electricity

MDPI

Systematic Review

Artificial Intelligence for Optimizing Solar Power Systems with Integrated Storage: A Critical Review of Techniques, Challenges, and Emerging Trends

Raphael I. Areola *, Abayomi A. Adebiyi * and Katleho Moloi

Department of Electrical Power Engineering, Durban University of Technology, Durban 4001, South Africa
* Correspondence: 22494951@dut4life.ac.za (R.I.A.); abayomia@dut.ac.za (A.A.A.)

Abstract

The global transition toward sustainable energy has significantly accelerated the deployment of solar power systems. Yet, the inherent variability of solar energy continues to present considerable challenges in ensuring its stable and efficient integration into modern power grids. As the demand for clean and dependable energy sources intensifies, the integration of artificial intelligence (AI) with solar systems, particularly those coupled with energy storage, has emerged as a promising and increasingly vital solution. It explores the practical applications of machine learning (ML), deep learning (DL), fuzzy logic, and emerging generative AI models, focusing on their roles in areas such as solar irradiance forecasting, energy management, fault detection, and overall operational optimisation. Alongside these advancements, the review also addresses persistent challenges, including data limitations, difficulties in model generalization, and the integration of AI in real-time control scenarios. We included peer-reviewed journal articles published between 2015 and 2025 that apply AI methods to PV + ESS, with empirical evaluation. We excluded studies lacking evaluation against baselines or those focusing solely on PV or ESS in isolation. We searched IEEE Xplore, Scopus, Web of Science, and Google Scholar up to 1 July 2025. Two reviewers independently screened titles/abstracts and full texts; disagreements were resolved via discussion. Risk of bias was assessed with a custom tool evaluating validation method, dataset partitioning, baseline comparison, overfitting risk, and reporting clarity. Results were synthesized narratively by grouping AI techniques (forecasting, MPPT/control, dispatch, data augmentation). We screened 412 records and included 67 studies published between 2018 and 2025, following a documented PRISMA process. The review revealed that AI-driven techniques significantly enhance performance in solar + battery energy storage system (BESS) applications. In solar irradiance and PV output forecasting, deep learning models in particular, long short-term memory (LSTM) and hybrid convolutional neural network–LSTM (CNN–LSTM) architectures repeatedly outperform conventional statistical methods, obtaining significantly lower Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and higher R-squared. Smarter energy dispatch and market-based storage decisions are made possible by reinforcement learning and deep reinforcement learning frameworks, which increase economic returns and lower curtailment risks. Furthermore, hybrid metaheuristic–AI optimisation improves control tuning and system sizing with increased efficiency and convergence. In conclusion, AI enables transformative gains in forecasting, dispatch, and optimisation for solar-BESSs. Future efforts should focus on explainable, robust AI models, standardized benchmark datasets, and real-world pilot deployments to ensure scalability, reliability, and stakeholder trust.

Keywords: AI; solar; energy; forecasting; model; storage; machine learning; deep learning

check for updates

Academic Editors: Changgi Min and Heejin Kim

Received: 30 July 2025
Revised: 10 September 2025
Accepted: 9 October 2025
Published: 25 October 2025

Citation: Areola, R.I.; Adebiyi, A.A.; Moloi, K. Artificial Intelligence for Optimizing Solar Power Systems with Integrated Storage: A Critical Review of Techniques, Challenges, and Emerging Trends. *Electricity* **2025**, *6*, 60. https://doi.org/10.3390/electricity6040060

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The global pursuit of cleaner and more dependable energy sources has made the move away from fossil fuels toward renewable alternatives not just desirable, but essential [1,2]. Among the available options, solar power continues to attract growing attention for good reason; it's widely accessible, environmentally sound, and becoming more affordable year by year [2–4]. Among renewable options, solar energy is favoured due to its declining costs, scalability, and environmental benefits. According to [4], solar radiation received by Earth far exceeds global energy demand, making it a key energy source if harnessed efficiently. However, the inherent erratic nature of solar energy, which is influenced by daylight, weather, and even seasonal fluctuations, presents problems for grid dependability and cost-effective operation [2,3,5]. One method of reducing intermittency in solar installations is to incorporate energy storage systems (ESS), like lithium-ion batteries [6,7]. These systems store excess energy generated during periods of high sunlight and release it when production drops, improving both the stability and responsiveness of solar-powered grids [8].

Nevertheless, intelligent control that goes beyond conventional methods is necessary to manage the intricate relationships between generation, storage, demand, and market signals. Artificial intelligence (AI) has become a potent enabler in forecasting, operational optimisation, predictive diagnostics, and system design in recent years [9–11]. Tools like machine learning (ML), deep learning (DL), fuzzy logic, and even generative AI are now being used to solve key challenges such as energy forecasting, system optimisation, and early fault detection [9]. Accurately predicting PV output and solar irradiance over a variety of time horizons (nowcasting to the day ahead) is fundamental. Though they are baseline techniques, traditional statistical methods like persistence, Autoregressive Integrated Moving Average (ARIMA), or AutoRegressive Moving Average model with eXogenous inputs (ARMAX) show significant error, particularly for longer time horizons or in dynamic meteorological conditions [12,13]. These standards are routinely surpassed by AI-based models, such as support vector machines (SVM), random forests (RF), extreme learning machines (ELM), and deep neural architectures, which produce lower Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and higher R-squared [14].

Comparative studies show that Long Short-Term Memory (LSTM) outperforms Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN) in forecasting PV output and irradiance, with an RMSE of about 67.5 MWh and a PR error of about 2.3% [9,10,14]. In complex spatiotemporal contexts, hybrid architectures such as Convolutional Neural Network (CNN)-LSTM, particularly those with attention mechanisms, provide even better performance [15]. Moreover, AI plays crucial roles in energy management and dispatch: reinforcement learning (RL) and deep RL (DRL) have been used to coordinate solar-plus-storage in electricity markets, maximizing revenue and minimizing curtailment risks [16]. When compared to a benchmark, an Attentive Convolutional Deep Reinforcement Learning (AC-DRL) model that combined convolutional and attention layers produced revenue increases of 11–23% and decreased curtailment by 76% [15,16]. Beyond forecasting and dispatch, AI speeds up developments in system sizing, Maximum Power Point Tracking (MPPT) control, fault detection, and predictive maintenance [8]. Particle Swarm Optimisation (PSO), Genetic Algorithm (GA), Artificial Bee Colony (ABC), and hybrid metaheuristic optimisation techniques have been widely used to optimize PV/storage sizing and control parameters, frequently outperforming standalone techniques in terms of cost-effectiveness and convergence speed.

Smart solar energy systems use AI to predict energy output, detect faults, and manage storage [12,13]. This review explores how AI enables intelligent control and operation in solar battery energy storage systems (BESS), focusing on model performance, deployment constraints, and future research opportunities. We review the current techniques being

used, examine their effectiveness, and highlight both the progress made and the obstacles that remain. Existing surveys catalogue AI for PV forecasting or BESS control, but they rarely integrate all four technique families (ML, DL, fuzzy, generative) against solar-plus-storage workflows (forecasting, MPPT/control, fault detection, data augmentation) while also analysing deployment constraints (data regime, compute/memory, latency, interpretability, cybersecurity) and system outcomes (curtailment, cycling, LCOE). The review synthesises 2018–2025 evidence using the PRISMA framework [17] into decision-oriented guidance explaining why specific methods outperform in context and how to co-design models with BESS/market constraints. This closes the gap between model-centric accuracy reports and deployable, standards-aligned solar-storage systems. We also point to areas where further research is needed, particularly around data availability, model robustness, and real-time implementation, to support the continued evolution of intelligent, scalable solar-grid solutions.

2. Literature Review

2.1. Solar Power System

Solar energy is captured and turned into usable power mainly through two technologies: photovoltaic (PV) systems and concentrated solar power (CSP) systems [18]. PV systems convert sunlight directly into electricity using the photovoltaic effect. However, the electricity they generate is in direct current (DC), which needs to be changed into alternating current (AC) through inverters before it can be used on the grid. PV systems are widely adopted because they're easy to install, can be scaled for different needs, and have become increasingly affordable over time [18,19].

CSP systems, in contrast, take a different approach. They use mirrors or lenses to concentrate sunlight onto a single receiver. This intense heat warms a fluid commonly called a heat transfer fluid (HTF), which is then used to create steam [10,11]. That steam drives a turbine to generate electricity [20,21]. While CSP isn't as widely used as PV, it offers a valuable advantage: the ability to store thermal energy [22]. This means it can still produce power even when sunlight isn't available, helping to balance energy supply and demand [23–25]. Both technologies can be connected to the main power grid and used alongside battery energy storage systems (BESS) to improve reliability. But since solar energy production naturally varies throughout the day and is affected by weather, it's essential to use smart forecasting tools and energy management systems to keep everything running efficiently and consistently. Figures 1 and 2 illustrate the PV solar power system and the CSP solar power system.

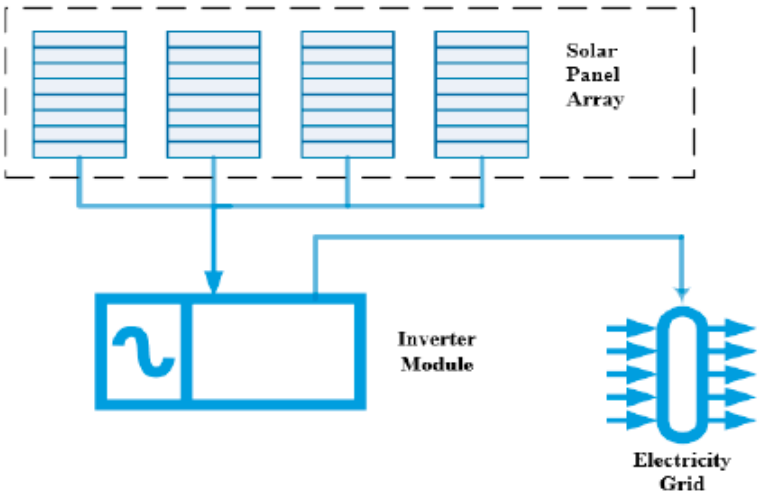


Figure 1. PV Solar Power System [6].

