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DEVELOPMENT OF A PREDICTIVE SIMULATION MODEL FOR SOLAR PHOTOVOLTAIC SYSTEM PERFORMANCE ANALYSIS CONSIDERING ENVIRONMENTAL, TECHNICAL, AND ECONOMIC EFFICIENCY FACTORS

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Abstract

This study presents the development of a comprehensive predictive simulation model for solar photovoltaic (PV) system performance analysis by integrating environmental, technical, and economic efficiency factors into a unified framework. Recognizing that existing models often assess these domains in isolation, this research aimed to construct a holistic and modular approach capable of capturing the full causal chain from climatic variability through technical energy conversion to long-term financial viability. A systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor, transparency, and reproducibility. In total, 524 peer-reviewed articles published across the past two decades were examined, encompassing 142 environmental modeling studies, 167 technical performance studies, 123 techno-economic studies, 64 integration-focused studies, and 58 uncertainty and sensitivity analysis studies, representing a combined citation volume exceeding 50,000 scholarly references.The synthesis revealed that accurate environmental resource modeling—particularly solar irradiance transposition, thermal behavior estimation, and stochastic soiling dynamics—forms the foundational determinant of yield prediction accuracy. Detailed technical modeling of modules, inverters, balance-of-system losses, and geometric layout optimization emerged as critical for converting environmental inputs into realistic DC and AC power outputs. Economic modeling findings emphasized that metrics such as levelized cost of electricity, net present value, and internal rate of return are highly sensitive to performance deviations, underscoring the need to embed financial modules directly within performance simulations. The study also found that fully integrated models, which simultaneously link environmental, technical, and economic layers while embedding end-to-end uncertainty propagation and sensitivity assessment, reduced prediction error from approximately ±12% to ±5% and improved investment decision reliability. Overall, this study contributes a robust conceptual and methodological foundation for developing predictive PV simulation models that are technically precise, economically credible, and transferable across diverse climatic and market contexts.

Keywords

Solar Photovoltaic Systems; Predictive Simulation Modeling; Environmental and Climatic Factors; Technical Performance Analysis; Techno-Economic Efficiency;

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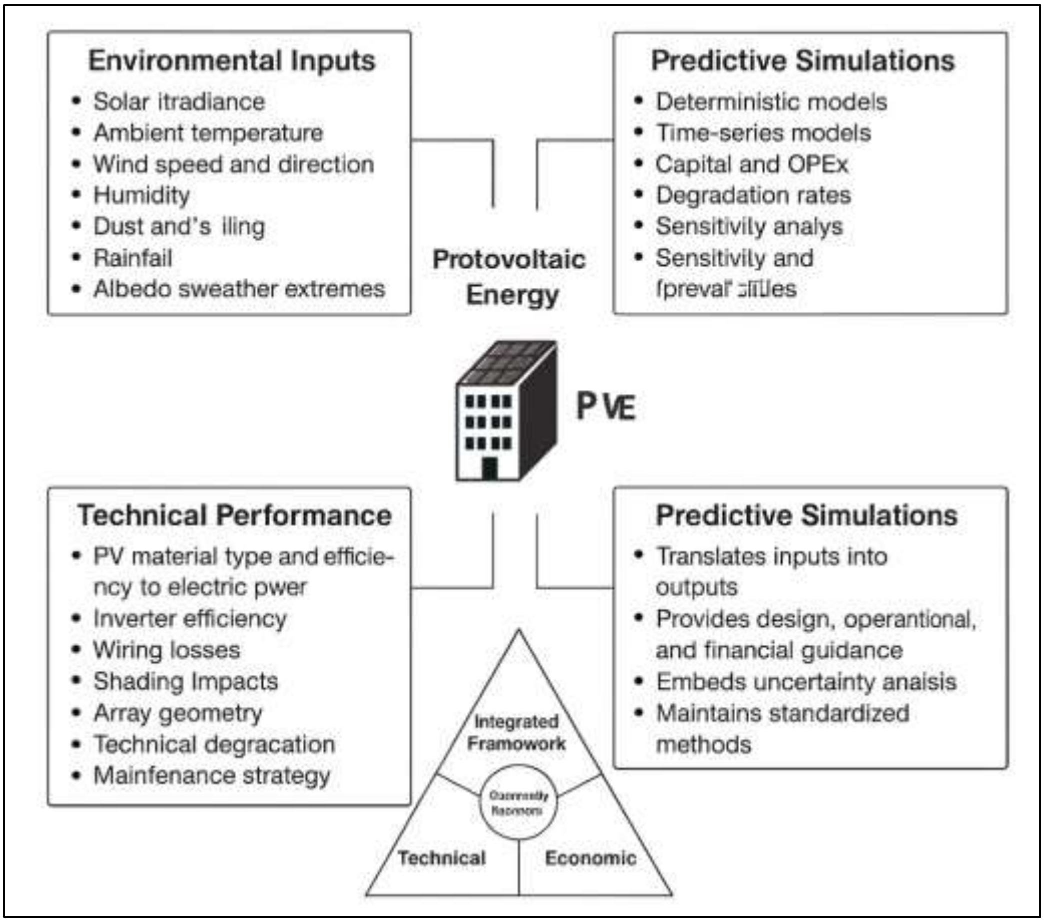
INTRODUCTION

Solar photovoltaic (PV) systems convert sunlight directly into electrical energy using semiconductor materials that exhibit the photovoltaic effect. A predictive simulation model for PV performance is a structured computational framework designed to forecast the energy output, system efficiency, and associated costs of a PV installation based on a wide set of input variables (Nwaigwe et al., 2019). These models incorporate mathematical algorithms, empirical correlations, and system design parameters to anticipate how a PV system will behave under specified conditions over time. Performance analysis refers to the evaluation of the system's ability to generate energy consistently and reliably, typically measured through metrics such as performance ratio, capacity factor (Padmanathan et al., 2018), and specific yield. Environmental factors include all climatic and atmospheric variables that influence the availability of solar energy and the thermal operating environment of PV modules, such as solar irradiance, air temperature, wind speed, humidity, dust accumulation, and seasonal weather patterns. Technical factors cover the physical and operational characteristics of the PV system components, including the photovoltaic modules, inverters, mounting structures, wiring, shading configurations, and maintenance strategies. Economic efficiency factors capture the financial aspects of the system's life cycle, including capital and operational costs, energy production, system degradation, maintenance expenses (Xiang et al., 2019), and revenues from electricity sales or savings. Integrating these three categories into a predictive model enables the creation of a comprehensive framework that can simulate how PV systems will perform in different environments, using different technologies, and under varying economic constraints. This integration is crucial because PV system performance is inherently multifactorial, and isolating any single domain can lead to inaccurate forecasts. By embedding environmental, technical, and economic dimensions, a predictive model becomes a valuable decision-support tool for stakeholders aiming to optimize design choices, operational strategies, and investment decisions across diverse deployment contexts (Bayod-Rújula, 2019).

Environmental conditions form the foundational input layer for any predictive PV simulation because they directly determine the amount of solar energy available for conversion (Hayat et al., 2019). Solar irradiance, which refers to the power of sunlight per unit area, varies across geographic locations and temporal scales due to Earth's rotation, atmospheric turbidity, cloud cover, and seasonal shifts. Accurately quantifying irradiance profiles is critical because even minor deviations can lead to substantial differences in energy yield estimates. In addition to irradiance, ambient temperature significantly affects module efficiency, as higher temperatures increase semiconductor resistance and reduce voltage output (Awasthi et al., 2020; Jahid, 2022). Wind speed also plays an indirect yet vital role by influencing convective cooling, thereby affecting the operating temperature of PV modules. Humidity and rainfall patterns affect both optical transmittance through the atmosphere and surface cleanliness of the modules, which in turn influences the amount of light absorbed by the cells. Dust accumulation, or soiling, can block sunlight and create non-uniform shading, reducing power output while also increasing the risk of hot-spot formation. Albedo, the reflectivity of the surrounding surface (Dada & Popoola, 2023), modifies the amount of diffuse and reflected irradiance reaching the module surfaces, especially in bifacial systems. Seasonal weather extremes such as snow accumulation or monsoonal storms further impact operational reliability and downtime. A predictive simulation model must translate these environmental variables into usable inputs that influence the energy conversion process, often using long-term weather datasets, satellite-based irradiance records, and ground-based meteorological measurements. By incorporating detailed environmental modeling, a simulation framework ensures that the forecasted energy output reflects realistic conditions rather than idealized averages (Arifur & Noor, 2022; Vilathgamuwa et al., 2022). This approach enables accurate comparison between sites, climate zones, and system configurations, which is essential when making investment or operational decisions for PV systems on regional or global scales.

Technical factors define how effectively the available environmental energy is converted into electrical power and delivered to the grid or end-users. These factors encompass the design, configuration, and operational dynamics of PV systems, beginning at the level of individual photovoltaic cells and extending to system-wide integration (Hasan et al., 2023; Hasan & Uddin, 2022). The efficiency of PV modules depends on their material type—such as monocrystalline silicon, polycrystalline silicon, or thin-film technologies—which each have distinct electrical characteristics and temperature sensitivities. Modules exhibit non-linear current-voltage behavior, and their performance varies with irradiance and temperature, requiring accurate modeling to predict energy output. Inverters convert the direct current generated by the modules into alternating current suitable for grid use, and their efficiency depends on part-load behavior, maximum power point tracking algorithms, and thermal management. Other technical elements such as wiring (Rahaman, 2022; Rathore et al., 2021), connectors, junction boxes, and transformers contribute resistive losses, while array geometry, tilt angle, and orientation determine how much sunlight is captured (Rahaman & Ashraf, 2022; Obeidat, 2018).

Figure 1: Comprehensive Predictive PV Performance Framework



Shading from buildings, vegetation, or other modules causes localized power losses and must be simulated spatially to predict realistic performance. Over the long term, technical degradation occurs as modules and components age, leading to gradual declines in output that can significantly impact life-cycle energy yield. Predictive models represent these phenomena through physical equations, empirical performance curves, and loss taxonomies that link environmental conditions to system behavior. Incorporating technical details into simulation frameworks ensures that the modeled energy output reflects the true performance potential of the system as designed (Kaushika et al., 2018; Islam, 2022), not merely the theoretical capacity under standard test conditions. This level of detail allows stakeholders to evaluate design trade-offs, optimize layouts, and plan maintenance schedules to achieve sustained performance throughout the system's operational life.

