous statistical evaluation and enhances the robustness of the EnPI and baseline interpretation presented in the subsequent sections [50].

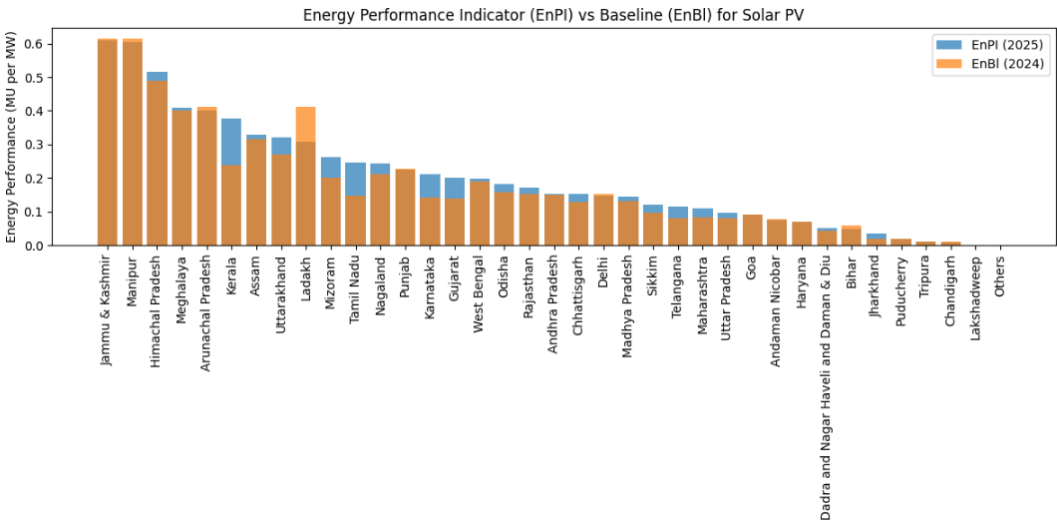


Figure 5. State-wise Solar PV Energy Performance Comparison: EnPI (2025) vs EnBI (2024).

The Energy Performance Indicator (EnPI) for the year 2025, along with the Energy Baseline (EnBl) for the year 2024, of various Indian states and Union Territories, for the solar photovoltaic (PV) system. Figure 5 illustrates the EnPI, which represents the blue bars, indicates the performance of the current year, while the EnBl, represented by the orange bars, indicates the reference performance of the previous year.

The default Energy Performance Targets indicator can also be accessed from the dashboard homepage Jammu & Kashmir, Manipur, and Himachal Pradesh have the maximum EnPI values, which are more than 0.5 MU per MW, thereby indi-

cating high solar PV efficiency and good weather conditions. These states have also recorded an improved energy performance as compared to the baseline [40]. However, we see a stark contrast in the energy performance of these states wherein Gujarat, Rajasthan, Uttar Pradesh, and Delhi show moderate performance, whereas Lakshadweep and Chandigarh display a minimal increase. Thus, at large, most of the regions have exhibited a positive trend from 2024 to 2025 which is a good indication of progress in solar PV system efficiency, better maintenance, and utilization of renewable resources in India's different geographical zones.