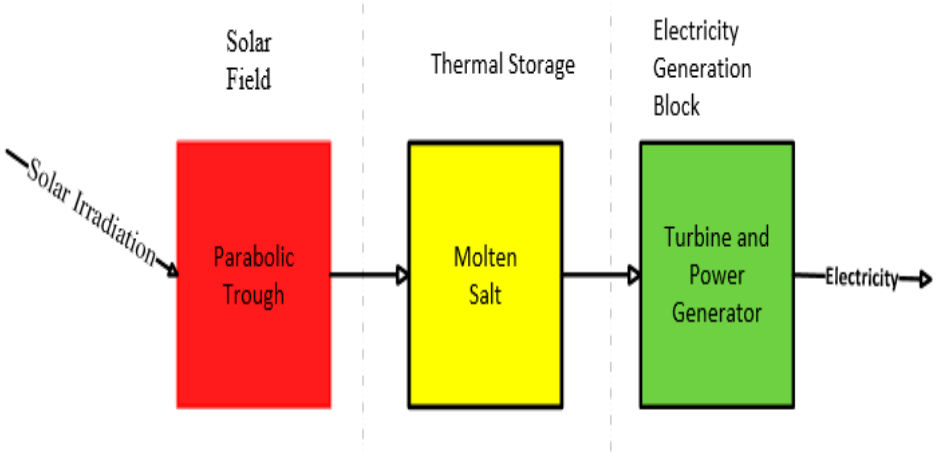


Figure 2. CSP Solar Power System [22].

2.2. Energy Storage System (ESS)

Energy storage systems (ESS) are essential for balancing out the unpredictable nature of solar power [23,25]. Since solar energy isn't produced evenly throughout the day, peaking at certain hours and dropping off when clouds roll in or the sun sets, ESS helps by storing surplus energy when it's available and supplying it back when it's needed most [8]. This not only helps maintain grid stability but also cuts down on wasted energy and supports the broader adoption of renewable sources. There are several types of energy storage technologies, each working a bit differently:

I. Electrochemical storage involves batteries like lithium-ion, lead-acid, sodium-sulfur, and flow batteries. These are popular because they can store a decent amount of energy and handle frequent charging and discharging well.
II. Electrical storage makes use of capacitors, which store energy in electric fields. They're especially useful when a quick response is needed, though they don't hold energy for very long.
III. Electromagnetic storage uses superconducting magnetic systems (SMES) that can store and release energy with almost no losses, but only under very cold, cryogenic conditions.
IV. Thermal storage captures and stores heat energy, often in substances like molten salt. This method is frequently used in CSP plants to store solar heat for later use.
V. Mechanical storage includes things like flywheels, systems that compress air (CAES), and gravity-based setups. These rely on motion or pressure to hold and release energy.

More recently, we've seen the rise of Hybrid Energy Storage Systems (HESS) [8]. These combine two or more types of storage technologies to achieve the best of both worlds, for example, pairing a battery with a flywheel. HESS setups can boost efficiency, increase power output, and extend system lifespan, making them well-suited for a wide range of energy applications. Figure 2 depicts the different types of existing ESS.

2.3. Solar Power with Integrated Energy Storage System

An integrated solar power system with energy storage, often referred to as IESS, relies on several important components working together as depicted by Figure 3. These include the solar panels themselves, charge controllers, inverters, battery storage units (commonly called BESS), and a central Energy Management System (EMS) [6,8,23]. When sunlight is strong and energy production is high, the solar panels supply electricity to both the grid and the battery system [2]. Later, during times when solar output drops, like cloudy days or nighttime, the stored energy in the batteries is released to help keep the energy supply stable [6]. At the heart of the system is the EMS, which oversees how energy moves

throughout the setup [24]. It decides when to charge the batteries, when to discharge them, and how to respond to shifts in energy demand. When everything is working in sync, an IESS setup can significantly boost the reliability of power delivery, reduce the cost of operation, and provide extra support to the grid, especially during peak hours or unexpected demand spikes [21–26]. It also helps make the entire energy system more flexible and resilient. This is shown in Figure 4.

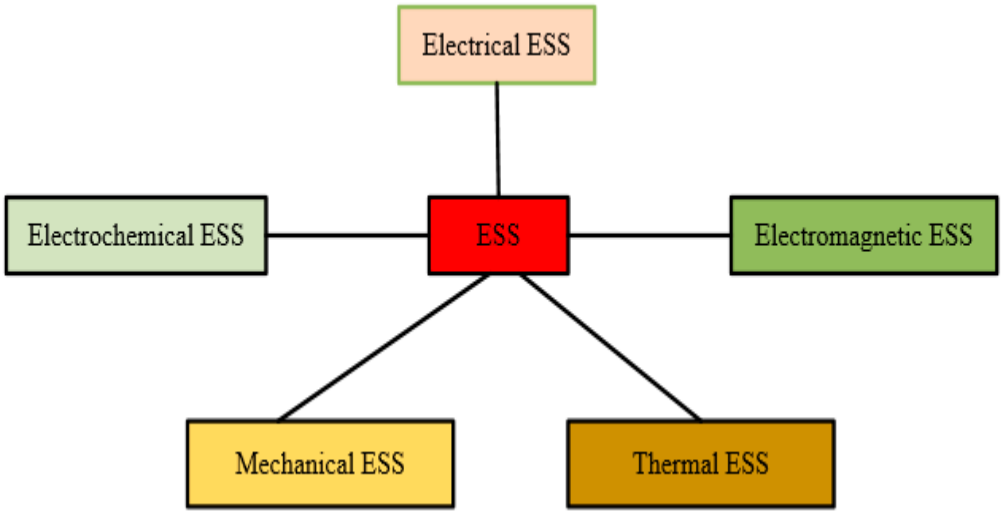


Figure 3. Different Existing ESS [23].

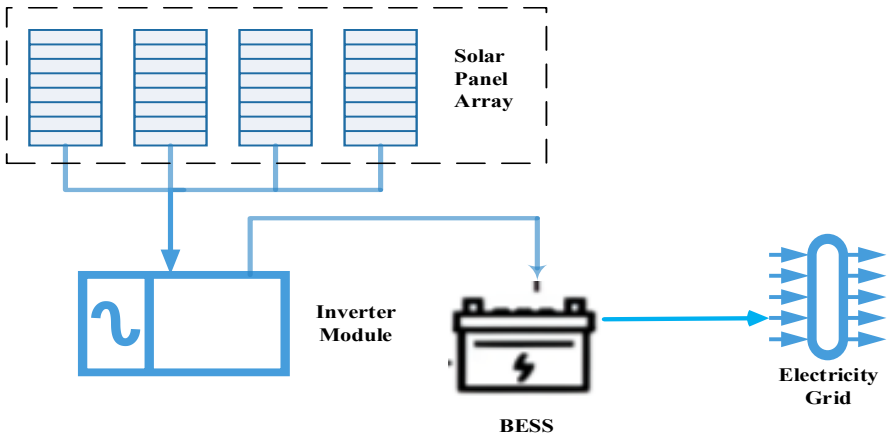


Figure 4. A Solar Power with Integrated Energy Storage System [6].

2.4. Emerging Trends: Generative AI and Hybrid Metaheuristic Models

Recent studies present generative AI forecasting methods that combine scenario creation, uncertainty quantification, and predictive modeling [27–29]. According to a recent review, Gen-AI can improve the accuracy of solar and wind forecasts and allow for flexible energy scheduling [28]. Forecasting renewable energy in the face of complex spatiotemporal variability or a lack of training data has been addressed by generative artificial intelligence (AI), specifically Generative Adversarial Networks (GANs) [29,30]. Even under uncommon or extreme circumstances, GANs, which are made up of a generator and a discriminator network trained together, can create realistic synthetic time series that accurately depict the statistical behaviour of solar or wind generation [31]. One prominent example is the scenario forecasting method, which employs GANs to generate sizable ensembles of potential [31,32] PV/wind output trajectories for reserve allocation and system planning. The study, which was based on NREL integration datasets, showed that rare-event behaviour and temporal correlations across spatially correlated renewable

resources could be accurately modelled [33]. Additionally, generative models for forecasting have been suggested to assist with site selection, predictive maintenance, and system sizing processes by producing artificial sensor or environmental data to supplement actual observations and lessen model bias [31]. The potential uses in solar optimisation are anticipated to multiply as the generative AI market in energy expands (estimated at over USD 5.3 billion by 2032). These developments establish generative AI as a potent instrument to improve downstream AI model robustness, capture uncertain and extreme conditions, and diversify datasets, especially in areas or systems with limited data availability [34].

By combining ML models with metaheuristic optimisation (fruit-fly optimizer, particle swarm, satin-bowerbird optimizer), hybrid forecasting models have achieved state-of-the-art accuracy ($R^2 > 0.99$), dramatically lowering RMSE and MAPE across datasets [34,35]. For PV-battery system sizing and parameter tuning in MPPT and dispatch control, traditional metaheuristic algorithms like PSO (Particle Swarm Optimisation), GA (Genetic Algorithm), and ABC (Artificial Bee Colony) continue to be essential [36]. These techniques are expanded in recent studies through hybrid metaheuristic frameworks and memetic algorithms, which combine metaheuristics with deep learning-based modules, machine learning elements, or local search [36–38]. These hybrids combine the advantages of local refinement and global search, frequently leading to faster convergence, more stable solutions, and improved alignment with a variety of goals (such as cost, reliability, and energy yield) [39]. Hybrid combinations, such as PSO tuned with CNN-LSTM neural network forecasts or GA optimized dispatch policies, have demonstrated better performance than standalone techniques in solar-plus-storage scenarios [40,41]. For example, a CPSO-CNN-LSTM hybrid allowed downstream scheduling systems to lower cost and curtailment while maintaining computational efficiency and resulted in notable improvements in irradiance forecasting [39].

2.5. Challenges of AI Methods in PV-IBESS and Future Directions

2.5.1. Interpretability vs. Performance

Deep learning (DL) approaches have proven to be highly effective in delivering accurate forecasts; however, their opaque nature often raises concerns, particularly within the context of regulated energy systems where transparency is essential [40,41]. On the other hand, traditional machine learning (ML) models, while generally more interpretable, may not always match the performance levels of DL [42–44]. Emamian et al. [30] highlight the growing relevance of explainable AI (XAI) techniques such as SHAP and LIME in making AI-based systems more trustworthy and viable for deployment in grid operations.