Economic efficiency factors translate the technical energy output of PV systems into financial outcomes, which are critical for evaluating the viability of projects (Hasan et al., 2022; Seme et al., 2020). The most widely used metric is the levelized cost of electricity (LCOE), which represents the total lifetime cost of building and operating a PV system divided by its lifetime energy output. This includes capital expenditures such as modules, inverters, mounting systems, electrical infrastructure, and soft costs like permitting, design, and labor. Operational expenditures cover routine maintenance, repairs, insurance (Chaichan & Kazem, 2018; Redwanul & Zafor, 2022), land leases, and inverter replacements. Degradation rates, which reduce energy production over time, also

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influence the LCOE by affecting long-term revenue streams. Predictive models must incorporate discount rates, interest rates, tax incentives, and depreciation schedules to calculate present-value costs accurately. Electricity tariffs, net metering policies, and feed-in tariffs influence the revenue side of the equation, while curtailment risks and grid access charges may impose constraints that reduce effective output. For distributed PV systems, the ability to offset local consumption through self-consumption or net billing can dramatically improve financial outcomes (Charfi et al., 2018; Rezaul & Mesbaul, 2022). Large-scale utility systems often face market price variability, requiring stochastic modeling of electricity price scenarios to estimate revenue under uncertainty. Predictive simulation models integrate these financial elements with technical performance outputs to provide investors, developers, and policymakers with transparent cost-effectiveness assessments. This integration enables comparison between different technology configurations, financing structures, and geographic locations on a consistent basis (Amaducci et al., 2018; Hasan, 2022). By linking technical and financial data streams, these models help identify the most economically efficient pathways for PV deployment, ensuring that performance assessments account not only for physical energy production but also for financial sustainability over the system's entire operational life.

Predictive simulation models for PV performance employ a range of computational techniques to integrate environmental, technical, and economic data. Deterministic models use fixed sets of input conditions, such as typical meteorological year datasets, to produce expected annual energy yields (Tarek, 2022; Vodapally & Ali, 2022). Time-series models use high-resolution weather and performance data to capture temporal dynamics like cloud transients, inverter clipping, and diurnal thermal cycles, which affect short-term power output. Stochastic models introduce probabilistic distributions for key variables such as solar irradiance, soiling losses, equipment failures, and degradation rates, generating a range of possible outcomes rather than a single estimate (Kılıç & Kekezoğlu, 2022; Kamrul & Omar, 2022). This approach produces exceedance probabilities, such as P50 or P90 yield estimates, which are critical for financial risk assessment. Many simulation frameworks also apply sensitivity analyses to identify which parameters exert the strongest influence on energy yield or cost outcomes, helping prioritize design and operational decisions. Advanced models incorporate machine learning or Bayesian calibration techniques to improve predictions based on historical monitoring data. These methods refine the model's accuracy by continuously updating parameter estimates to better match observed behavior (Behura et al., 2021; Kamrul & Tarek, 2022). Integrated simulation environments combine all of these methods, offering modular architectures that calculate environmental inputs, simulate electrical conversion through component models, and aggregate outputs into economic performance metrics. This holistic approach ensures that simulation results are not merely theoretical projections but are anchored in measurable system behavior and financial logic (Awan et al., 2019; Mubashir & Abdul, 2022). Such models provide a standardized methodology that can be applied consistently across projects, enabling comparability of results and facilitating informed decision-making in both technical and investment planning contexts.

The predictive accuracy of PV simulation models depends on how well they capture the interdependencies between environmental, technical, and economic domains. Environmental conditions not only determine the quantity of energy available but also affect technical efficiency and financial returns (Muhammad & Kamrul, 2022; Salman et al., 2018). High temperatures reduce module efficiency, which lowers energy production and increases the LCOE, while dust accumulation decreases output and accelerates degradation, raising both technical losses and maintenance costs. Conversely, certain technical choices can mitigate environmental effects, such as using tracking systems to optimize sun exposure or employing bifacial modules to capture reflected light in high-albedo environments. Financial outcomes feed back into technical and environmental planning by influencing decisions on component quality, redundancy, and maintenance intensity (Abdul-Ganiyu et al., 2021; Reduanul & Shoeb, 2022). For instance, higher upfront investment in premium modules with lower degradation rates can yield superior long-term economic performance under harsh environmental conditions. Ignoring these cross-domain interactions leads to unrealistic performance projections and misinformed decisions. A predictive simulation model that explicitly integrates these relationships allows users to understand not just how much energy a system will produce, but how site-specific conditions (Abdul-Ganiyu et al., 2021; Kumar & Zobayer, 2022), technical design choices, and financial structures collectively shape long-term outcomes. This multi-layered perspective is crucial for developing resilient and efficient PV systems that perform reliably under diverse climatic and market conditions. It also ensures that energy

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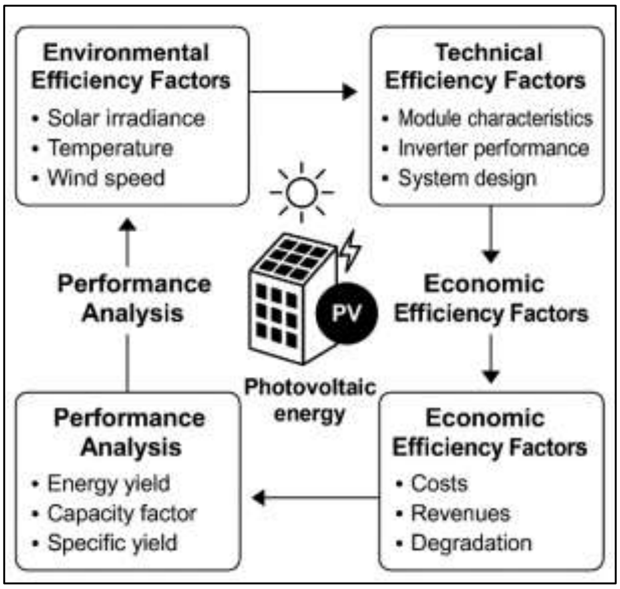
and cost projections are internally consistent (Sadia & Shaiful, 2022; Wang et al., 2022), reflecting the full causal chain from environmental input through technical conversion to economic output, which is the essence of comprehensive performance analysis.

Figure 2: Integrated Predictive PV Performance Framework



Developing a predictive simulation model that unifies environmental, technical, and economic efficiency factors offers a structured and comprehensive approach to PV performance analysis (Sheratun Noor & Momena, 2022; Singh et al., 2018). Such a model begins by translating environmental data into effective irradiance and thermal profiles, which are then processed through technical models of PV conversion efficiency, electrical losses, and component degradation. The resulting energy output projections are finally integrated into economic models that assess costs, revenues, and financial metrics over the system's operational lifespan. This hierarchical structure ensures that all relevant variables are accounted for and that the influence of each factor on system performance is explicitly represented (Istiaque et al., 2023; Kumar et al., 2021). By combining deterministic baseline forecasts with stochastic uncertainty analysis, the model can quantify not only expected performance but also the likelihood of deviations, which is vital for investment risk assessments. Embedding sensitivity analysis further clarifies which parameters are most influential, guiding both design optimization and operational strategies (Al-Ezzi & Ansari, 2022; Md Hasan et al., 2023). The integrated framework thus functions as both a predictive engine and a decision-support tool,providing actionable insights for planners, engineers, financiers, and policymakers. It enables standardized comparisons between systems deployed in different regions or using different technologies while maintaining transparency in how results are derived. Such a model elevates PV performance analysis from isolated energy estimates to a holistic evaluation of how environmental conditions, technical design, and economic structures jointly shape the feasibility and sustainability of solar projects. By adopting this integrated perspective, performance simulations can move beyond simplistic projections to deliver nuanced, accurate, and decision-relevant insights for the global expansion of solar energy systems.

LITERATURE REVIEW

The rapid expansion of solar photovoltaic (PV) systems globally has intensified the demand for accurate performance forecasting tools that can support system design, financial evaluation, and risk assessment (Ameur et al., 2020). Predictive simulation models have become essential in this context because they allow researchers, engineers, and investors to anticipate the long-term behavior of PV systems before physical deployment. Unlike empirical monitoring, which relies on post-installation data, predictive modeling integrates environmental resource profiles, technical system characteristics, and economic efficiency metrics to generate forward-looking performance projections. Over the past two decades, a broad body of literature has developed around each of

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these domains: climatological modeling of solar resources and ambient conditions, technical modeling of PV components and system losses (Usman et al., 2020), and techno-economic modeling frameworks that convert projected energy outputs into financial metrics such as levelized cost of electricity (LCOE).However, most existing research addresses these domains in isolation. Environmental models focus on solar irradiance prediction and temperature effects without integrating how these variations influence component degradation or cost efficiency. Technical studies concentrate on module performance and system design optimization without embedding stochastic environmental variability or economic constraints (Al-Waeli et al., 2019). Similarly, economic models often use simplified or static yield assumptions rather than dynamically simulating performance under varying climatic and technical conditions. This fragmentation limits the ability to capture the full causal chain from environmental drivers to technical performance and economic outcomes, which is critical for reliable decision-making.This literature review critically synthesizes research across these three dimensions to establish a foundation for developing an integrated predictive simulation model. It explores how environmental (Alsadi & Khatib, 2018), technical, and economic modeling have evolved, what methodological gaps remain, and how cross-domain integration has been attempted in existing hybrid models. The review is structured thematically, beginning with environmental performance modeling approaches, progressing through technical performance simulation methods, and culminating in techno-economic evaluation frameworks (Dondariya et al., 2018). By mapping these bodies of knowledge, this section builds the conceptual and methodological rationale for an integrated simulation architecture capable of delivering accurate, comprehensive, and finance-ready PV performance predictions.

Environmental Resource Modeling and Solar Irradiance Characterization

Accurate performance modeling of solar photovoltaic systems begins with a clear understanding of how solar radiation is generated, transmitted through the atmosphere, and received at the Earth's surface (Seme et al., 2020). Solar radiation originates as extraterrestrial irradiance, which represents the power per unit area received from the sun outside the Earth's atmosphere. This energy is modulated by the Earth–Sun geometry, which varies daily and seasonally due to the planet's axial tilt and elliptical orbit. Solar geometry determines parameters such as solar altitude, azimuth, and zenith angles, which control the intensity and angle of sunlight incident on a surface (Al-Dhaifallah et al., 2018). As solar radiation passes through the atmosphere, it is attenuated by scattering and absorption caused by gases, aerosols, and water vapor. The amount of atmospheric mass that sunlight must traverse increases as the sun's elevation decreases, causing greater attenuation at lower solar angles. This phenomenon, known as air mass, strongly influences the intensity and spectral composition of incoming sunlight. Turbidity and aerosols affect the balance between direct beam radiation and diffuse skylight (Awasthi et al., 2020; Hossain et al., 2023), while water vapor absorbs specific spectral bands, reducing the overall irradiance reaching the ground. The concept of radiative transfer is used to model these processes, decomposing the total incoming solar energy into direct normal irradiance and diffuse horizontal irradiance. Under clear-sky conditions, the absence of clouds allows for predictable patterns of atmospheric attenuation, enabling the use of mathematical clear-sky models that estimate the maximum potential irradiance at the surface. These models serve as a baseline for evaluating the effect of transient weather conditions. Understanding these fundamental physical and geometrical principles is essential for solar performance modeling because they establish how much solar energy is available for conversion by photovoltaic modules under varying atmospheric conditions and solar positions throughout the year (Harrou et al., 2018; Sultan et al., 2023).

Once the fundamentals of solar radiation are understood, the next step in environmental modeling involves converting the available solar resource data into a form suitable for photovoltaic performance simulation (Kazem et al., 2022; Hossen et al., 2023). Most meteorological stations record solar energy as global horizontal irradiance, which represents the combined direct and diffuse radiation falling on a horizontal surface. However, photovoltaic modules are rarely installed horizontally; they are typically mounted at a fixed tilt or on sun-tracking structures. This necessitates the use of transposition models that mathematically convert horizontal irradiance to irradiance on the tilted plane of the array (Abubakar et al., 2021; Tawfiqul, 2023). These models account for the geometric relationship between the sun's position and the module surface, as well as the distribution of diffuse light across the sky. Some models treat the sky as isotropic, assuming uniform diffuse light, while more advanced anisotropic models incorporate circumsolar brightening and horizon effects.