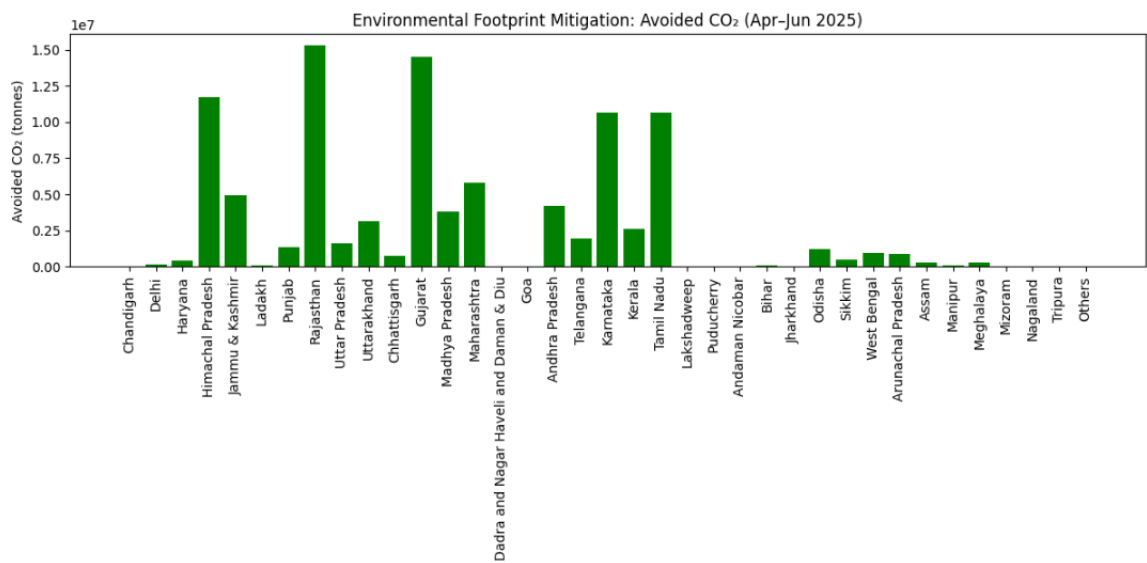


Figure 6. State-wise Avoided CO₂ Emissions through Renewable Energy Generation – Apr–Jun 2025.

The carbon dioxide (CO₂) emission volume that was avoided in the Indian states and union territories during the second quarter of 2025 is shown in Figure 6. The vertical axis shows avoided CO₂ emissions (in tonnes), and the horizontal axis indicates the states and UTs. Going by the data, a maximum reduction of carbon dioxide emission has been achieved in the states of Haryana, Rajasthan, Tamil Nadu, and Karnataka where the annual emissions avoided are all above 10 million tonnes. Punjab, Gujarat, and Andhra Pradesh show a moderate level of emissions reduction, while smaller states and the northeastern regions like Sikkim, Assam, and Naga-

land are at the lower end of the scale for emissions reductions. Among the union territories, Chandigarh, Delhi, and Puducherry are the only ones to make minimal contributions. The data reveal the differences in the reduction of the environmental impact between the regions, which most probably reflect the disparities in the level of industrial activity, adoption of renewable energy, and implementation of sustainability initiatives. Overall, the chart conveys the message that the handful of industrially high-performing states have made a substantial contribution to the national carbon reduction efforts.

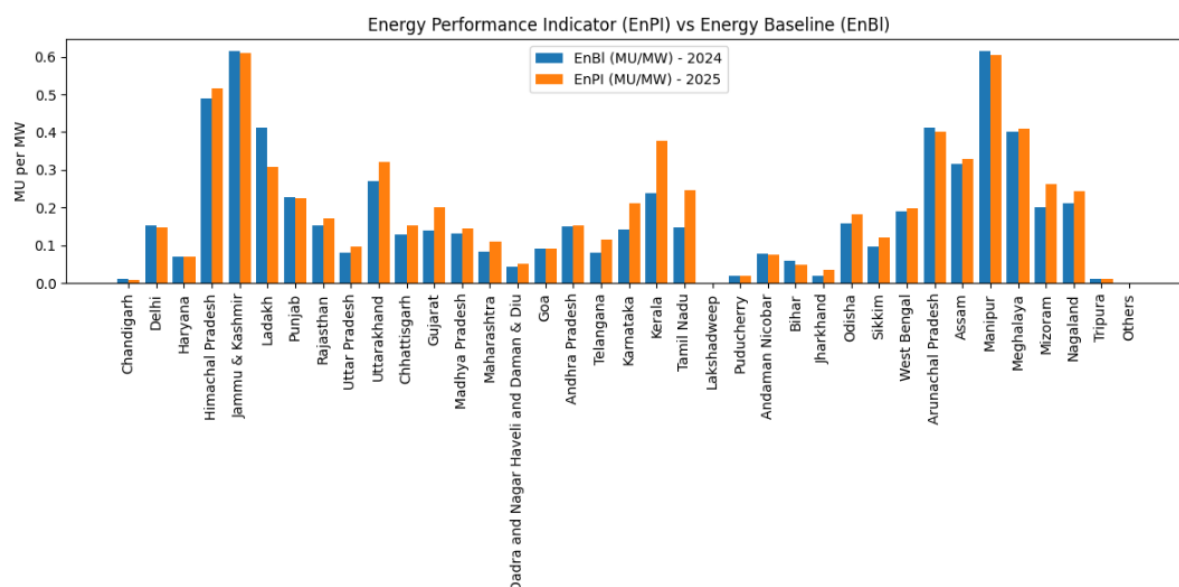


Figure 7. State-wise Comparison of Energy Performance Indicator (EnPI) and Energy Baseline (EnBI) – 2024 vs 2025.