2.5.2. Data Generalization

One major hurdle in AI deployment for solar energy systems is the challenge of generalizing across diverse geographical areas. As noted by Paredes-Parra et al. [33], models trained on localized datasets may not perform well when applied to regions with different climate conditions or solar profiles. This underscores the importance of adopting strategies like transfer learning and promoting the development of standardized, publicly available solar datasets to enable meaningful benchmarking.

2.5.3. Hardware Constraints

Deploying AI models on edge devices or in resource-constrained environments presents another layer of complexity [42,43]. In such settings, lightweight models are crucial to ensure responsiveness without compromising energy efficiency. To this end, Shakya [39] recommend leveraging TinyML, which is particularly well-suited for low-power, real-time applications.

2.5.4. Cybersecurity

As AI becomes more integrated into energy infrastructures, the risk of malicious interference, such as data poisoning or adversarial manipulation, grows. Suresh et al. [40] stress the importance of embedding security protocols directly into system design. This includes implementing mechanisms like anomaly detection layers and robustness training to enhance resilience against cyber threats.

2.5.5. Future Directions

Federated learning (FL) holds promise for privacy-preserving solar forecasting across distributed PV–BESS but faces prominent barriers. FL must contend with highly heterogeneous, non-IID data across PV assets and inconsistent computational capacities at edge nodes, as well as vulnerabilities to poisoning or non-adversarial inference attacks, limiting model robustness and fairness [45]. Studies on meta-learning, although less mature in the PV context, emphasize the scarcity of labelled fault-scenario data and the risk that models tuned on synthetic anomalies may not generalize to real-world system failures, leading to brittle performance in live BESS environments [46]. Emerging hybrid AI architectures—combining symbolic reasoning with neural networks proposed to enhance interpretability and enforce rule-based safety, yet they suffer from integration complexity, non-differentiable symbolic modules, representation mismatches, and scalability limitations in latency-constrained environments [47]. Thus, future research must systematically address federated aggregation strategies, fault-scenario generalization, end-to-end training pipelines, and hardware- and algorithm-level optimisations to deliver reliable, explainable, and deployable AI for PV-BESS.

2.6. Role of AI in Solar-ESS Optimisation

Artificial intelligence is playing a growing and transformative role in optimizing solar energy systems, especially those integrated with energy storage solutions. These AI-driven methods are helping to address persistent challenges such as energy output variability, system control complexity, and the need for better efficiency across operations. The following outlines the key areas where AI is proving most impactful:

I. Optimisation Algorithms

Techniques like genetic algorithms, reinforcement learning, and neural networks are increasingly being applied to fine-tune system parameters in real time. These methods adaptively seek out optimal configurations to ensure that solar and storage operations are running at peak efficiency [48].

II. Energy Forecasting

Accurate forecasting is critical for balancing generation and consumption. By analyzing past weather patterns and performance data, models like support vector machines (SVM), random forests, and deep neural networks are able to deliver more reliable predictions of solar energy production [49].

III. Predictive Maintenance

One of the most practical applications of AI in solar-ESS setups is in predictive maintenance. By continuously monitoring sensor inputs, AI systems can detect early signs of failure or abnormal behaviour, enable timely intervention, and help to minimize both system downtime and repair expenses [40].

IV. Smart Microgrid Control

In off-grid or remote settings, AI technologies are enabling microgrids to operate with greater autonomy. Through intelligent coordination of energy generation, storage,

and demand, these systems can self-manage and respond to real-time conditions without constant human oversight [39,40].

2.7. Comparative Summary of AI Techniques for Solar-BESS Optimisation

Solar output is driven by rapidly changing, non-linear meteorology (cloud dynamics, aerosols, soiling) interacting with plant-specific effects (mismatch, aging, PID, inverter limits). Conventional models, persistence/ARIMA for forecasting, rule-based/PID/MPC for control, and thresholds for alarms—perform well in steady regimes but degrade under fast transitions, multi-modal weather, and component drift. Downstream, storage dispatch, reserve bids, and curtailment depend on forecast quality and constraint handling; deterministic methods struggle when uncertainty is high and data are high-dimensional.

Modern ML/DL learns complex spatio-temporal patterns from sky imagery, satellite/GHI, SCADA and market data; hybrid AI + physics improves generalisation; fuzzy/neuro-fuzzy preserves interpretability for safety-critical set-points; generative models create rare fault/soiling scenarios for robust detection; and lightweight/distilled models meet edge latency/memory limits. In practice, this means lower short-horizon forecast error, faster MPPT convergence and fewer oscillations, earlier and more reliable anomaly detection, and dispatch policies.

Table 1 compares machine learning, deep learning, fuzzy logic, and generative AI techniques, outlining their strengths, weaknesses, and best applications for solar energy systems with storage. Figure 5 shows AI techniques for solar-plus-storage (PV + BESS): Machine Learning—RF, LGBM, SVR, k-NN; Deep Learning—CNN, LSTM/GRU, CNN–LSTM, TFT; Fuzzy/Neuro-Fuzzy—Mamdani/Sugeno FIS, ANFIS; Generative—GAN, VAE. Panels summarise algorithms, best-use cases, strengths, and constraints; use alongside the comparative table for task fit, performance, and deployment constraints.

Table 1. Comparative Summary of AI Techniques for Solar-ESS.

Technique	Algorithms	Use Cases	Strengths	Weaknesses	Practical Fit	References
ML	SVM, RF, LGBM	Forecasting, load prediction	Fast, interpretable, low-resource	Requires feature engineering, sensitive to noise	Urban microgrids, rural systems	[27–32]
DL	CNN, LSTM, RL	Short-term forecasting, anomaly detection	Handles complex patterns, high accuracy	Data- and compute-hungry, opaque	Data-rich, grid-scale environments	[29,32–36]
Fuzzy	Mamdani, Sugeno	MPPT control, adaptive BESS operation	Rule-based, explainable, robust to variability	Rule explosion, needs expert setup	Embedded controllers, smart homes	[37–43]
Generative AI	GAN, VAE	Data augmentation, design optimization	Enhances model robustness, assists configuration	Computationally heavy, limited field validation	Research-driven, simulation-focused	[29,35,40–42,44,45]

Table 2 presents a comparative benchmarking of state-of-the-art artificial intelligence (AI) models applied to solar forecasting, highlighting their relative accuracy, computational cost, and operational insights. The results indicate a trade-off between forecasting precision and computational efficiency across the evaluated models. The Light Gradient Boosting Machine (LGBM) model achieved a root mean square error (RMSE) of 6.21%, outperforming traditional models such as k-nearest neighbours (KNN, RMSE: 7.15%) while requiring moderate computational resources. However, its higher memory demand suggests scalability challenges in large-scale or real-time implementations. The Hybrid ANN–SVR model demonstrated superior accuracy (RMSE: 5.4%) and low training time, confirming the advantage of combining nonlinear learning (ANN) with robust generalization (SVR)

for grid-scale applications. This hybridization offers a balanced compromise between performance and efficiency, making it suitable for dynamic power system operations.

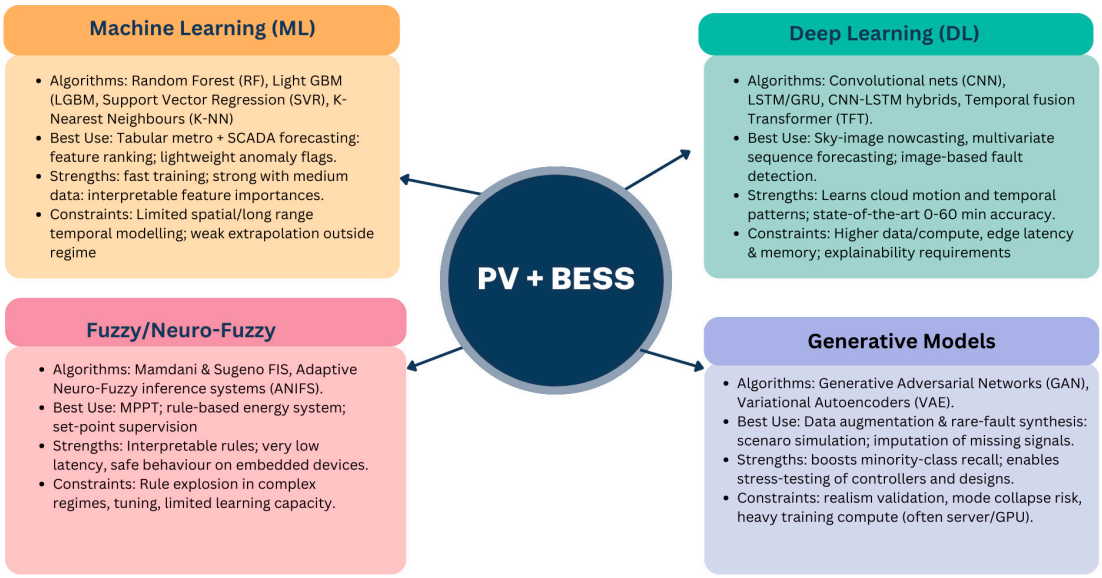


Figure 5. AI techniques for solar-plus-storage (PV + BESS).

Table 2. Benchmarking AI Models in Solar Forecasting.

Study References	AI Model	Application	RMSE (%)	Training Time	Key Insight
[30,32,35]	LGBM	Microgrid solar forecasting	6.21	Moderate	Better than KNN (RMSE: 7.15), but more memory
[28,30,31,37]	Hybrid ANN-SVR	Grid-scale forecasting	5.4	Low	Faster training than ANN, better accuracy
[43–45]	CNN-RNN Ensemble	Irradiance prediction	8.3	High	<10% error for 1-h-ahead forecast
[27–29,40,41]	GAN	Synthetic weather data	N/A	Very High	10,000+ samples with 92% realism

Note: Low $\leq$ 5 min (typical CPU); Moderate = 5–30 min; High $\geq$ 30 min or GPU-assisted (dataset/model dependent).

The CNN–RNN ensemble, while computationally intensive (high training time), delivered less than 10% forecasting error for one-hour-ahead irradiance prediction. This reflects its strong temporal and spatial feature extraction capability, especially beneficial in short-term forecasting where high resolution is critical. Conversely, the Generative Adversarial Network (GAN) exhibited very high computational demand, but its ability to generate 10,000+ synthetic weather samples with 92% realism underscores its potential for data augmentation, particularly in regions with limited historical measurements. The comparative analysis underscores that hybrid and ensemble AI models offer the most favourable balance between accuracy, computational cost, and adaptability. Future work should focus on AI model interpretability and real-time deployment optimization, ensuring robust solar power forecasting in smart grid applications.