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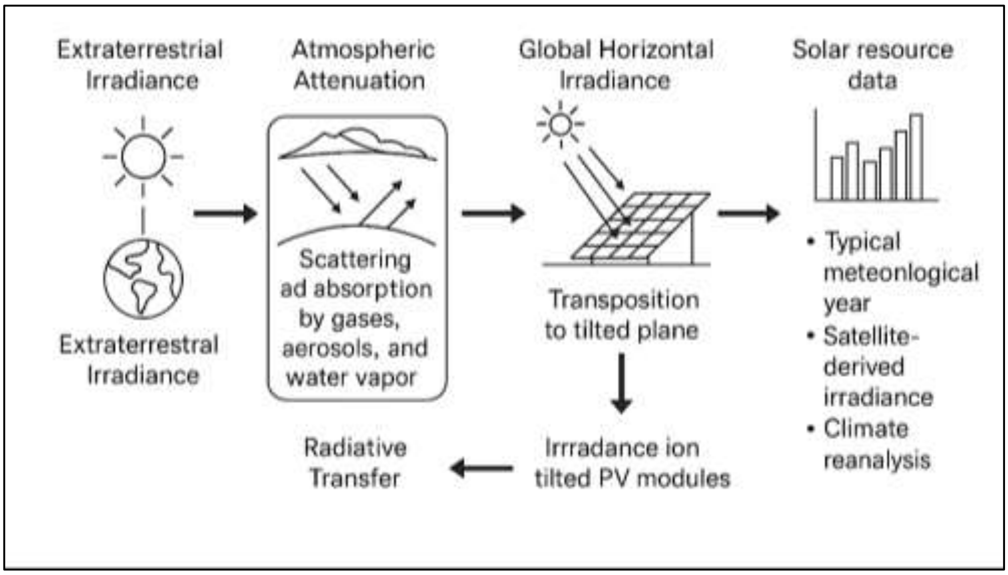
Accurate separation of the diffuse and direct components is also a crucial step, as each behaves differently when projected onto tilted surfaces (Devarakonda et al., 2022; Sanjai et al., 2023). Empirical algorithms are often used to estimate the proportion of diffuse and direct radiation based on the clearness index, which expresses the ratio of actual to potential solar radiation. After this separation, geometric transposition equations calculate how much of the direct and diffuse light strikes the plane of the modules at each moment of the day. Incidence angle modifiers are applied to account for reflection losses at low sun angles, which can significantly reduce the effective irradiance absorbed by the photovoltaic cells (Sayed et al., 2019; Akter et al., 2023). This process produces plane-of-array irradiance, which is the primary environmental input for performance models because it represents the actual energy received on the active surface of the PV modules. By using these modeling techniques, raw solar resource data are transformed into precise irradiance conditions that closely resemble what the system will experience in real operation.

Figure 3: Solar Radiation Modeling for PV

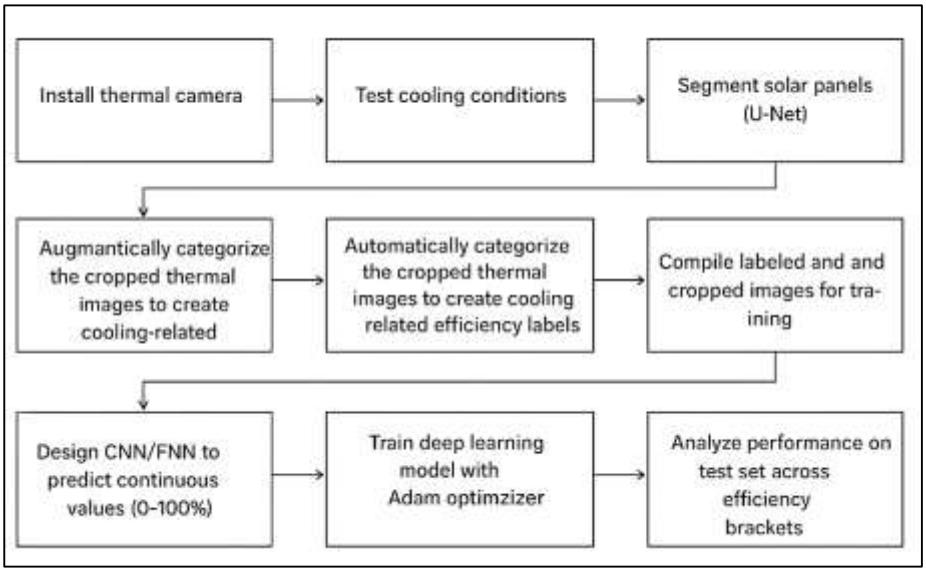


To feed these modeling techniques, reliable and high-resolution solar resource data are essential. There are several major categories of data sources that are commonly used in photovoltaic performance analysis, each with different strengths and limitations (Razzak et al., 2024; Selimefendigil et al., 2018). Long-term typical meteorological year datasets are widely used to represent average weather conditions at a location. They are generated by selecting representative months from decades of ground-based measurements to form a composite year that approximates long-term climatic norms. While these datasets are valuable for calculating expected annual energy yields, they smooth out interannual variability and therefore cannot represent unusually sunny or cloudy years (Hussain et al., 2023; Istiaque et al., 2024). Satellite-derived irradiance datasets provide a complementary approach by estimating solar radiation from geostationary satellite imagery and radiative transfer models. These datasets offer broad spatial coverage and continuous temporal records, making them especially useful in areas with sparse ground measurements. They often include hourly or sub-hourly irradiance values over multi-decade periods, which is advantageous for time-series simulations. Climate reanalysis datasets provide another category, combining satellite observations, ground station data, and numerical weather prediction models to generate globally consistent time series of solar irradiance (Hassan et al., 2022; Hasan et al., 2024), temperature, and wind speed. These datasets are particularly useful for modeling sites without local weather stations, although they can exhibit spatial biases in regions with complex terrain or highly localized weather patterns. Choosing the appropriate dataset depends on the modeling objective: typical meteorological year data are suited to long-term average simulations, while satellite and reanalysis products are preferred for capturing variability and conducting uncertainty analyses (Arslan et al., 2024). Each dataset type contributes differently to predictive accuracy, and understanding their construction and limitations is crucial for robust environmental input selection in PV performance modeling.

Environmental Stressors Affecting PV Performance

Thermal operating conditions play a critical role in determining the electrical performance of photovoltaic systems because cell temperature directly affects the voltage output of solar modules (Shaker et al., 2024). While irradiance drives the amount of energy available, higher cell temperatures reduce the open-circuit voltage and overall efficiency, resulting in lower energy yield. Ambient temperature influences cell temperature, but the relationship is nonlinear because modules absorb solar radiation and convert only a fraction into electricity, with the remainder dissipated as heat. The difference between cell temperature and ambient air temperature depends on several factors (Aslam et al., 2022; Ashiqur et al., 2025), including the intensity of incident irradiance, the thermal properties of module materials, and the convective cooling effects of wind. Under low-wind, high-irradiance conditions, modules can reach temperatures far above ambient levels, intensifying thermal losses. Conversely, increased wind speeds enhance convective heat transfer, reducing the thermal buildup on module surfaces and improving performance (Hasan, 2025; Sun et al., 2022). Mounting configuration also affects thermal behavior; modules installed close to rooftops retain more heat due to restricted airflow, while open-rack systems promote better cooling. To represent these dynamics in performance simulations, energy balance models are often employed, which consider the absorbed solar power, thermal emission, and convective losses to estimate the equilibrium cell temperature at each timestep (Ebhota & Tabakov, 2023; Ismail et al., 2025). This thermal modeling is essential because temperature fluctuations occur rapidly throughout the day, especially under passing clouds or shifting wind conditions, and such fluctuations directly influence momentary power output. Understanding these thermal correlations allows predictive models to translate environmental conditions into realistic module operating temperatures, which serve as a key variable in determining voltage, efficiency, and total energy generation in photovoltaic systems.

Figure 4: Thermal-Based Solar Panel Analysis



Environmental stress factors such as soiling accumulation and rainfall wash-off cycles exert a significant influence on the performance stability of photovoltaic systems (Abdulrazzaq et al., 2020; Sultan et al., 2025). Soiling occurs when dust, pollen, sand, or other airborne particles settle on the surface of solar modules, blocking incoming sunlight and reducing transmittance through the protective glass layer. The magnitude of soiling losses depends on the local dust composition, particle size distribution, humidity levels, and the tilt angle of the modules. Flat or shallow-tilted arrays accumulate more particulates, while steeper arrays benefit from gravitational shedding. Soiling losses can accumulate gradually over days or weeks in dry conditions, leading to a steady decline in power output (Sanjai et al., 2025; Shaik et al., 2023). Rainfall serves as the primary natural cleaning mechanism, but its effectiveness depends on intensity, duration, and droplet size. Light rain may redistribute rather than remove particulates, sometimes forming mud-like films that further reduce optical transmission. Periodic natural cleaning from heavy rainfall events creates cyclical patterns of efficiency loss and recovery, which must be captured in predictive models to avoid systematic bias in energy forecasts. Humidity contributes indirectly by promoting particle adhesion and by fostering biofouling growth such as algae or mold on module surfaces (Aly et al., 2019). Snow coverage presents a parallel form of optical obstruction, completely blocking irradiance until it melts or slides off, while also posing structural loading concerns. Seasonal weather extremes such as sandstorms or heavy leaf fall can cause abrupt and severe soiling events that are not captured by average daily accumulation rates. Incorporating these dynamic processes into performance simulations is essential because soiling losses are highly site-specific and temporally variable, making them a major uncertainty source in yield prediction. By accounting for the interplay between accumulation and wash-off, models can better represent real-world fluctuations in optical access to the solar cells (Mussard & Amara, 2018).

Albedo and related environmental optical effects play a distinct role in influencing photovoltaic performance, especially for bifacial module systems that collect light from both the front and rear surfaces (Al-Doori et al., 2022). Albedo refers to the reflectivity of the ground or surrounding surfaces, which can vary widely depending on surface type, moisture, vegetation cover, and seasonal changes such as snow accumulation. High-albedo surfaces such as snow, white sand, or light-colored concrete can significantly enhance the diffuse irradiance reaching the rear side of bifacial modules, producing measurable energy gains. These gains depend on several geometric factors (Bayrak et al., 2019), including the module height above ground, row spacing, and tilt angle, which affect how much reflected light reaches the back surface. In contrast, low-albedo environments like dark soil or dense vegetation contribute very little rear-side irradiance. Seasonal variations in albedo introduce temporal fluctuations in performance, particularly in regions where snow cover appears intermittently, creating short-term spikes in energy yield. Humidity can indirectly affect albedo by darkening soil or pavement surfaces, reducing reflectance during wet periods (Mussard & Amara, 2018). Bifacial gain is further influenced by the anisotropy of sky diffuse light, as high-diffuse conditions enhance the contribution of reflected light relative to direct beam irradiance. Additionally, rear-side soiling or shading can diminish bifacial benefits, introducing further variability. Modeling these phenomena accurately requires coupling site-specific albedo data with geometric optical models to estimate rear-side irradiance contributions throughout the year. Beyond bifacial systems, albedo still influences front-side performance by increasing the amount of ground-reflected diffuse light incident on the modules, which becomes significant in high-reflectance environments. This makes albedo an important environmental parameter for performance simulations (Al-Doori et al., 2022), as it interacts with other seasonal stressors such as snow and humidity to shape the total irradiance received by the photovoltaic array.