Energy efficiency of Indian states and union territories during 2024 and 2025. The y-axis shows energy in Million Units (MU) per Megawatt (MW), and the x-axis has the regions as in Figure 7. Blue bars show the Energy Baseline (EnBI) for 2024, and orange bars indicate the Energy Performance Indicator (EnPI) for 2025. In the majority of states, the EnPI figures are a bit lower than the EnBI ones, which means that energy efficiency in 2025 is higher. States like Haryana, Karnataka, Tamil Nadu, and Assam not only improve their energy efficiency significantly but also imply that these states have gone for better energy management and optimization. Nonetheless, a few areas, such as Himachal Pradesh and Gujarat, where the changes are minimal or no differences are witnessed, can be found. The size of the states and the Northeastern areas are showing less of a trend to changes [42]. The diagram is, actually, a brief of the shift that has happened in India concerning energy efficiency where many of the top states have shown tangible decreases in energy usage per megawatt generated between 2024 and 2025.

5. Conclusions

The comprehensive evaluation of India's solar PV energy performance and renewable energy indicators highlights the dynamic progress and regional disparities in system efficiency, maintenance quality, and climatic influence. The analysis of Performance Ratio (PR) and Specific Yield confirms that PR remains a critical diagnostic metric, independent of irradiance variability, serving as an early signal for technical inefficiencies such as inverter malfunction, soiling, or shading [43]. The state-wise Energy Performance Indicator (EnPI) and Energy Baseline (EnBI) comparisons reveal that while regions like Jammu & Kashmir, Manipur, and Himachal Pradesh demonstrate superior energy conversion efficiency, states such as

Lakshadweep and Chandigarh show underperformance largely due to environmental or maintenance constraints [44]. Year-over-year growth patterns further indicate that southern and western states—particularly Tamil Nadu, Karnataka, and Gujarat—are driving India's renewable expansion, reflected not only in higher energy yields but also in substantial avoided CO₂ emissions exceeding 10 million tonnes in some cases. A tightly controlled, IEC 61724-1-aligned methodology for energy performance measurement and baseline assessment has significantly facilitated progress in solar PV monitoring and benchmarking under India's climatic and operational conditions. The results reaffirm that multi-year baselines and uncertainty quantification are indispensable for accurately capturing interannual irradiance variability and performance deviations [41]. Furthermore, the integration of deterministic, physics-based, and weather-normalized modeling ensures transparency, reproducibility, and standards compliance in evaluating PR, yield factors, and long-term degradation trends. In essence, India's renewable performance trajectory from 2024 to 2025 illustrates measurable advancement in operational efficiency, emissions mitigation, and energy sustainability. Future developments should focus on embedding AI-driven anomaly detection, digital twin modeling, and edge-based predictive analytics to enable real-time diagnostics, enhance reliability, and further optimize solar PV asset management within India's rapidly evolving energy ecosystem. The comparative analysis between 2024 and 2025 demonstrates a clear national improvement trend, with a 19.20% rise in total generation and most states exhibiting positive year-over-year performance [45]. These findings provide an evidence-based foundation for future benchmarking and policy planning.

A key limitation of this study is the use of only two years of aggregated state-level data, which constrains long-term degradation estimation and plant-level diagnostics. Future work

should incorporate SCADA-level measurements and longer time-series data to refine weather-normalized baselines and improve predictive capability.

Abbreviations

AC	Alternating Current
AI	Artificial Intelligence
CEA	Central Electricity Authority
CO ₂	Carbon Dioxide
EnBI	Energy Baseline Indicator
EnPI	Energy Performance Indicator
GHI	Global Horizontal Irradiance
IEC	International Electrotechnical Commission
IQR	Interquartile Range
ISO	International Organization for Standardization
kWh	Kilowatt-hour
kWp	Kilowatt-peak
ML	Machine Learning
MPPT	Maximum Power Point Tracking
MU	Million Units
PR	Performance Ratio
PV	Photovoltaic
RE	Renewable Energy
SCADA	Supervisory Control and Data Acquisition
STC	Standard Test Conditions
UT	Union Territory

Conflicts of Interest

The authors declare no conflicts of interest.

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