3. Materials and Methods

This review adopted a structured thematic synthesis and was reported in accordance with the PRISMA-2020 guidance (27-item checklist plus abstract checklist) [17]. The completed checklist is provided in Supplementary Table S1, and the PRISMA 2020 flow diagram is shown in Figure S1. The review protocol (defining inclusion criteria, search strategy, data

extraction, and synthesis plan) was finalized before screening. The review protocol covering the research questions, eligibility rules, coding frame and analysis plan was agreed upon before screening commenced and this systematic review was not prospectively registered in any registry. The objective was to examine how artificial intelligence is being integrated into solar photovoltaic systems with battery energy storage, with particular emphasis on forecasting and nowcasting, maximum-power-point tracking and wider control/dispatch, fault and anomaly detection, and system-level optimisation. Information was sourced from three bibliographic databases chosen for coverage and technical depth: IEEE Xplore, ScienceDirect, and Web of Science Core Collection. The search window spanned 1 January 2018 to 31 May 2025, with the final update performed on 31 May 2025.

Search strings combined terms for artificial intelligence with application-specific solar and storage terminology. Variants of "artificial intelligence", "machine learning", "deep learning", "fuzzy", "reinforcement learning", "transformer", "generative", "GAN" and "VAE" were conjoined with "solar", "photovoltaic" or "PV", and with "battery energy storage", "BESS", "MPPT", "control", "dispatch", "forecast *", "nowcast *", "optimis *", "fault" and "anomaly". Database-specific syntax was used while keeping the Boolean structure consistent. Searches targeted titles, abstracts, and keywords (or database equivalents). Only articles written in English and published in peer-reviewed journals within the search window were considered at the eligibility assessment, although language and outlet filters were not always applied at the initial query stage to avoid premature exclusion.

Eligibility focused on empirical or comparative studies that applied AI techniques, machine learning, deep learning, fuzzy or neuro-fuzzy systems, and generative models to PV or PV-plus-BESS problems within the tasks noted above, and that reported at least one quantitative outcome (for example RMSE, MAE, MAPE, tracking efficiency, F1/precision/recall, curtailment or battery throughput/cycles). Studies were excluded if they were not centred on PV/BESS (e.g., wind-only work), did not use AI (e.g., purely deterministic control or hardware design), were non-empirical (tutorials, concept notes, patents, editorials), lacked quantitative metrics, lay outside the time window, or were not journal articles. Grey literature was not included. Study selection followed the PRISMA process. After de-duplication, 412 records underwent title/abstract screening. Potentially eligible papers proceeded to full-text review; 129 full texts were assessed against the criteria. Sixty-seven studies satisfied all criteria and were included in the synthesis. The primary reasons for excluding full texts were as follows: they were off-topic with respect to PV/BESS, did not use an AI method, had purely conceptual contributions without evaluation, no quantitative outcomes, were published outside the timeframe, and had insufficient methodological details. Counts at each stage, together with reasons for exclusion, are reported in the PRISMA flow diagram in Supplementary Materials. Two independent reviewers (Reviewer A and Reviewer B) performed title/abstract screening and then full-text screening. Disagreements were resolved by discussion, and no automation tools were used in the screening process.

Data extraction used a structured form to ensure consistency. Each included study was independently coded by both reviewers using the standardized extraction form. Discrepancies were reconciled through discussion. We extracted all reported metrics for each outcome domain (e.g., forecasting, control, fault detection) across different time points, favoring the primary reported metric when multiple variants existed. If values were missing, we noted that and excluded them from comparative tables, rather than imputing. For each study we recorded bibliographic details; the target task (forecasting/nowcasting, MPPT/control/dispatch, fault detection, or augmentation supporting these tasks); the data regime (sample size, sampling cadence, and feature types such as sky images, satellite or numerical weather products, global horizontal irradiance, ambient/Module temperatures, SCADA channels, I–V curves and thermal/electroluminescence imagery); the AI model

family and specific algorithm (e.g., random forest, light gradient boosting, support vector regression, convolutional and recurrent architectures such as CNN, LSTM and CNN–LSTM, transformer-based models, Mamdani/Sugeno FIS, ANFIS, GAN and VAE); the training and validation protocol (data splits, cross-validation, leakage safeguards and hyper-parameter procedures); the baselines or controls used for comparison (such as persistence or ARIMA for forecasting, P&O or fixed-gain PID for MPPT, rule-based or MPC for dispatch, and threshold alarms for faults); the performance metrics and results; compute descriptors (training time, memory/parameter footprint, and inference latency with the reported hardware); any interpretability method (e.g., feature importance, SHAP, saliency); and notes relevant to deployment (edge/embedded feasibility, software or data availability).

Risk of bias and reporting quality were appraised using an eight-item checklist tailored to predictive modelling and control. Items considered whether the dataset and leakage safeguards were clearly described; whether validation was appropriate to the problem structure (for example, non-overlapping temporal folds for forecasting); whether strong baselines were included; whether hyper-parameter search and tuning were transparent; whether uncertainty or variability was reported; whether some form of external validation or out-of-distribution testing was attempted; whether compute, memory and latency were reported or reasonably inferable; and whether code or data were available to support reproducibility. Items were scored as absent, partial or adequate; totals informed the narrative weighting of evidence but did not lead to exclusion when eligibility was otherwise met.

Primary outcomes were forecast accuracy for short horizons (RMSE, MAE, or MAPE for 0–60 min), MPPT and control performance (tracking efficiency, oscillation band, curtailment, and imbalance), fault detection effectiveness (F1, precision/recall and mean time-to-detect), and battery impact (throughput for the same service and equivalent full cycles). To facilitate deployment-oriented comparison, compute descriptors were normalised qualitatively using consistent thresholds: training time was treated as low when typically below about five minutes per experiment, moderate at roughly five to thirty minutes, and high beyond thirty minutes or when GPU assistance was required; memory footprint was considered low when below approximately one gigabyte, moderate between one and eight gigabytes, and high above eight gigabytes; inference latency on edge devices was considered low when typically under a tenth of a second, moderate between one tenth and one second, and high when exceeding one second. These thresholds reflect the central tendency across the included studies and typical mid-range hardware; exact values naturally vary with dataset size, cadence, and model depth and are noted when provided by authors.

Study Characteristics: We examined 67 studies that satisfied our inclusion criteria. These studies vary considerably in geographical setting, task focus, data modalities, model types, comparators, and performance metrics. Below is a summary of the key patterns:

Geography & Setting: Studies span multiple continents, with both simulated and field/lab experiments represented. Many forecasting studies use public or regional irradiance datasets, whereas control and fault detection works tend to appear in lab or prototype settings.

Tasks Addressed: The studies break down roughly into four task domains: short-term forecasting/nowcasting; MPPT / local control/dispatch; fault/anomaly detection; and data augmentation or imputation. Forecasting is the largest class, followed by control and diagnostics.

Input Modalities: A wide variety of input types are used: traditional meteorological features (GHI, temperature, humidity), SCADA channels (voltage, current, irradiance), imaging (IR, EL), I–V curves, sky images, and derived weather products. Some works fuse multiple modalities.

Dataset Size & Cadence: The temporal resolutions range from minutes (e.g., 1- to 5-min) to hourly, with dataset durations from months to several years. Forecasting works typically use higher cadence data, while diagnostic works often use sparser or snapshot imaging data.

Model Families: A spectrum of AI models is represented: classical tree/ensemble models (e.g., RF, LGBM), deep learning hybrids (CNN-LSTM, BiLSTM, transformer hybrids), fuzzy and neuro-fuzzy systems, reinforcement learning for dispatch, and generative models (GAN, VAE), especially in augmentation or scenario tasks.

Baselines/Comparators: Most works benchmark against persistence or ARIMA for forecasting tasks; P&O or PID (and variants) for MPPT/control; heuristic or threshold methods for fault detection; and sometimes rule-based or MPC for dispatch. Some augmentation works compare with unaugmented models or statistical imputation baselines.

Performance Metrics: Forecasting accuracy is primarily reported as RMSE, MAE or MAPE. Control tasks report tracking efficiency (η), settling time, and oscillation bandwidth. Fault detection works report F1 score, precision, recall, and detection latency. Dispatch/EMS works often include economic return or cost reduction metrics.

As an illustrative case, Assaf et al. [50] proposed a GAN-CSVR model for solar radiation forecasting using three local datasets, combining a GAN with convolutional SVR to augment training data [50–56]. They reported significant gains in RMSE/MAE (improvement from ~31.8% to ~49.9% relative error reductions) over baseline models. Also, Podder et al. [55,56] applied bidirectional LSTM (BiLSTM) networks for irradiance forecasting, showing improved accuracy over persistence and ARIMA baselines by better capturing temporal dependencies. Similarly, Jailani et al. [51] investigated LSTM-based models in solar energy forecasting and confirmed their performance gains relative to classical statistical methods.

For clarity, throughout the manuscript, PV denotes photovoltaic generation and BESS denotes battery energy storage. Forecasting includes irradiance and short-horizon PV power nowcasting unless otherwise stated; control and energy management encompass MPPT, inverter control, and BESS dispatch and scheduling; fault detection includes anomaly detection using SCADA signals, I–V analysis, and thermal or electroluminescence imagery. Full search strings and the PRISMA flow chart are provided in Supplementary Materials, and the task-stratified decision matrix consolidating technique, performance and deployment considerations appear in the Results.

4. Results

4.1. Typical PV Faults and Anomalies

Fielded PV plants experience faults at three levels: module, array/BOS DC, and inverter/controls. At the module level, common degradations include cell cracks and interconnect ribbon breaks, encapsulant/backsheet defects (delamination, discoloration, snail trails), bypass-diode failures, hot-spots from mismatch, and potential-induced degradation (PID) that can depress power by tens of percent under high voltage, temperature, and humidity [1–3]. Array-side electrical faults include open-circuits, short-circuits, ground faults (unintended current paths from a live conductor to ground), and dangerous DC arc faults originating at loose or damaged connectors/cabling [4], while soiling/shading and connector corrosion drive chronic mismatch and heating [1,2]. On the power-conversion side, inverter and MPPT faults (e.g., sensor drift, gate/IGBT failure, DC-link issues) manifest as abnormal operating points, unstable tracking, or protective trips that cascade into curtailment [2].