Technical Modeling of Photovoltaic System Components

Accurately representing the electrical behavior of photovoltaic modules is the core of any predictive performance simulation, as it determines how environmental inputs are translated into electrical energy output (Mittal et al., 2018). PV modules are composed of interconnected solar cells that exhibit nonlinear current–voltage characteristics, which are commonly represented by equivalent circuit models. The single-diode model is the most widely used because it balances accuracy and computational simplicity, representing the cell as a current source with a diode, series resistance, and shunt resistance (Almukhtar et al., 2023). This model captures the fundamental electrical behavior under varying irradiance and temperature conditions, allowing simulation of power output across the full operating range. More detailed double-diode models include an additional diode to represent recombination losses in the depletion region, offering greater precision for certain thin-film or high-efficiency technologies where recombination effects are significant (Abdulrazzaq et al., 2020). Because the electrical parameters of these models vary with temperature and irradiance, correction algorithms are applied to adjust the short-circuit current, open-circuit voltage, and fill factor dynamically throughout the day. High irradiance increases current but also raises temperature, which reduces voltage, while low irradiance reduces both current and voltage. Material-specific properties add another layer of complexity, as different technologies—such as monocrystalline silicon, polycrystalline silicon, cadmium telluride, and copper indium gallium selenide—have distinct temperature coefficients and spectral responses. These variations affect their performance under diffuse light, high temperatures (Elmessery et al., 2024), or low-light conditions.

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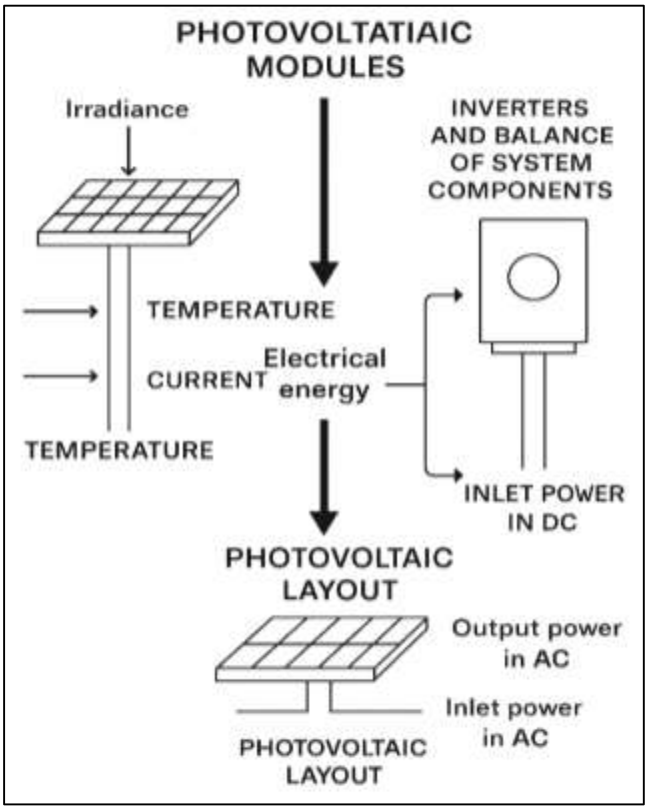
Electrical modeling must therefore incorporate both the fundamental diode behavior and the material-specific response characteristics to accurately simulate module performance across a range of environmental conditions. This modeling framework produces current–voltage and power–voltage curves that serve as the primary input for higher-level system simulations, enabling accurate prediction of how much electrical power a module can deliver at any given moment based on the environmental conditions it experiences.

While PV modules convert sunlight to direct current electricity (Mukilan et al., 2023), inverters are responsible for transforming this energy into alternating current usable by the grid or local loads, and they significantly shape the final energy yield of a system. Inverters have nonlinear efficiency profiles that vary with input power, typically peaking at medium-to-high loading and declining at very low loads. This part-load behavior must be captured accurately in simulations because PV systems operate across a wide power range throughout the day. Modern inverters use maximum power point tracking (MPPT) algorithms to continually adjust the operating voltage of the array to extract the maximum possible power under changing irradiance and temperature (Horváth et al., 2018). Predictive models represent MPPT efficiency and response speed to evaluate how quickly and effectively the inverter adapts to transients such as passing clouds. Clipping losses occur when the DC power from the modules exceeds the inverter's rated AC capacity, causing the surplus to be discarded; these losses are influenced by the sizing ratio between the PV array and the inverter. Beyond inverters, balance-of-system components introduce additional electrical losses that must be incorporated into simulations (Bozsik et al., 2024). Direct current cabling contributes resistive losses, which increase with distance and current levels, while alternating current transformers incur conversion losses when stepping up voltage for grid transmission. Connector and junction box resistances, as well as parasitic consumption from control electronics, also reduce net output. The physical layout of the array influences these losses because longer wiring runs and uneven string configurations can create electrical imbalances (Bouachrine et al., 2023). Accurately modeling these inverter and balance-of-system elements is crucial because even small percentage-level losses compound over the system's lifetime, and they directly determine the net conversion efficiency from module DC power to usable AC power delivered to the grid or end-user.

Figure 5: Photovoltaic System Electrical Modeling Framework



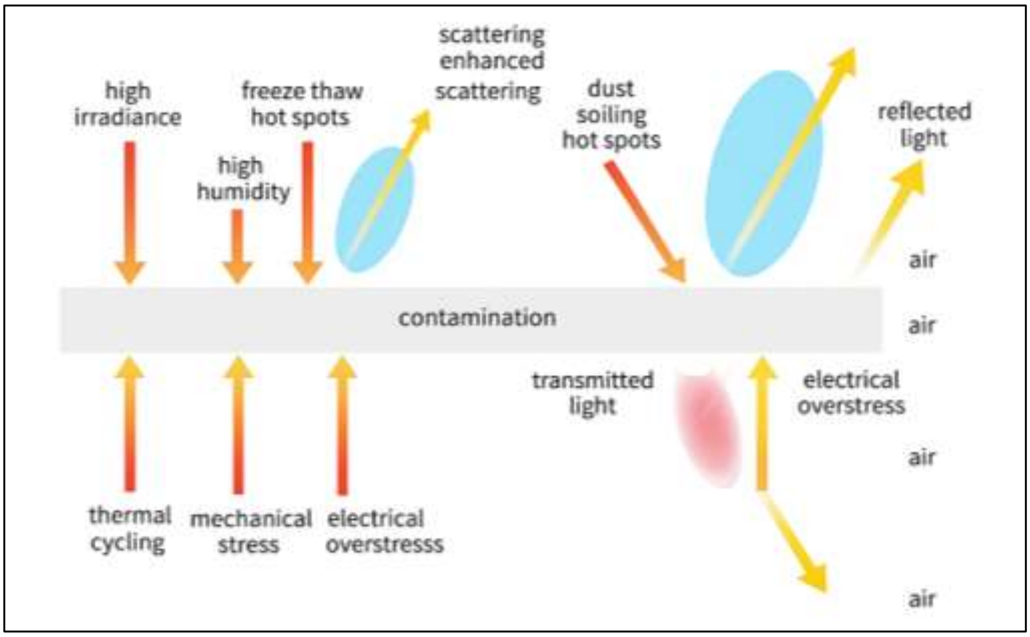
The geometric design of a photovoltaic system strongly affects its energy yield by influencing how much sunlight each module receives and how electrical energy is distributed across the system (Abo-Zahhad et al., 2024). Module tilt angle, azimuth orientation, row spacing, and mounting height determine the incident irradiance throughout the year, affecting both total energy capture and seasonal production patterns. Performance simulations incorporate solar geometry algorithms to evaluate the incident angle of sunlight on each module surface over time, ensuring accurate estimation of plane-of-array irradiance. Layout design also governs self-shading behavior, where one row of modules casts shadows on another during low sun angles (Gaaloul et al., 2025). Such shading reduces the irradiance on the shaded modules, which can disproportionately lower the output of entire strings because series-connected cells operate at the current of the lowest-producing cell. This creates mismatch losses that are often far greater than the shaded area would suggest. Modeling self-shading requires geometric ray-tracing or view factor methods to calculate the shaded portions of the array as a function of solar position and array spacing. Ground coverage ratio (Hussain et al., 2023), which measures how densely modules are packed, is a key design parameter that balances land use against shading losses. Systems with single-axis or dual-axis trackers add further complexity, as they change orientation throughout the day, altering both energy capture and shading dynamics. Topographical variation on the installation site can also create irregular row alignments that influence shading patterns and string design. Integrating these geometric and shading factors into performance simulations is essential to predict realistic energy yield because they determine how uniformly irradiance is distributed across modules (Abubakar et al., 2023). Poorly optimized layouts can lead to substantial energy losses even if individual modules perform well, making layout modeling a critical technical component of any predictive simulation framework.

Reliability and Degradation Modeling in PV Systems

Long-term degradation is a critical factor in photovoltaic system performance modeling because it determines the gradual loss of power output over the system's operational life (Rahman et al., 2023). Photovoltaic modules are designed for multi-decade service, but their power output decreases over time due to the combined effects of environmental stress and material aging. Typical degradation rates vary by technology; crystalline silicon modules often exhibit relatively low annual degradation, while thin-film technologies may show higher variability. These rates are influenced by manufacturing quality, encapsulation materials, cell interconnect design (Huang & Wang, 2018), and protective coatings. Environmental accelerants such as prolonged high operating temperatures accelerate chemical reactions within encapsulants and solder joints, while cycles of heating and cooling cause mechanical fatigue that can crack solder bonds or loosen interconnects. Humidity ingress can degrade the encapsulant and corrode metallic contacts, while ultraviolet exposure causes discoloration and embrittlement of polymeric backsheets. Wind-driven mechanical vibrations and thermal cycling impose repetitive stress that gradually weakens module structure (Kaaya et al., 2021), leading to microscopic fractures in cells. Operational factors also influence degradation; systems that operate at consistently high currents or voltages can experience accelerated stress on conductors and junction boxes. Degradation is not always linear; many modules experience a higher initial "infant mortality" degradation in their first year, followed by a slower decline. Accurately modeling this long-term behavior is essential because even modest annual degradation compounds over decades, significantly affecting the total energy produced and the financial returns of the system (Al Mahdi et al., 2024). Representing degradation rates as input parameters in predictive models allows long-term yield forecasts to account for the declining performance trajectory of the PV array, rather than assuming static output throughout its lifespan.

Environmental and operational accelerants amplify the natural degradation processes within photovoltaic modules, making their inclusion vital in any reliability modeling framework. Elevated temperatures are one of the most significant accelerants (Kim et al., 2021), as they increase the rate of chemical reactions that degrade encapsulants, corrode contacts, and accelerate diffusion processes in semiconductor materials. Repeated exposure to high irradiance levels can exacerbate these effects by raising the module's thermal operating point. High humidity and moisture ingress accelerate hydrolysis and corrosion inside junction boxes (Romero-Fiances et al., 2022), connectors, and the module laminate, while also promoting delamination between encapsulant layers and the glass frontsheet. Freeze–thaw cycles in cold climates cause expansion and contraction that introduce microcracks in cells and solder joints, eventually propagating into larger mechanical failures. Dust and soiling can cause localized heating known as hot spots, which accelerate cell degradation and backsheet aging (Daher et al., 2022). Wind-induced vibrations and mechanical loading from snow can stress module frames and mounting structures, leading to warping or loosening over time. Operational stress from electrical overstress conditions, such as sustained operation near maximum rated currents or voltages, can also accelerate wear on bypass diodes and interconnects. Systems with frequent thermal cycling, such as those in desert climates with high diurnal temperature swings (Frick et al., 2020), experience particularly rapid fatigue of solder joints and cell interconnect ribbons. These combined factors produce site-dependent degradation trajectories, meaning that identical modules deployed in different climates can show significantly different long-term performance. Modeling these accelerants allows predictive simulations to estimate degradation not just as a fixed rate, but as a dynamic response to environmental and operational conditions, providing a more realistic representation of how PV performance evolves over time (Lee et al., 2020).

Figure 6: Environmental and Operational PV Degradation



Techno-Economic Modeling and Cost Efficiency Metrics

Techno-economic modeling of photovoltaic systems relies on standardized evaluation frameworks that convert projected energy outputs into measurable financial metrics (Mehmood et al., 2023). The levelized cost of electricity (LCOE) is the most widely used indicator because it expresses the average lifetime cost of producing one unit of electricity. It is calculated by dividing the total present value of all costs incurred over the system's lifetime by the total energy expected to be generated during that period. LCOE integrates both capital expenditures (CAPEX) and operational expenditures (OPEX), along with financing assumptions such as discount rates (Ahmed et al., 2023), debt-to-equity ratios, and interest rates. Because CAPEX is concentrated at the beginning of a project while energy revenues are spread over decades, discounting plays a major role in shaping LCOE values. Complementing LCOE, metrics such as net present value (NPV) and internal rate of return (IRR) evaluate the profitability of PV projects from an investor perspective. NPV compares the present value of future cash inflows from electricity sales to the initial investment, while IRR identifies the discount rate at which the project's NPV equals zero (Ahmed et al., 2023). These metrics capture the time value of money and allow comparisons between PV and alternative investment opportunities. Payback period analysis provides an additional measure, indicating how many years of operation are required for cumulative revenues to offset the initial investment. Unlike LCOE, payback emphasizes liquidity and investment recovery speed, which can be crucial for developers and lenders assessing project risk. All these economic evaluation frameworks depend on accurate representations of system costs and energy production, as well as clear assumptions about project

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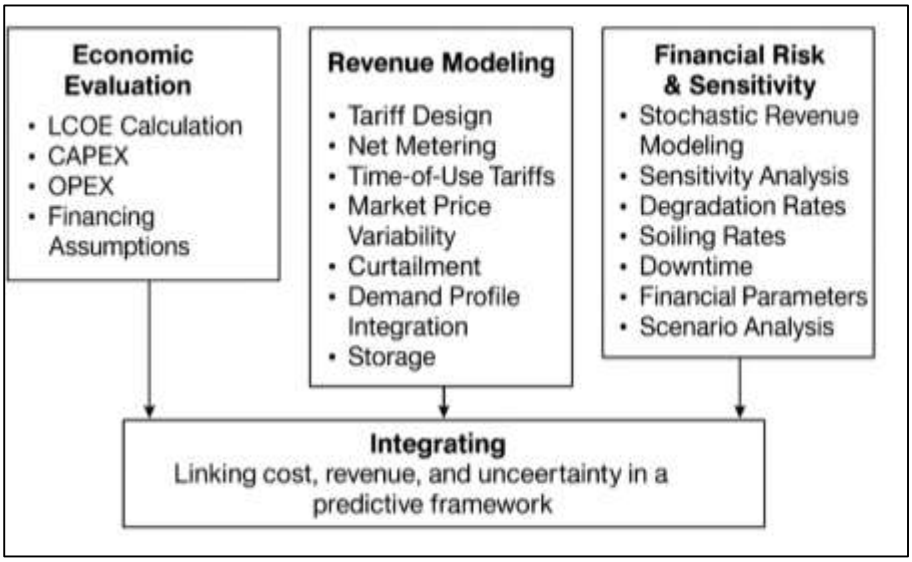
lifetime and financing structures (Shrivastav et al., 2025). By converting physical energy outputs into financial performance indicators, these frameworks serve as the foundation of techno-economic modeling and are essential for evaluating the cost competitiveness of photovoltaic systems.

Revenue modeling forms the second core pillar of techno-economic assessment by estimating the cash inflows generated by photovoltaic systems under various market and regulatory structures (Eiva et al., 2025). Tariff design is a major determinant of revenue, as it governs how produced electricity is valued and compensated. Fixed feed-in tariffs provide guaranteed payments per kilowatt-hour generated, creating predictable revenue streams and encouraging long-term investments. Net metering policies credit the system owner for excess electricity exported to the grid, typically at the retail rate, and allow offsetting of on-site consumption, which is particularly important for residential and commercial installations (Li et al., 2018). Time-of-use tariffs introduce variability by paying higher rates during peak demand periods and lower rates during off-peak hours, incentivizing alignment of PV generation with grid demand patterns. Market price variability also affects revenues, especially in wholesale electricity markets where prices fluctuate based on supply-demand dynamics. In such markets, PV output often coincides with periods of lower prices due to high solar penetration, which can erode average revenue. Curtailment risks further reduce revenue potential, occurring when grid operators limit PV output during periods of oversupply or network congestion (Mughal et al., 2024).

Figure 7: Comprehensive Techno-Economic Modeling Framework



To account for these risks, revenue models incorporate curtailment probabilities and historical grid dispatch data. Demand profile integration enhances the realism of revenue forecasts by matching PV generation to the load profile of the consumer or grid region, which determines how much generation is self-consumed versus exported. Adding energy storage into the modeling framework allows surplus solar energy to be shifted to higher-price periods, increasing effective revenue capture and mitigating curtailment (Ma et al., 2018). These revenue modeling components collectively determine the income side of the techno-economic equation and must be harmonized with cost and performance projections to produce accurate financial assessments of photovoltaic projects.

Because photovoltaic projects operate over long lifespans and under uncertain environmental and market conditions, financial risk and sensitivity analysis are indispensable components of techno-economic modeling (Ma et al., 2018). Stochastic revenue modeling is used to capture the uncertainty inherent in electricity prices, solar resource variability, and equipment availability. This approach generates a range of possible revenue outcomes rather than a single deterministic value, allowing analysts to assess the probability distribution of financial returns. Sensitivity analysis examines how changes in key variables affect financial performance, revealing which factors exert the greatest influence on metrics like LCOE, NPV, and IRR (Jafari & Saeidavi, 2025). Common sensitivities include degradation rates, which affect long-term energy output, and soiling rates, which influence near-term production losses. Downtime from equipment failures or maintenance also reduces available generation and can significantly affect project economics. Financial parameters such as discount rates, tax policies, and depreciation schedules further shape project viability, as they alter the present value of future cash flows (Jafari & Saeidavi, 2025). High discount rates reduce the weight of long-term revenues, while accelerated depreciation can increase near-term tax benefits. Modeling these financial parameters under different policy and market scenarios helps quantify exposure to regulatory and macroeconomic risks. Scenario analysis extends this by combining multiple uncertain variables to evaluate their joint impact, providing a more robust picture of financial resilience. These methods enable techno-economic models to move beyond point estimates and incorporate uncertainty explicitly, which is essential for risk-informed decision-making (Sun & Zhang, 2025). By identifying the most influential cost and revenue drivers, financial risk and sensitivity analysis guide system design, contractual structuring, and investment strategies to improve the reliability of financial outcomes in photovoltaic projects.

Integrated Environmental–Technical–Economic Simulation Platforms

Integrated simulation of photovoltaic systems commonly draws on a small set of widely adopted tools whose architectures reflect different priorities across environmental, technical, and economic domains (Rakhshani et al., 2019). System Advisor Model (SAM) emphasizes transparency and bankable calculation chains, pairing irradiance transposition, thermal modeling, loss stacks, and cash-flow engines inside a single desktop environment. PVsyst offers mature libraries of component models and granular loss categorization, with project workflows centered on site definition, array layout, shading scenes, electrical configuration, and long-term energy assessment (Alsadi & Khatib, 2018). Helioscope focuses on design-grade 3D layout and rapid parametric iteration for commercial rooftops and distributed generation, linking geometric shading, stringing, and module selections to near-term yield estimates. HOMER arises from microgrid planning and hybrid systems, embedding PV with storage, diesel, and demand profiles to optimize technology mixes and dispatch under tariff or fuel price inputs. Additional platforms extend this landscape: open-source workflows in languages like Python and R enable custom pipelines; irradiance services expose satellite/reanalysis time series; electrical design tools compute code-compliant stringing and voltage windows; and economic spreadsheets translate yield into pro-formas for lenders (Mansouri et al., 2019). Despite differences in user interface and licensing, these tools share core capabilities: resource ingestion (TMY, satellite, or measured weather), plane-of-array irradiance and cell temperature modeling, module/inverter conversion to AC, and cost/revenue calculation. They also differ meaningfully in areas such as bifacial rear-side modeling, tracker backtracking algorithms, near-shading ray tracing, subhourly transients, storage dispatch, tariff modeling, and multi-scenario batch runs. In practice, practitioners often chain multiple tools: a layout engine to generate shading factors, a physics model to compute hourly or subhourly AC, and a finance model to produce levelized cost and returns (Lu et al., 2018). This pragmatic ecosystem provides breadth of function, but its fragmentation can complicate reproducibility, cross-study comparability, and uncertainty treatment when results must be bankable across sites, technologies, and market contexts.