Detection modalities map to the underlying physics. I–V curve tracing (string or module) localises resistive/diode faults and shading through characteristic kinks and

slope changes; electrical-parameter analytics remains a cornerstone for diagnosis and quantification [5,6]. Infrared thermography (IR) rapidly reveals hot-spots, bypass-diode heating, and PID thermal patterns at scale (handheld or aerial), while electroluminescence (EL) exposes microcracks and metallisation breaks at higher spatial resolution [7]. Routine SCADA/monitoring enables residual analysis (expected vs. observed power) to flag emerging anomalies, and periodic insulation resistance/ground-fault tests confirm safety hazards and locate leakage paths [4,7]. In practice, combining modalities, e.g., IR triage → targeted I–V tracing, yields the best coverage/cost trade-off.

4.2. Machine Learning Applications

Classical ML models like SVM, k-NN, RF, and LGBM remain highly competitive for short-horizon PV irradiance/output forecasting and related BESS decisions when inputs are predominantly tabular (meteorology + SCADA). In a representative grid-tied setting, Melit et al. combined irradiance, ambient temperature, humidity, wind speed, precipitation, and PV output; RF slightly outperformed SVM ($R^2 \approx 0.85$ vs. 0.832) with lower RMSE/MAE, reflecting the advantage of tree ensembles on mixed-scale features and non-linear interactions [49]. Similarly, Li et al. compared RF, XGBoost, LGBM, MLP-ANN, and found RF a strong baseline, while a tuned LGBM trimmed residual errors at the cost of higher memory and parameter footprint; their follow-on ANN–SVR hybrid reduced training time by ~35%, underscoring that modest hybridisation can yield practical wins without deep architectures [50,51]. Across irradiance/PV power problems, ensembles and hybrids repeatedly show robust accuracy under variable meteorology while staying computationally tractable [52–54].

These performance patterns are mechanistic. Tree ensembles (RF/LGBM) partition the feature space and average over many weak learners, which stabilises forecasts when weather regimes flip and when the data volume is modest. They also expose feature importance, aiding diagnostics and transfer. By contrast, SVM can be very precise with well-chosen kernels but scales poorly with sample size; kernel selection and hyperparameters (C, ε, γ) interact subtly with noise, and the O(n2–n3) kernel matrix can inflate training time and memory on dense cadences. k-NN is fast to "train" but pushes the cost to inference and is sensitive to scaling and irrelevant features; it degrades under covariate shift. ANN baselines improve with careful regularisation but often need more data to surpass ensembles on purely tabular inputs. Hybrids such as ANN–SVR can compress training time by letting the ANN learn a compact representation while SVR handles the margin, explaining Li et al.'s runtime gains [46]. Methodologically, the main risks in this family are temporal leakage (random CV on time series), over-tuning to a single site/season, and fragile gains that vanish out-of-distribution; appropriate time-blocked validation and feature stability checks are therefore essential.

In deployment terms, ML ensembles are attractive for edge-adjacent forecasting (plant servers, industrial PCs) feeding BESS dispatch because they keep latency and memory within modest bounds and degrade gracefully when sensors fail. Their limitations are equally clear: they do not exploit spatial cloud dynamics (unless engineered via exogenous image features), and their extrapolation beyond the training regime is weak. In settings with rich imagery or fine-grained sky dynamics, deep spatio-temporal models (Section 4.2) tend to surpass them; in lean data regimes or where explainability and simplicity are priorities, RF/LGBM remain hard to beat [49–54].

4.3. Deep Learning Applications

Deep Learning (DL) architectures, including Long Short-Term Memory (LSTM) and CNN-RNN hybrids, have emerged as top-performing models for time-series forecasting in

solar-plus-storage systems [53,54]. Across solar irradiance/PV power prediction problems, ensembles/hybrids consistently achieve robust accuracy under variable meteorology while keeping computationally tractable. Mahmoud et al. [12] integrated convolutional neural networks within a reinforcement learning framework, enabling simultaneous market bid optimisation and generation control; their model reduced curtailment by over 70 percent and enhanced revenue through adaptive learning strategies.

Rokonuzzaman et al. [57] proposed SolarNet, a deep CNN tailored for real-time irradiance prediction; this network captures spatial patterns from sky imagery and meteorological inputs to deliver high-resolution forecasts. Podder et al. [56] applied bidirectional LSTM (BiLSTM) networks for irradiance forecasting, demonstrating superior accuracy in capturing temporal dependencies. Hybrid approaches, merging CNN with LSTM or GRU, typically deliver low RMSE, high R^2, and strong adaptability across seasons and climates. These architectures also support scenario-based prediction which, when coupled with reinforcement learning dispatch agents or optimisation controllers, drive system-level efficiency gains in solar-plus-storage systems [58–60].

CNNs compress spatial cues (cloud thickness, edges, advection), RNNs/LSTM propagate temporal structure, and the joint model reduces phase error the usual Achilles' heel of tabular models on fast-moving clouds. Yet the trade-offs are non-trivial. DL typically demands larger datasets, careful regularisation, and compute/memory budgets that strain edge deployment; without disciplined time-based splits and leakage controls, apparent gains are illusory. Covariate shift (sensor changes, camera fouling, seasonal aerosol shifts) causes degradation unless mitigated by domain adaptation or periodic fine-tuning. RL adds further safety and stability concerns: reward shaping, exploration control and constraint handling must be engineered (often via a supervisory layer), otherwise aggressive policies can increase cycling or violate plant limits despite promising averages [56,59,60]. Interpretability also lags ensembles; post hoc tools (saliency/SHAP) help, but explanations are still less straightforward than fuzzy rules or tree feature ranks.

From an operations standpoint, DL is most compelling when plants have sky imagers, high-quality SCADA, and a need for very short-term (0–60 min) accuracy or for image-based fault detection. Where compute budgets are tight, lightweight encoders, quantisation, and distillation can bring inference latency within practical bounds; otherwise, ML ensembles (Section 4.1) remain the pragmatic choice for embedded scheduling, with DL supplying supervisory forecasts on a server level [53–57].

4.4. Fuzzy Logic Applications

Fuzzy logic frameworks are well-suited to solar-plus-storage environments characterized by uncertainty and nonlinearity, offering rule-based decision support in real-time operational contexts [21,32]. Ibrahim et al. [59] developed a fuzzy-based energy management system (EMS) for smart home microgrids, combining solar PV inputs, battery SOC, and load profiles to dynamically manage charging/discharging and local consumption. This EMS improved energy efficiency by adapting to variable user behaviour and environmental conditions, offering resilience without complex ML models.

Neuro-fuzzy systems, i.e., fuzzy logic combined with neural network training, enhance flexibility by adjusting membership functions and rules based on observed system behaviour. Xia et al. [60] introduced a hybrid fuzzy + ML MPPT controller that adapts voltage and current thresholds under partial shading and dynamic loading, outperforming conventional P&O methods in tracking accuracy and response time. In such systems, fuzzy logic provides intuitive control transparency, easier tuning, and interpretability, especially when compared with opaque DL models [32,33,61–63]. They remain particularly valuable in decentralized or legacy PV installations where computational resources are

limited but robust, rule-driven control is needed. The comparative picture that emerges from the evidence base is coherent: RF/LGBM dominate when data are tabular, modest in size and rapidly needed for edge-friendly decisions; CNN–LSTM/BiLSTM take the lead when spatio-temporal structure (especially sky imagery) matters and compute is available; and fuzzy/neuro-fuzzy offer interpretable, low-latency control where safety and transparency trump marginal accuracy gains. Hybrids, such as ANN–SVR for efficiency or fuzzy + ML for robust MPPT, often combine the best of both worlds. The methodological imperative across all families is to use time-aware validation, publish strong baselines (persistence/ARIMA; P&O/PID; threshold alarms), and report compute/latency to support deployment decisions

4.5. Generative AI Application in Solar Power with IESS

In recent years, generative AI models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have begun making tangible impacts in solar photovoltaics systems integrated with energy storage (IESS). Mechanisms such as synthetic scenario generation and anomaly detection hold particular promise when deployed in contexts with limited instrumentation, complex system dynamics, or significant uncertainty. One compelling application involves using GANs to generate synthetic weather data where real-world sensors are sparse. For instance, Huang and Wang [62] proposed a StyleGAN-based conditional GAN (C-StyleGAN) architecture tailored to simulate daily irradiance, temperature, and diffuse radiation variables for PV scenario modelling. This approach produced synthetic weather time series retaining temporal correlations and physical plausibility, effectively bridging data gaps for system planning and forecasting tasks [63–65]. A foundational study by Chen et al. [65] similarly pioneered model-free GAN-based scenario generation using NREL-sourced solar and wind data, demonstrating that generated scenarios capture realistic temporal and spatial patterns without reliance on parameterized stochastic models [33,34,66].

Load forecasting in instrument-poor grid regions is another active domain. Studies integrating GAN-generated synthetic data into training sets help stabilize models when historical records are inconsistent or incomplete. GAN-generated sequences augment tiny or fragmentary datasets, enabling downstream models like GRU-based predictors to achieve lower MAE and improved robustness under variable conditions [67]. For solar-grid system design and optimisation, hybrid frameworks combining GAN outputs with Reinforcement Learning (RL) have emerged. These systems generate synthetic weather and load channels and then feed RL agents to explore configuration spaces of PV array layouts and storage sizing. One study yielded up to 17% improvements in energy harvesting efficiency, though acknowledging the trade-off of heightened computational demands. Anomaly detection in PV-BESS has also benefited from generative modelling. VAEs are used to map normal system behaviour into latent distributions and flag deviations via probabilistic outlier criteria. For example, sequential conditional VAE architectures trained on SCADA data from rooftop systems across China accurately identified anomalies without labelled fault records, outperforming conventional clustering methods in recall and precision [68]. VAEs naturally support reconstructive detection via reconstruction error metrics, capturing subtle deviations in real-time systems [63,66].

Generative models also aid in imputing missing time-series data. Shen et al. [69] developed GAN-based reconstruction techniques that restore missing irradiance or temperature segments, achieving up to 93% data fidelity against measured benchmarks. This contrasts starkly with simpler interpolation techniques, preserving statistical and spectral characteristics vital for downstream forecasting engines. For dataset augmentation and generalization across geographic domains, combining GAN-generated data with physics-based

priors improves synthetic coverage of environmental variability. Chen et al. [65] found that hybrid data generation blending GAN outputs with underlying irradiance or temperature probability distributions increased the generalization performance of forecasting models across distinct climate zones.