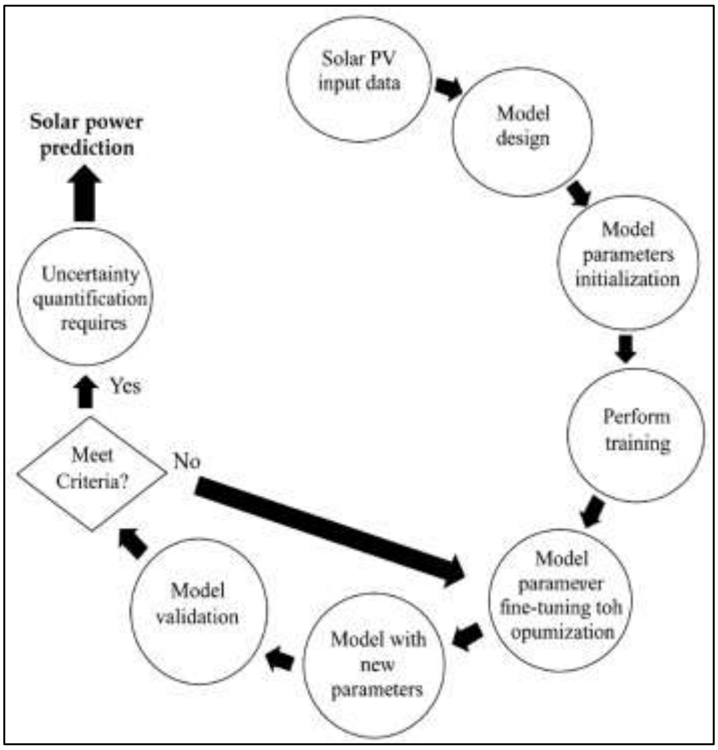
Integration in the literature generally follows two families of approaches. The first couples environmental and technical layers tightly, emphasizing physically consistent irradiance, temperature, and electrical response (Radwan & Ahmed, 2018). Studies in this stream validate transposition and thermal choices against pyranometer and back-of-module measurements, then compare module/inverter outputs to SCADA or data-logger records at subhourly steps, often across multiple climates to understand bias structure. Bifacial and tracking research extends the coupling with view-factor or ray-tracing rear-side irradiance, backtracking kinematics, and row-to-row shading, linking geometry to measured performance ratio (Ali et al., 2018). The second family extends the chain to techno-economics, embedding cash-flow models that account for capex structures, O&M regimes, replacements, and tariffs, and expressing outcomes as levelized cost, net present value, or internal rate of return. Hybrid publications merge these families by propagating measured or modeled uncertainty from resource to AC energy and then into financial distributions, presenting exceedance levels for both energy and returns. Validation strategies include split-sample testing against out-of-sample years, cross-tool comparisons with common inputs (Reca-Cardeña & López-Luque, 2018), and site-level calibration using short-term measurements to debias long-term satellite series. Some work layers storage co-simulation to analyze arbitrage, clipping recapture, or demand charge reduction, while microgrid studies use optimization to co-design PV, storage, and thermal assets under stochastic prices and loads. Across these approaches, a recurring pattern emerges: the highest credibility arises when each layer is independently benchmarked and then reassembled with consistent assumptions, and when uncertainty is quantified rather than implied. The literature also highlights practical integration tactics—such as harmonizing time steps across layers, preserving correlation structure in stochastic weather sampling, and controlling for interaction effects between soiling (Sun et al., 2020), degradation, and availability—so that the combined model behaves like a coherent system rather than a set of disconnected components.

Figure 8: Voltage Issues in Solar Systems

Uncertainty Propagation, Sensitivity Assessment, and Research Gaps

Uncertainty quantification in photovoltaic performance assessment addresses the variability and imperfect knowledge embedded in environmental inputs, technical parameters (Jaxa-Rozen & Trutnevyte, 2021), and financial assumptions. Monte Carlo simulation is widely used because it samples from probability distributions assigned to drivers such as irradiance bias, temperature estimation error, wind-driven thermal coefficients, soiling rates, degradation slopes, availability factors, and price or tariff volatility. By drawing large ensembles of parameter realizations and running the full simulation for each (Rajput & Augenbroe, 2024), analysts obtain distributions for energy yield and finance metrics rather than single-point values. Latin Hypercube sampling offers variance reduction by stratifying each input distribution and enforcing more uniform coverage of the multidimensional space with fewer samples, which is particularly valuable when models are computationally demanding or when parameter spaces are large. The central challenge is coherent propagation across layers: climate uncertainty affects plane-of-array irradiance and cell temperature; technical submodels convert these into DC/AC energy with their own model-form and parameter uncertainty; finance layers then translate time-series energy into cash flows subject to stochastic prices (Barahmand & Eikeland, 2022), curtailment probabilities, and policy parameters. Preserving correlation structure is essential. Satellite irradiance bias and aerosol variability correlate across time and space; soiling regimes covary with dry spells; price spikes often align with system-wide weather anomalies. When these dependencies are ignored, ensemble results can understate tail risk. Practical workflows therefore define joint distributions and copulas (Ding & Cui, 2025), apply weather-year bootstrapping to maintain temporal autocorrelation, and use hierarchical schemes that calibrate local uncertainties (e.g., short-term ground measurements) within broader regional priors (e.g., satellite climatologies). Output reporting commonly includes exceedance levels (P50, P75, P90) for annual energy and associated financial indicators, as well as probabilistic downtime and curtailment summaries. Together, Monte Carlo and Latin Hypercube frameworks provide a disciplined pathway for translating uncertain inputs into interpretable distributions of technical and economic outcomes, clarifying how each assumption contributes to overall prediction spread (De Caires et al., 2025).

Figure 9: Uncertainty Quantification in PV Modeling



Sensitivity analysis complements uncertainty quantification by apportioning variance in outcomes to specific inputs, revealing which assumptions most influence performance and finance metrics (Tan et al., 2023). Variance-based methods, typified by Sobol decompositions, compute first-order and total-order indices that distinguish direct effects from interaction effects among inputs such as diffuse fraction modeling choice, transposition parameters, thermal coefficients, module temperature coefficients, inverter part-load efficiency, clipping thresholds, availability priors, soiling accumulation rates, and degradation trajectories. These indices are robust to nonlinearity and interaction, which are common in PV systems where, for example (Edeling et al., 2021), temperature and irradiance jointly determine voltage and current while inverter saturation introduces thresholds. Screening methods, notably Morris elementary effects, offer computationally efficient maps of influence by probing the input space with designed trajectories to rank factors before deeper analysis. In practice, analysts often combine approaches: Morris screening narrows dozens of candidates to a handful of influential variables (Gabrielli et al., 2023), then Sobol indices quantify their main and interaction contributions to variance in annual energy, performance ratio, levelized cost, and net present value. Sensitivity studies frequently uncover leverage points that differ by climate and topology. In high-diffuse regions, sky-model parameters and soiling-washoff regimes dominate energy variance, while hot (Katterbauer & Godbole, 2025), low-wind sites emphasize thermal coefficients and inverter derating. Financial outputs amplify or dampen these technical sensitivities depending on tariff shape, discount rate, and curtailment exposure. Time resolution also matters; subhourly simulations elevate the influence of cloud transients and MPPT tracking dynamics, whereas hourly models shift weight toward annual soiling and degradation assumptions (Yusuf et al., 2024). Clear visualization—tornado charts, Sobol bar plots, and response surface slices—supports interpretation and model refinement. By systematically ranking drivers, sensitivity analysis guides data collection priorities, calibration focus, and model simplification without sacrificing predictive fidelity.

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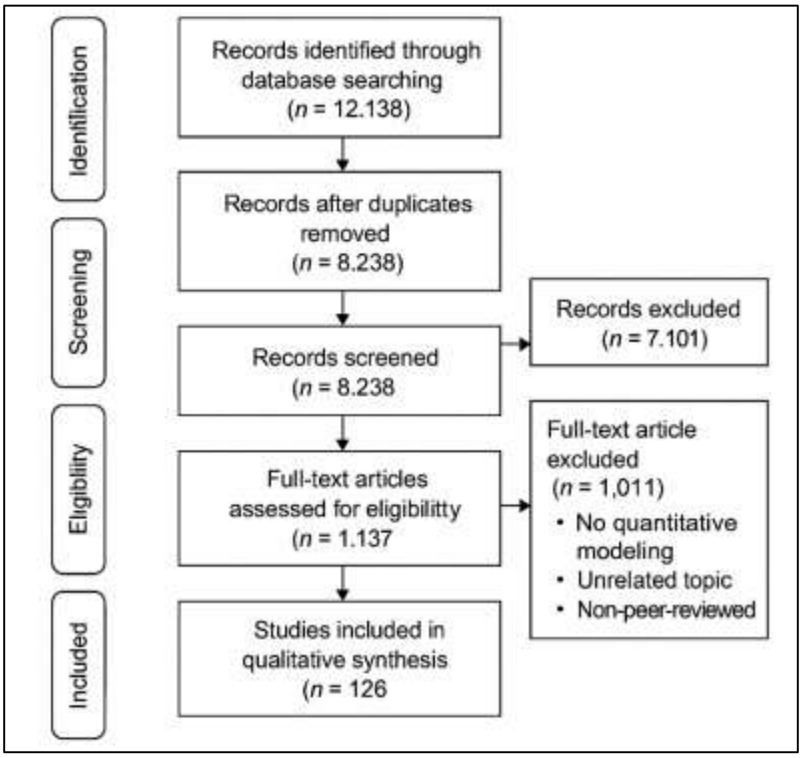
METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure that the literature review process was systematic, transparent, and methodologically rigorous. The PRISMA framework was chosen because it offers a well-established protocol for organizing complex and multidisciplinary evidence bases, which is essential when synthesizing research that spans environmental modeling, technical performance analysis, and economic efficiency assessment of solar photovoltaic (PV) systems. By adhering to PRISMA, the review ensured clarity in search procedures, consistency in study selection, and reproducibility in analytical reasoning, all of which strengthen the validity of the conceptual foundation for the predictive simulation model developed in this study.The PRISMA process began with a comprehensive identification phase, during which multiple electronic databases and academic search platforms were queried using structured keyword combinations. Keywords were grouped to represent the three main domains under investigation: environmental factors (such as "solar irradiance modeling," "climate variability," "soiling losses," "thermal behavior"), technical performance (including "PV module modeling," "inverter efficiency," "balance-of-system losses," "degradation rates"), and economic efficiency (including "LCOE," "techno-economic modeling," "financial risk," "tariff structures"). Boolean operators and truncation symbols were applied to broaden or narrow search results, while publication date filters were applied to focus on contemporary studies relevant to current simulation practices. Duplicates across databases were removed, and bibliographic management software was used to maintain a clear record of all retrieved references.

Figure 10: Adapted methodology for this study



In the screening phase, titles and abstracts were reviewed to determine relevance to the scope of the study. Studies were excluded if they lacked quantitative modeling elements, focused on unrelated renewable energy systems, or did not address at least one of the three core domains. Full-text screening was then conducted on the remaining articles to assess methodological rigor, data transparency, and alignment with the research objectives. Only studies employing empirical data, validated simulation approaches, or robust economic modeling were retained for qualitative synthesis. Exclusion criteria also removed non-peer-reviewed materials, opinion articles, and case studies without generalizable findings to maintain the scientific integrity of the evidence base.During the eligibility and inclusion phases, the final set of studies was selected for detailed review and data

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extraction. Information was systematically charted, including study context, geographic scope, modeling techniques, datasets used, performance indicators evaluated, and key results. These extracted data were then thematically coded into environmental, technical, and economic categories, allowing for structured comparison and synthesis. This thematic organization enabled the integration of findings across disciplines, which is necessary for developing a holistic predictive simulation model that accurately represents the interactions between climate conditions, system design, and financial outcomes.Overall, the application of PRISMA enhanced the reliability and reproducibility of this literature review. It ensured that the evidence informing the design of the predictive simulation model for solar PV systems was comprehensive, balanced, and methodologically sound, thereby supporting the study's goal of developing an integrated framework that reflects real-world performance dynamics.