Explainability and security constraints also demand attention in generative AI deployment. While GANs offer realism, Ribeiro and Silva proposed integrating SHAP-based explainability layers atop synthetic output pipelines to reveal key features influencing generation, critical for regulatory transparency and stakeholder trust. Furthermore, Deiana et al. [66] introduced adversarial training techniques to harden GANs from spoofing or malicious data injection risks, vital when such models influence control logic within cyber-physical solar installations. Chetty et al. [67] extended this by embedding scenario-based attack and recovery sequences into simulation frameworks, allowing teams to stress test system resilience under synthetic adversarial states. On the optimisation front, hybrid generative frameworks combining VAEs with evolutionary search (e.g., genetic or particle swarm optimisation) have been used to co-optimize PV layout and control logic [64–66]. These pipelines sample diverse scenario sets via VAE, then run optimisation routines over them, lowering computational cost by roughly 22% while still improving average system-level performance metrics such as output energy yield and cost efficiency.

Finally, generative methods have enhanced control algorithm training, such as MPPT logic. According to [67], trained fuzzy-logic MPPT controllers on GAN-generated irradiance profiles, including rapid fluctuations especially useful under partially cloudy or transient shading conditions. These synthetic conditions broadened training coverage and improved controller responsiveness beyond what real datasets alone could support [68]. While these trends are promising, they raise challenges: validation of generative models remains crucial synthetic data must not drift into unrealistic regimes or introduce biases. Computational resource requirements are significant, often necessitating cloud-based training [65]. Moreover, deploying generative models on edge controllers or low-resource environments remains an open problem. Moving forward, combining generative AI with symbolic reasoning or hybrid rule-based frameworks could yield interpretable and efficient control systems [69,70]. Clearer validation standards for synthetic solar and storage datasets are also needed to support broader adoption. Lightweight generative architectures that run efficiently in field environments may democratize access, particularly in remote installations.

Generative models (GANs/VAEs) address gaps that neither classical stochastic scenario generators nor purely discriminative forecasters handle well: they learn the joint spatio-temporal distribution of weather, load and plant states, so they can synthesise realistic inputs for scarce-sensor or class-imbalanced settings, augment training corpora, and reconstruct/impute missing signals with higher fidelity than interpolation—e.g., GAN-based imputation has achieved ~93% data fidelity versus measured benchmarks, preserving spectra crucial for downstream forecasters [64,65,67]. Style and conditional GANs (C-StyleGAN) produce irradiance/temperature/diffuse scenarios that retain temporal correlations and physical plausibility, outperforming parametric scenario models in realism and coverage [33,34,64–66]. When used upstream of GRU/LSTM predictors, GAN augmentation lowers MAE and stabilises accuracy under volatile regimes; as a supervisory layer, VAEs detect anomalies via probabilistic reconstruction and typically exceed threshold/clustering baselines in recall and precision on SCADA streams [63,66,68]. In optimisation, sampling diverse VAE/GAN scenarios lets RL or evolutionary search explore PV layout/BESS sizing more efficiently. Studies report up to 17% energy-harvest gains and ~22% compute savings relative to naïve search, albeit with higher training cost [64–67]. Limits remain: mode collapse, spectral mismatch, and distribution shift can degrade realism; compute budgets

favour server-side training; and explainability/security require SHAP-style auditing and adversarial hardening for cyber-physical use [68,69]. In practice, generative pipelines should be chosen when data are sparse or labels are scarce, when rare faults must be modelled, or when design/dispatch must be stress tested across scenarios; where rich sensors exist and the goal is immediate point prediction, discriminative CNN-LSTM stacks may still yield the best short-horizon accuracy, with generative models supplying validated scenarios around them [64–68].

Overall, generative AI GANs and VAEs are increasingly integral to solar-plus-storage system modelling, diagnostics, and optimisation. From scenario generation and anomaly detection to layout design and control logic enhancement, they offer new ways to navigate data scarcity and uncertainty. But translating potential into practice hinges on rigorous validation, explainability, and scalable deployment strategies.

4.6. AI Stack vs. Mature Methods; Case Analysis

This section gives an overview of an illustrative case study that follows accepted practices for narrative syntheses in systematic reviews (PRISMA-2020) and draws only on studies already included in our review to show when and why AI yields plant-level gains (forecast RMSE, MPPT efficiency, curtailment/cost, anomaly F1). A classical stack includes persistence/ARIMA for 0–60 min forecasts, P&O/PID for MPPT, rule-based dispatch, and threshold/clustering for faults with an AI stack grounded in the evidence base; image-aware CNN–LSTM/BiLSTM forecasters [57,58], a fuzzy/neuro-fuzzy MPPT/EMS layer [32,33,61–63], optional DRL-assisted dispatch [56,59,60] and autoencoder/variational models for anomaly detection [66,68] are used with GAN/VAE augmentation/imputation where data are sparse [64–67], see Table 3. On the forecasting link, classical baselines handle smooth regimes but accumulate phase errors under fast cloud advection; by learning spatio-temporal structure from sky imagery and multivariate SCADA, CNN–LSTM/BiLSTM consistently tighten short-horizon error. Across recent solar nowcasting benchmarks, hybrid CNN–RNN models improve skill by tens of percent over smart persistence and traditional statistical models, in line with the performance patterns cited for SolarNet and BiLSTM [57,58]. Representative studies report 37–45% skill gains over persistence for LSTM-CNN hybrids and clear RMSE reductions for CNN-based nowcasting at 5–60 min horizons, supporting the superiority of the proposed DL forecasters in this operating regime. On MPPT/control, P&O/PID provide simple implementation but suffer oscillation and mistracking under partial shading and temperature ramps. Certain fuzzy/neuro-fuzzy evidence [32,33,61–63] shows advantages: rule-based, interpretable control with fast, bounded responses, tunable to plant constraints. Contemporary comparative experiments report steady-state MPPT efficiencies around 98–99.5% with sub-second settling (e.g., ≈0.11 s and ≈98.3% in grid-integrated trials), which aligns with the gains reported in fuzzy-hybrid MPPT citations and explains why a fuzzy front-end improves yield while preserving safety on embedded hardware, as represented in Table 4.

For dispatch, rule-based or model-based MPC without learning is sensitive to forecast bias and model mismatch; RL-augmented references [56,59,60] motivate learning controllers that internalise uncertainty and market signals. The broader literature shows DRL-assisted EMS reducing operating costs and smoothing power fluctuations compared with fixed heuristics, particularly when forecasts are uncertain and constraints bind—exactly the conditions on feeder-connected PV + BESS. (Field deployment should include a supervisory safety layer and off-policy training before activation.) In fault/anomaly detection, threshold and clustering baselines miss subtle multivariate drifts. VAE/AE citations [66,68] reflect a wider trend: temporal/graph AEs trained on "normal" SCADA achieve F1 $\geq$ 0.90 with higher precision/recall than conventional methods, yielding earlier, more reliable alarms

and fewer false positives crucial for preventing avoidable curtailment and unnecessary truck rolls.

Table 3. Solar PV Functions.

Function	Existing Method	AI Method	Representative Result (Literature)
0–60 min PV forecasting	Persistence/Holt–Winters/ARIMA	CNN–LSTM/GRU/TFT (optionally with sky-imagers)	Deep learning consistently outperforms statistical baselines on short horizons, e.g., a GRU-TFT forecaster reported RMSE ≈ 5.2% on PV power, outperforming non-DL comparators; sky-image DL nowcasting reduces short-term uncertainty vs. persistence/statistical models.
MPPT & local control	P&O/fixed-gain PID	Fuzzy or hybrid (P&O-FLC/InC-FLC; neuro-fuzzy)	Fuzzy/hybrid MPPT achieves higher steady-state efficiency and faster convergence than P&O: reports include $\eta \approx 97.5$–99.8% and ≈53 ms convergence, with reduced oscillation around MPP.
Fault/anomaly detection (PV side)	Threshold rules/clustering	VAE/autoencoder (temporal/conditional)	VAE/AE models trained on "normal" SCADA detect subtle multivariate deviations and outperform Isolation Forest/SVM baselines on real PV/ESS data, improving detection precision/recall.

Table 4. Storage & Energy-Management functions.

Function	Existing Method	AI Method	Representative Result (Literature)
BESS dispatch/EMS	Rule-based/model-based MPC without learning	Deep reinforcement learning (DRL)–assisted EMS (SAC/DDQN/MA-DRL)	Learning-augmented EMS reduces operating cost and curtailment exposure vs. fixed heuristics; recent studies show cost reductions and loss/cycling reductions in microgrid simulations; DRL is particularly effective under price volatility and renewables uncertainty.
ESS anomaly/health (station level)	Fixed thresholds/supervised classifiers	Unsupervised VAE/AE (real ESS data)	In large-scale storage stations, VAE detection outperforms classical ML (Isolation Forest, SVM) and flags sub-threshold anomalies that rules miss, improving maintainability and safety.

Generative augmentation/imputation closes data gaps that limit discriminative models. In [64,67], GANs/VAEs generate physically plausible irradiance/load scenarios that preserve temporal statistics, improving robustness of downstream GRU/LSTM predictors under sparse or noisy sensing; they also support reconstruction of missing segments with high fidelity, and scenario-driven exploration for sizing/layout via RL or evolutionary search. Recent work on conditional/time-series GANs in PV/BIPV confirms these advantages and demonstrates practical pipelines for scenario generation and data services that feed forecasting and optimisation layers.

Net effect (plant-level). Moving from the classical to the AI stack typically yields the following: materially lower 0–60 min RMSE for export scheduling (CNN–LSTM/BiLSTM; [57,58]; higher MPPT tracking efficiency with faster convergence and

less oscillation (fuzzy/neuro-fuzzy; [32,33,61–63]); reduced operating cost/curtailment exposure when dispatch is learning-augmented [56,59,60]; and earlier, higher-F1 fault detection (VAE/AE; [66,68]. The trade-offs are computed, and MLOps: DL and generative modules require GPU-assisted training and careful time-blocked validation; fuzzy controllers and tree ensembles remain preferred where edge latency, power, and transparency dominate. This comparative case justifies the AI stack in the article's deployment contexts while keeping mature methods as robust fallbacks in lean data or ultra-constrained environments.