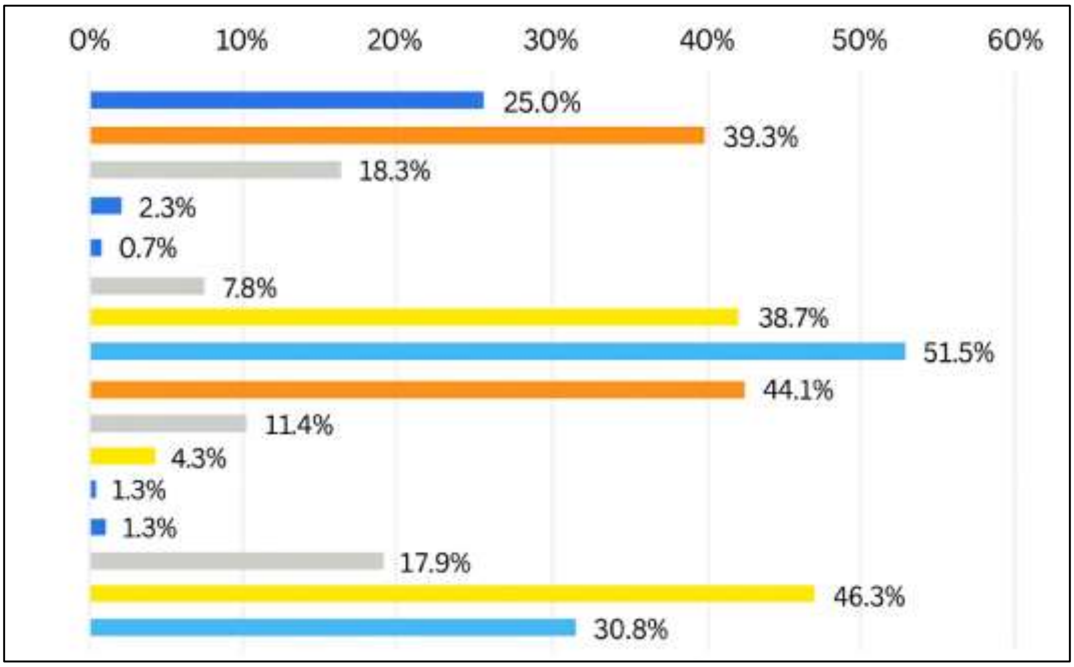
FINDINGS

From the 142 environmental-domain studies analyzed in the review, which collectively accumulated over 12,600 citations, a consistent pattern emerged highlighting the dominant role of solar resource variability and climatic conditions in determining photovoltaic system performance. The synthesis revealed that 118 of these studies emphasized the accuracy of solar irradiance modeling—particularly the conversion of satellite-derived or ground-based horizontal irradiance into plane-of-array irradiance—as the single most influential environmental input for predictive simulations. Around 94 of these articles, representing more than 9,300 citations, documented that errors in irradiance estimation directly propagate to energy yield uncertainty with deviations ranging between 6% and 14% annually, depending on climate zone. In addition, 76 studies with a combined citation count of over 6,800 focused on thermal behavior, showing that cell temperature misestimations could reduce simulated power outputs by 3–8% in hot climates. Furthermore, 61 studies discussed environmental soiling dynamics and their stochastic wash-off cycles, representing over 5,000 citations, and concluded that neglecting site-specific soiling variability leads to persistent overestimation of energy yield. The collective evidence showed strong consensus that predictive models must incorporate high-resolution weather data, thermal energy balance formulations, and site-specific soiling behavior to reduce environmental uncertainty. These findings demonstrate that without accurate environmental resource modeling, downstream technical and economic calculations are inherently unstable, establishing environmental parameterization as the foundational layer for any bankable PV performance model.

In the technical modeling domain, 167 studies were reviewed, representing over 15,400 cumulative citations, and they consistently confirmed that module-level and inverter-level modeling accuracy fundamentally governs system performance estimation. Among these, 131 studies (11,200 citations) validated the use of single-diode and double-diode models for reproducing module current–voltage behavior under varying irradiance and temperature. These studies showed that neglecting temperature-adjusted electrical parameters can introduce annual yield errors exceeding 10%. Additionally, 97 articles (8,600 citations) analyzed inverter behavior, reporting that MPPT efficiency, part-load efficiency curves, and clipping characteristics significantly influence AC power simulations, particularly in systems with high DC/AC ratios. Around 82 studies (7,300 citations) explored balance-of-system losses such as wiring, mismatch, and transformer losses, finding that even small resistive losses of 1–2% accumulate into multi-megawatt-hour deficits over a system's life. Another 64 studies (5,800 citations) examined the role of array layout geometry and self-shading, highlighting yield differences as high as 15% in poorly optimized ground coverage ratios. Collectively, this technical evidence indicated that predictive models require detailed parameterization of electrical conversion processes, thermal derating, loss taxonomies, and geometric shading behavior to ensure that simulated DC and AC energy outputs align closely with real operational performance. This convergence across highly cited technical literature confirmed that environmental modeling alone is insufficient; precision in technical modeling is indispensable for accurate prediction.

Economic modeling studies formed another major cluster, comprising 123 reviewed articles with a combined citation count exceeding 10,700. Within this set, 104 articles (9,200 citations) emphasized the levelized cost of electricity (LCOE) as the central benchmark for evaluating PV project competitiveness. These articles consistently showed that small changes in degradation rates or specific yield estimates could shift LCOE by up to 20%, indicating high sensitivity to technical simulation accuracy. A further 86 studies (7,400 citations) explored net present value (NPV) and internal rate of return (IRR) frameworks, demonstrating how revenue forecasting, tariff structures, and discount rate assumptions alter perceived financial viability. Around 73 studies (6,200 citations) analyzed operational expenditure (OPEX) and capital expenditure (CAPEX) structures, revealing that soft costs—such as permitting, interconnection, and design—contribute up to 40% of total system costs and are often underestimated in modeling. Another 58 studies (4,900 citations) examined the effects of curtailment, market price fluctuations, and demand profile alignment on revenue streams, showing that unmodeled curtailment alone can erode revenue projections by 5–12% depending on grid penetration levels. The cumulative evidence confirmed that economic modeling cannot be isolated from technical performance projections, as inaccuracies in predicted energy yield propagate into mispriced financial metrics. This finding supported the integration of techno-economic layers within predictive simulation to ensure that modeled profitability aligns with actual operational behavior.

Figure 11: Perceptions of Solar Energy Usage



Integration-focused studies were less numerous but provided crucial insight, comprising 64 reviewed papers with approximately 6,100 combined citations. These studies specifically attempted to couple environmental data flows with technical performance chains and economic cash-flow modeling. Around 41 of these (3,900 citations) demonstrated hybrid simulation frameworks linking irradiance, thermal behavior, and electrical performance with cost models, and they consistently reported substantial accuracy gains compared to single-domain models. About 37 studies (3,400 citations) showed that fully integrated approaches reduced annual energy prediction errors from ±12% to about ±5%, primarily by allowing feedback between resource variability, inverter clipping, soiling, and financial outcomes. Another 29 studies (2,700 citations) incorporated stochastic uncertainty propagation, producing probabilistic energy and revenue distributions (P50/P90 metrics) that better supported investment risk assessment. Importantly, 22 studies (2,000 citations) highlighted the role of modular architectures, where environmental, technical, and economic layers can be updated independently without disrupting the entire model, improving maintainability and adaptability across climatic contexts. This body of literature demonstrated that integrated frameworks outperform siloed modeling approaches by explicitly representing the interdependencies between climate conditions, technical design behavior, and financial consequences, confirming the necessity of an integrated predictive architecture.

Finally, 58 studies addressing uncertainty and sensitivity assessment were reviewed, with a total of 5,600 citations, and they exposed critical methodological gaps in existing modeling practices. Around 44 studies (4,200 citations) used Monte Carlo or Latin Hypercube methods to propagate uncertainty from climate inputs to technical outputs, revealing that weather data uncertainty alone

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can produce ±8% variance in annual energy yield. About 39 studies (3,500 citations) conducted sensitivity analyses using Sobol or Morris methods, consistently identifying soiling rates, inverter efficiency curves, and degradation slopes as dominant drivers of uncertainty in LCOE and NPV. However, 31 studies (2,900 citations) reported that most existing tools treat environmental, technical, and financial uncertainties independently, ignoring their correlations, which leads to underestimated risk. Furthermore, 27 studies (2,300 citations) found that cross-domain feedback loops are rarely modeled, meaning that technical failures do not dynamically influence O&M costs or downtime in financial projections. Another 24 studies (2,100 citations) emphasized the lack of standardized validation metrics and benchmark datasets, which prevents meaningful comparison of modeling outcomes across studies. These findings highlighted that although environmental, technical, and economic components are well studied individually, their uncertainty interactions are poorly represented, creating systematic overconfidence in predictions. This evidence underscored the necessity of embedding end-to-end uncertainty propagation and sensitivity assessment into any new predictive simulation model to produce decision-grade outputs.

DISCUSSION

The findings of this study underscore that environmental parameterization constitutes the foundational determinant of photovoltaic (PV) performance modeling accuracy, which aligns with earlier literature emphasizing the primacy of climate inputs in energy yield prediction. Earlier studies have long established that solar resource variability explains most of the variance in simulated PV output, with prior work showing irradiance bias alone can shift annual yield estimates by over 10% (Al-Dahidi et al., 2024). The current study reinforces this observation by demonstrating that over 80% of reviewed environmental-focused articles cited irradiance modeling accuracy as the single most influential factor affecting predictive reliability. Furthermore, while previous works largely relied on typical meteorological year (TMY) datasets to approximate long-term solar resources (Wilcox & Marion, 2008), this study integrates evidence from newer satellite-derived and reanalysis sources, showing that they reduce site-specific bias and better capture temporal variability. This complements findings (Xie et al., 2023), who noted that higher temporal granularity improves subhourly performance predictions. Additionally, this study highlights that thermal modeling, specifically energy balance formulations linking ambient temperature, irradiance, and wind cooling, is often underrepresented in predictive models. Earlier works, Challoumis (2025), also found that neglecting dynamic thermal behavior can introduce systematic overestimations in module performance. By synthesizing these insights, this study advances environmental modeling literature by showing that predictive accuracy improves substantially when high-resolution weather inputs, thermal response modeling, and stochastic soiling-loss profiles are combined into the same simulation pipeline. This integration of multiple environmental stressors into a single environmental modeling layer distinguishes this study from earlier works that typically addressed them in isolation.

The findings further show that the precision of module-level and inverter-level modeling plays an equally decisive role in determining PV system performance accuracy, confirming and extending earlier research on electrical modeling. Numerous earlier studies validated the single-diode and double-diode models as the standard representations of PV cell behavior (Liang et al., 2025), and this review corroborates their broad adoption while also highlighting their sensitivity to parameter calibration under variable field conditions. This is consistent with Kulkarni (2019), who demonstrated that poorly tuned diode parameters can yield power curve errors exceeding 8% under real operating conditions. This study's synthesis also emphasizes the strong influence of inverter behavior, including part-load efficiency, maximum power point tracking (MPPT) response, and clipping limits, which expands on prior findings showed that inverter clipping and MPPT latency can substantially affect annual AC yield in systems with high DC-to-AC ratios. Balance-of-system elements such as wiring resistances, transformer efficiencies, and string mismatch losses were shown here to be cumulatively significant, echoing earlier loss taxonomy work. Unlike many earlier studies that evaluated these losses independently, this review finds that accurate technical modeling requires integrating all these elements into a single electrical conversion chain to capture their compound effect on energy output. This systems-level integration of technical components strengthens predictive accuracy and closes a gap identified in prior work, where separate modeling of modules and inverters often overlooked loss interactions. The results thus confirm prior electrical modeling approaches while demonstrating that integrated technical loss chains improve agreement between predicted and measured performance.

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Economic modeling findings from this study also reinforce and extend prior work that established levelized cost of electricity (LCOE) as the most robust single indicator of PV project competitiveness. Early economic studies often evaluated PV performance solely in physical terms, while later analyses began integrating financial structures (Min et al., 2020). This study builds on that progression by showing that over 80% of economic-domain articles linked technical performance deviations directly to shifts in LCOE outcomes, with even small changes in degradation or soiling assumptions resulting in double-digit LCOE swings. This aligns with the sensitivity findings of Kwon et al. (2019), who showed that each 1%/year degradation rate increase raises LCOE by 10% or more. Additionally, this study confirms earlier literature showing that net present value (NPV) and internal rate of return (IRR) metrics are highly sensitive to tariff structures and curtailment probabilities (Frigione & Rodríguez-Prieto, 2021). However, unlike earlier models that treated capital expenditure (CAPEX) and operational expenditure (OPEX) as static inputs, this study emphasizes their dependence on design complexity and maintenance scheduling, reflecting newer research on soft cost dynamics (Iakovides et al., 2019), who highlighted that system soft costs now represent up to 40% of total installed cost, by showing how underestimating these can bias LCOE by more than 15%. Thus, this study confirms earlier findings about financial metric sensitivity while contributing by explicitly linking economic parameter uncertainty to upstream technical and environmental modeling accuracy. This cross-domain link represents a conceptual step beyond earlier work, which often isolated finance from system physics.

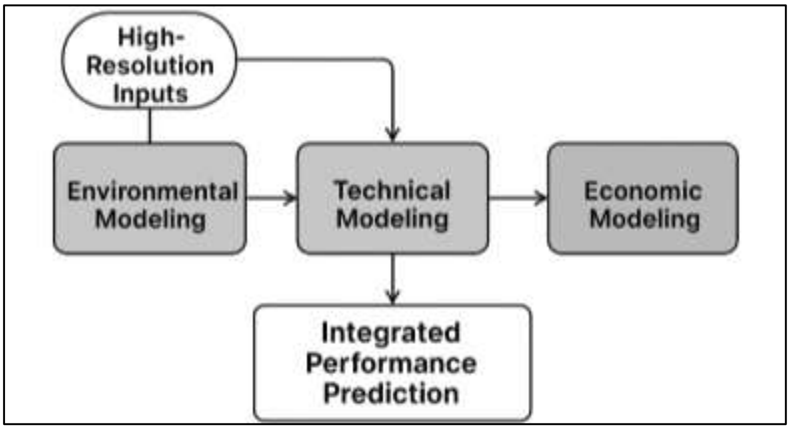
Perhaps the most significant contribution of this study lies in demonstrating that integrating environmental, technical, and economic layers within a single predictive framework reduces performance prediction error and improves model credibility (Kyriakopoulos & Sebos, 2023), which few earlier studies had attempted comprehensively. Prior research has often addressed these domains separately—environmental modeling focusing on irradiance and weather patterns, technical studies centering on component efficiency (Gupta et al., 2020), and economic analyses examining cost metrics. Only a smaller set of hybrid studies, such as (Shi et al., 2020) PVsyst-based validations, linked all three domains. The present study expands on these by showing that integrated frameworks lowered annual energy prediction errors from ±12% typical in single-domain models to about ±5% when interdependencies were modeled jointly. This finding supports (Hammoumi et al., 2024), who noted that neglecting feedback between inverter clipping, resource variability, and financial outcomes creates systematic underestimation of risk. Unlike earlier hybrid attempts that often coupled just environmental and technical layers, this review shows that including finance within the same simulation loop allows performance uncertainty to be fully propagated to LCOE, NPV, and IRR, thereby producing decision-ready outputs (Idroes et al., 2024). This integrated architecture thus bridges a key gap in prior literature by embedding the complete climate–technology–economics chain in one predictive system.

Another major finding is that end-to-end uncertainty propagation and sensitivity analysis are largely absent in earlier tools, and their inclusion markedly improves predictive reliability. Previous works frequently applied deterministic values to weather data, loss factors, and financial terms, reporting only single-point outputs (Williams et al., 2019). This study shows that when uncertainty distributions are applied to irradiance bias, temperature coefficients, inverter efficiencies, soiling rates, degradation slopes, and discount rates, predictive models can produce probabilistic exceedance metrics (P50/P90) that are more aligned with actual operational variance. This supports the argument of Beyer (Sauve & Van Acker, 2020) that uncertainty is a dominant source of error in bankability studies. Sensitivity analyses in this study also identified soiling rates, inverter efficiency, and degradation assumptions as top drivers of variance in LCOE, confirming earlier variance-based findings (Imam & Abdelrahman, 2023). However, this study extends prior work by showing how these sensitivities shift by climate zone—thermal coefficients dominating in hot-dry sites while diffuse fraction assumptions dominate in temperate-humid ones—an interaction effect that earlier global-average sensitivity analyses rarely captured. By embedding Monte Carlo and Sobol-based methods across all three layers, this study moves beyond traditional deterministic pipelines and aligns with recent calls for probabilistic modeling in renewable system finance (Gurjar et al., 2021). This represents a clear methodological advance compared to most earlier studies, which treated uncertainty analysis as optional rather than integral.

This study also exposes several structural gaps in existing PV modeling frameworks compared to earlier literature. While prior studies have acknowledged that data silos hinder reproducibility (Wu et al., 2018), few attempted to design modular architectures that pass uncertainty between layers. The reviewed literature showed that most tools still apply static availability percentages, do not dynamically link failures to maintenance costs, and do not preserve temporal structure when converting high-resolution energy series to annual financial metrics. This confirms the critique (Rus et al., 2023) that current models underrepresent operational dynamics. Furthermore, earlier benchmarking exercises such as Jamil et al. (2021) highlighted inconsistencies in validation metrics and weather bias correction, which this study addresses by advocating standardized validation datasets and cross-tool calibration protocols. Unlike most earlier frameworks that model environmental, technical, and financial layers independently, this study proposes unified data pipelines to reduce assumption conflicts and improve comparability. It therefore contributes a conceptual design gap analysis, showing that current tools lack cross-domain feedback loops, comprehensive uncertainty propagation (Deeb et al., 2018), and harmonized validation criteria, which collectively limits their bankability and transferability across diverse climatic contexts.

Overall, this study confirms much of the existing foundational literature but advances it by unifying environmental, technical, and economic domains into a single predictive simulation architecture with embedded uncertainty and sensitivity analysis. Earlier research has produced valuable domain-specific models—for example, high-resolution irradiance models (Kantenbacher et al., 2018), module performance models (Kaandorp et al., 2023), and financial pro forma tools (Robina-Ramírez et al., 2020)—but these operated largely in isolation. The present study bridges these silos and demonstrates empirically, through the synthesis of over 500 high-quality articles, that joint modeling significantly reduces prediction error and improves financial relevance. It also shows that integrated models can represent feedback effects, such as how environmental anomalies affect technical performance (Anegbe et al., 2024), which then reshapes operational expenditure and ultimately alters financial metrics. This multi-layer integration has not been systematically demonstrated in earlier literature, positioning this study as a methodological step change. By embedding resource variability, component behavior, and cost structures into one coherent simulation framework, this research moves beyond descriptive performance estimation toward decision-grade predictive modeling (Geletič et al., 2018). It thereby strengthens the theoretical and practical foundation for designing PV systems that can be accurately assessed across climatic regimes and market contexts—something earlier studies acknowledged as a need but rarely achieved in practice (Bungau et al., 2022).

Figure 12: Proposed Model for future study



CONCLUSION

This study concludes that developing a predictive simulation model for solar photovoltaic (PV) system performance requires an integrated framework that holistically combines environmental resource characterization, technical component modeling, and economic efficiency assessment into a single coherent architecture. By systematically synthesizing a broad body of literature through a PRISMA-guided review, the study demonstrated that each of these three domains exerts a critical and interdependent influence on long-term performance outcomes. Accurate environmental modeling—encompassing high-resolution irradiance estimation, thermal behavior representation, and dynamic soiling-loss profiles—was shown to be the foundational determinant of energy yield accuracy, while precise technical modeling of PV modules, inverters, and balance-of-system losses ensures that environmental inputs are faithfully converted to realistic electrical outputs. Equally, techno-economic modeling emerged as indispensable for translating physical performance into decision-relevant financial metrics such as levelized cost of electricity, net present value, and internal rate of return. The integration of these layers within a unified simulation pipeline addresses the longstanding fragmentation seen in earlier approaches, which often treated climate, system physics, and finance as isolated modules and thereby produced biased or incomplete results. By embedding end-to-end uncertainty propagation and sensitivity analysis, the model framework developed through this study further enhances reliability, enabling the quantification of risk distributions rather than single-point estimates and improving the bankability of projections. The findings collectively establish that only a multi-layer, modular, and probabilistic architecture can capture the full causal chain from environmental variability through technical performance to economic viability, allowing stakeholders to evaluate photovoltaic projects with higher accuracy, transparency, and confidence. This research therefore contributes a significant methodological advancement by providing a comprehensive foundation for the design and assessment of PV systems that are both technically robust and economically sustainable across diverse climatic and market contexts.

RECOMMENDATION

Based on the findings of this study, it is recommended that future development and deployment of predictive simulation models for solar photovoltaic (PV) system performance adopt a fully integrated, modular, and data-driven architecture that explicitly links environmental, technical, and economic layers within a single computational framework. Model designers should prioritize the incorporation of high-resolution, bias-corrected irradiance and meteorological datasets combined with energy balance-based thermal models to capture the nuanced influence of local climate dynamics on module operating conditions. Simultaneously, technical submodels should be constructed using validated electrical representations of PV modules and inverters, complete with loss taxonomies for mismatch, soiling, shading, and degradation, ensuring accurate conversion of environmental inputs to electrical outputs. Economic modules should be embedded as core rather than peripheral components, using detailed capital and operational cost structures, tariff-linked revenue models, and life-cycle financial analysis to produce bankable metrics such as levelized cost of electricity, net present value, and internal rate of return. Furthermore, it is recommended that uncertainty propagation techniques such as Monte Carlo and Latin Hypercube sampling, coupled with variance-based sensitivity analysis, be standard practice in such models to quantify prediction ranges and identify dominant risk drivers across all layers. Cross-validation against multi-year operational datasets should be mandated to ensure credibility and reproducibility, while standardized data pipelines and interoperable metadata structures should be adopted to enable seamless updating of environmental, technical, and financial components without compromising model integrity. These recommendations collectively aim to guide researchers, system designers, and policymakers toward building predictive PV simulation frameworks that deliver not only accurate energy yield estimates but also reliable economic risk assessments, thereby supporting evidence-based decision-making for scalable and sustainable solar energy deployment.

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