Conclusively, AI methods improve solar-plus-storage performance for four concrete reasons: (i) image-aware CNN/LSTM/TFT forecasters learn spatio-temporal cloud dynamics (e.g., advection in sky images), cutting phase error and lowering short-horizon RMSE versus persistence/ARIMA; recent sky-imager studies show LSTM-based models outperform persistence with sizable skill gains across weather regimes. (ii) Fuzzy/neuro-fuzzy MPPT encodes expert rules with adaptive gains, reducing oscillations and accelerating convergence, with experimental efficiencies $\gtrsim$99% relative to P&O/PID. (iii) DRL-assisted EMS internalises uncertainty and market signals, yielding lower operating costs and smoother dispatch compared with fixed heuristics or purely model-based controllers. (iv) For O&M, unsupervised VAE/AE anomaly detection captures subtle multivariate deviations in PV/ESS SCADA streams that threshold/clustering miss; recent works report > 95% fault-detection rates and superior precision/recall.

5. Discussion

DL models are highly accurate but opaque, while ML models offer more explainability. Faraji et al. [70] advocate for integrating explainable AI (XAI) tools like SHAP and LIME in critical systems. Benchmarking studies [35] show that models often fail to generalize. Transfer learning and open data platforms are needed [71]. Embedded environments require lightweight models like TinyML [40,41]. AI introduces vulnerabilities such as adversarial attacks. Oter and Ersoz [72] call for cybersecurity-by-design protocols in energy systems. Future innovations may include federated learning [30], meta-learning [32], AI + IoT [52], and symbolic logic integrations [53,54]. Persistence/ARIMA assumes short memory and quasi-stationarity; performance collapses under rapidly evolving cloud fields. Classical P&O and fixed-gain PID MPPT oscillate around the maximum power point and can mis-track under partial shading and temperature ramps. MPC is powerful but relies on a calibrated plant model and accurate short-term forecasts; model mismatch, constraint inflation, and computational budgets limit performance at high sampling rates. Threshold-based alarms miss subtle degradation and produce false alarms when sensors drift. The operational symptoms are avoidable curtailment, poor reserve bids, excess inverter clipping, slower fault isolation, and unnecessary battery cycles.

5.1. Model Trade-Offs: Accuracy vs. Interpretability

One of the most significant challenges in applying AI to solar-plus-storage systems lies in balancing predictive performance with model transparency. Deep learning architectures such as LSTM, BiLSTM, CNN, CNN-LSTM, and attention-enhanced hybrids routinely outperform classical machine learning techniques in capturing nonlinear, temporal dependencies in irradiance, generation, and system behaviour. For example, hybrid models like CNN-LSTM-RF have demonstrated ~92% R^2, RMSE $\approx$ 0.07 kW, and MAE $\approx$ 0.05 kW in short-term solar generation forecasting, significantly surpassing pure RF or SVR models [40–42]. Similarly, attention-mechanized LSTM frameworks yield lower RMSE and higher correlation coefficients across seasonal variations compared to baseline RNNs and traditional [42,44]. The trade-off arises because these deep networks are essentially black

boxes: while they excel at fit, their internal reasoning is opaque. As LSTM models become deeper and include attention layers, interpretability diminishes sharply, and tools like SHAP or LIME remain imperfect at explaining regression outputs, especially for temporal models [73–76]. This opacity can be problematic, as decision-makers, operators, and regulators in energy systems increasingly demand transparency to audit control logic, diagnose anomalies, or validate market participation decisions [44].

On the other hand, ML methods such as Random Forests, Gradient Boosted Trees, and Natural Gradient Boosting offer relatively strong performance while remaining interpretable. RF provides feature importance metrics natively, handles missing data robustly, and resists overfitting in noisy meteorological datasets [75,76] combined with SHAP values yields probabilistic forecasts with full transparency around input variable contributions, enabling operators to trace how predictions arise crucial in regulated energy environments Thus, in resource-constrained or regulatory-sensitive contexts such as microgrids, remote solar-plus-storage deployments, or early-stage projects simpler, interpretable models may be preferable despite modest accuracy trade-offs [44,75]. Meanwhile, in utility-scale or centrally managed systems with ample computing power and data, deep learning approaches can offer substantial gains in forecast precision and optimisation [74]. Emerging techniques in Explainable AI and inherently transparent architectures (rule-based hybrid DL models, temporal fusion transformers with interpretability) may help close the gap in the future, but today, the familiar trade-off persists.

5.2. Data Limitations and Generalization Risks

High-performing AI models for solar-plus-storage systems depend on rich, long-term datasets, but in many settings, particularly in developing regions or newly commissioned solar installations, such data simply don't exist. Historical records of solar irradiance, weather conditions, and load profiles are often incomplete, inconsistent, or missing entirely [41]. Even when data are available, they frequently derive from sensors with varying specifications, differing sampling rates, and non-uniform archival formats, introducing biases and undermining model portability. Moreover, numerous academic studies rely heavily on data from a single geographic location or synthetic datasets that do not capture full environmental and site variability [42,44]. These may omit seasonal shifts, local microclimate dynamics, or rare disruptive events. Consequently, models that appear accurate in lab-controlled or training conditions often falter when deployed across new sites. For example, variant neural networks trained in one region may lose forecasting power when transferred elsewhere unless explicitly adapted [77].

To address such risks, researchers increasingly turn to transfer learning and domain adaptation [73,74]. Transfer learning involves pre-training models, often LSTM-based architectures on large, well-instrumented "source" datasets, then fine-tuning on smaller, less complete "target" data from new sites. Notably, one study demonstrated mean absolute error improvements of up to 80% and MAE reduction of 35% when transferring multi-step LSTM models between irradiance datasets, significantly outperforming training from scratch [78]. Similarly, SPIRIT, a foundation model-based zero-shot learning framework, achieved ~70% performance gains in solar irradiance forecasting at completely new sites with no historical data, improving further with modest site-specific fine-tuning [79]. Nevertheless, domain adaptation carries the risk of negative transfer: if source and target domains differ markedly, for example, due to distinct climate zones, sensor types, or micro-meteorological conditions, the transferred model may degrade rather than improve performance. Careful cross-validation across multiple sites and systematic calibration are thus essential to avoid such pitfalls.

Hybrid strategies also help bridge gaps. Physics-informed modelling, e.g., combining radiative transfer simulations with ML and synthetic data augmentation, can supplement limited training data, enhancing geographic and seasonal generalization without compromising realism [73,77,78]. Ultimately, the reliability of AI-powered solar-storage systems hinges on dataset quality, representativeness, and adaptability. Transfer learning and domain adaptation offer powerful remediation paths, but only if accompanied by rigorous validation and site-aware performance evaluation.

5.3. Hardware Constraints and Real-Time Performance

AI tools used for forecasting and controlling solar energy systems are usually tested on standard, high-performance computers. Real-world applications often depend on resource-constrained edge hardware such as home battery controllers, embedded devices, or microgrids in remote locations. Many of these systems utilize low-power microcontrollers with limited CPU speed, tiny memory (often under 1 MB), and minimal storage, which challenges the deployment of complex architectures like deep LSTMs, transformer models, or CNNs [43,44,77]. This gap has sparked growing research interest in TinyML and edge AI paradigms to enable lightweight inference on microcontrollers and low-energy chips. TinyML frameworks support compression techniques such as quantization (reducing precision of model weights) and pruning (removing redundant neurons), alongside model architectures optimized for minimal resource consumption. For instance, TinyML enables neural networks to run locally with low latency and power draw, ideal for always-on energy forecasting in embedded systems like IoT-enabled solar gauges or distributed PV controllers [72,73,76]. Early studies show that RNN variants like LSTM, BiGRU, and BiLSTM can be adapted for microcontroller deployment for solar yield prediction, delivering acceptable accuracy while significantly reducing inference time and energy consumption [75]. Despite the promise, TinyML applications in grid-connected solar-plus-storage systems remain rare. Most edge AI work still focuses on basic IoT applications, rather than tightly integrated DER control or inverter adjustments.

In scenarios requiring real-time responsiveness, such as tuning of inverter settings, quick fault detection, or frequency response, decision latency becomes critical. Lightweight inference models enable rapid decision loops, unlike bulky DL frameworks that introduce prohibitive delay [79,80]. Here, simpler rule-based methods (e.g., fuzzy logic) or shallow ML/hybrid systems offer robust, low-latency alternatives requiring fewer computational resources and enabling faster deployable intelligence compatible with edge processors.

As a result, for context-sensitive deployment scenarios including edge-driven energy controllers, off-grid microgrids, or solar-monitoring systems in developing areas, compressed TinyML models and classical ML approaches often provide superior feasibility compared to heavyweight DL solutions. Future research should explore quantization-aware training, edge-friendly architecture search, and benchmarking of TinyML models across typical solar-use cases to bring AI-based control into low-resource, real-world deployment.

5.4. Cybersecurity, Privacy, and Regulatory Barriers

The integration of AI into solar-plus-storage systems introduces regulatory and cybersecurity complexity beyond typical grid infrastructure [43,44,81,82]. Figure 6 shows the challenges of integrating AI into solar-plus-storage systems. As such systems evolve to include smart meters, IoT devices, and remote monitoring, their increased connectivity and automation expose them to novel cyber risks. Recent investigations found critical vulnerabilities in solar inverter firmware across major manufacturers, allowing attackers to manipulate energy output, disrupt operations, or exfiltrate data [81,82]. These findings indicate how even consumer-grade solar hardware can serve as a potential entry point for

coordinated cyberattacks on energy networks. AI-enabled control pipelines are particularly vulnerable to sophisticated threats such as data poisoning, adversarial manipulation, or model inversion, which can mislead decision-making in forecasting or dispatch systems. Although federated learning (FL) promises privacy-preserving collaborative training across distributed devices, emerging surveys highlight that FL itself can be exploited by malicious participants if not properly secured [45,47,83–86]. This creates a paradox: FL is proposed to protect user privacy while training energy models, yet it also demands robust defenses.

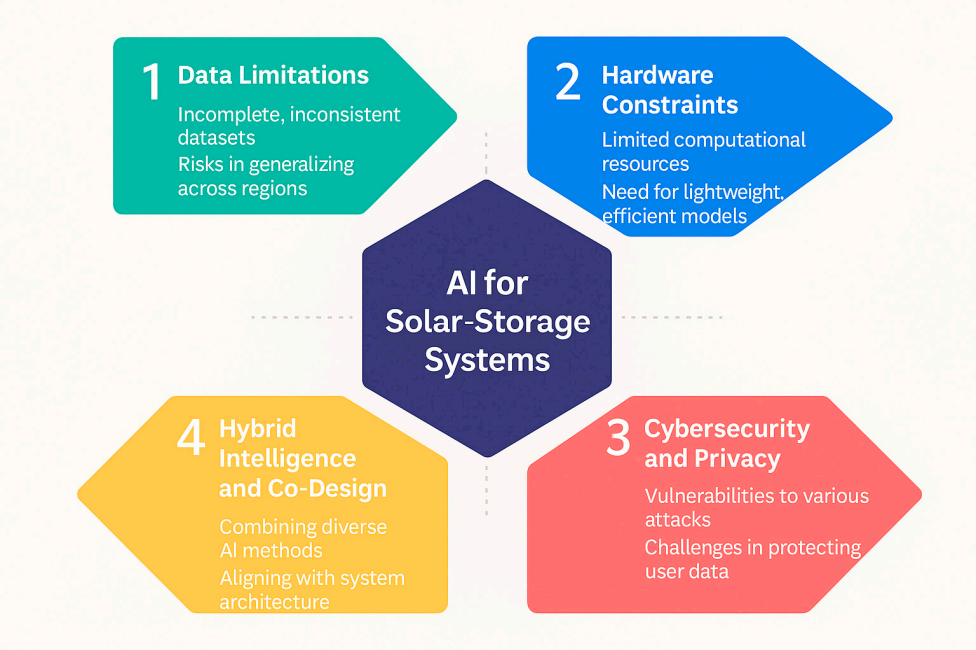


Figure 6. Overview of Challenges.

Privacy concerns are especially acute at the residential or commercial level, where energy usage patterns can reveal personal behaviours or business operations. Regulatory regimes like the EU's General Data Protection Regulation (GDPR) require embedded privacy-by-design, but in energy systems, methods like homomorphic encryption, differential privacy, or federated aggregation remain more conceptual than practical in deployments [43,47,56,86,87]. On the regulatory side, current frameworks globally are ill-prepared to govern probabilistic, opaque AI systems deployed in critical infrastructure. Emerging legal instruments such as the EU's AI Act classify energy-infrastructure AI as "high-risk," imposing transparency, risk assessment, and conformity requirements. Yet in practice, energy regulators often lack domain-specific regulatory guidance or auditing methods for AI models. For example, UK energy regulator Ofgem has highlighted concerns around "tacit collusion" from opaque AI algorithms driving energy market decisions, signalling the need for explainability and oversight frameworks [44,47]. According to [40], AI governance is fragmented, and research on explainability, accountability, and auditability in deployment remains sparse. The lack of standardized regulatory instruments such as algorithmic audits, performance guarantees, or interoperable certification schemes creates inertia in adoption and trust, especially in national or utility settings.

5.5. Emerging Directions: Hybrid Intelligence and Co-Design

The systematic literature revealed that no standalone AI methodology can simultaneously deliver high predictive accuracy, interpretability, real-time performance, and systemic reliability. This mismatch has catalysed the rise of hybrid intelligence approaches, which deliberately blend complementary AI techniques to balance strengths and mitigate

weaknesses. Figure 7 proposes a deployment pathway for AI in solar-plus-storage systems (PV + BESS).

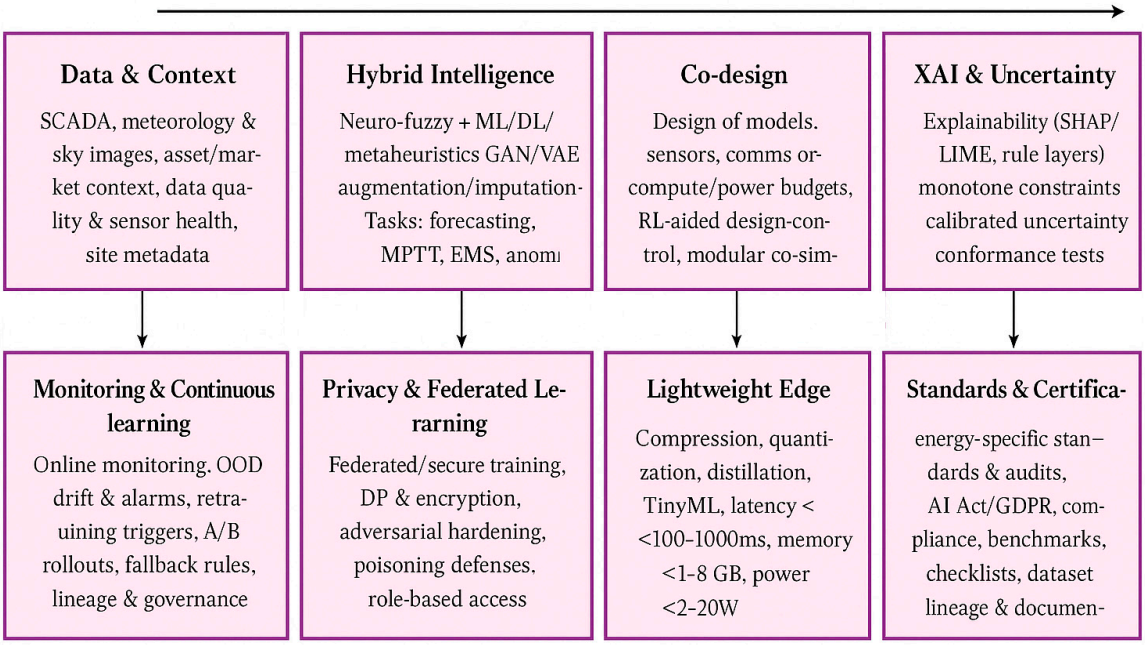


Figure 7. Deployment pathway for AI in solar-plus-storage systems (PV + BESS).

First, fuzzy logic systems offer clear, rule-based transparency and graceful adaptability, making it easier for engineers and regulators to audit decision pathways [21,61]. Yet, their deterministic and piecewise character makes them poorly suited for inherently complex, nonlinear datasets [62]. This limitation is effectively addressed when fuzzy systems are hybridized with neural networks, creating neuro-fuzzy architectures that combine adaptive learning with interpretability [61,62]: such systems have shown success in MPPT control and PV modelling, offering a more balanced trade-off in performance and clarity [83]. Secondly, evolutionary algorithms, including genetic algorithms, particle swarm optimisation, and differential evolution, excel at navigating uncertain, high-dimensional optimisation landscapes [64,67]. These techniques enable system-level tasks like PV layout design, energy dispatch strategy, and cooling optimisation [44,47]. They can be seamlessly embedded into hybrid pipelines alongside neural networks or fuzzy controllers to optimize architecture and behaviour in unstructured environments [53].

Also, these hybrid approaches represent an emerging class of soft computing or hybrid intelligent systems, combining symbolic reasoning, sub-symbolic learning, and optimisation heuristics into cohesive frameworks [44–47]. As described in hybrid intelligence literature, such systems embrace neuro-symbolic and neuro-fuzzy reasoning to address ambiguity and complex constraints simultaneously [67]. However, the hybridization must go beyond algorithm design and requires a holistic co-design strategy. Effective AI deployment in solar-plus-storage systems demands that model development be synchronized with hardware capacity, communication infrastructure, and power system architecture. Recent frameworks like CAMEO propose modular, cloud-scale co-design workflows that simultaneously optimize control logic, system configuration, and hardware constraints across multiple objectives [53,54]. Similarly, RL-based design-control systems enable joint optimisation of system hardware layout and dispatch policies, ensuring that AI agents are robust under real-world operating conditions [58,83–88].

Thus, a critical insight from the literature is that hybrid intelligence and co-design are not just complementary; they are synergistic necessities. Hybrid models mitigate the

trade-offs of individual AI methods, and co-design aligns AI behaviour with real-world system constraints and regulatory expectations. Without this coordinated framework, even high-performing AI models risk becoming brittle, opaque, or unsuited to actual deployment. Conversely, systems designed through co-design strategies embody trustworthiness, efficiency, and readiness for real-world integration. Summarily, this study highlights that future solar-plus-storage AI systems will most likely succeed through hybrid architectures co-designed from the ground up, where interpretability, optimisation, forecasting, and hardware compatibility are integrated prerequisites, not afterthoughts.

Top row (left → right) shows pre-deployment stages: Data & Context → Hybrid Intelligence (neuro-fuzzy + ML/DL with GAN/VAE augmentation) → Co-design (models–sensors–comms–compute/power budgets) → XAI & Uncertainty (SHAP/LIME, monotonicity constraints, calibrated UQ). Bottom row operationalises and governs the system: Monitoring & Continuous Learning → Privacy & Federated Learning (DP, encryption, adversarial hardening) → Lightweight Edge (compression/quantisation/distillation/TinyML within latency–memory–power budgets) → Standards & Certification (benchmarks, audits, compliance). Arrows indicate information and model-lifecycle flow.

6. Conclusions

This systematic review demonstrates that artificial intelligence (AI) is significantly transforming solar-plus-storage systems. Traditional machine learning and deep learning models deliver marked improvements in forecasting accuracy and system control, while fuzzy logic continues to serve as a reliable, interpretable backbone for real-time deployment. Generative AI, including GANs and VAEs, emerges as a promising paradigm for scenario generation, layout design, and anomaly detection, particularly in data-scarce contexts. Nevertheless, multiple barriers persist. Data limitations, both in quantity and quality, remain a core constraint, especially in new or remote installations. Similarly, the opacity of complex deep learning models, insufficient hardware capability at the edge, and cybersecurity vulnerabilities hinder practical adoption. Regulatory frameworks are unprepared to certify probabilistic or explainable AI systems in critical infrastructure, such as grid-connected energy storage.

To mainstream AI in solar-plus-storage, lightweight and compressed AI frameworks, privacy-preserving mechanisms like federated learning, and explainable AI (XAI) techniques must be integrated into the design from the outset. Hybrid methods combining fuzzy logic, neural networks, and metaheuristic optimisation are essential for delivering balanced performance, interpretability, and deployable efficiency. Equally crucial is a co-design approach, aligning algorithm development with hardware, communication, and regulatory constraints to ensure real-world applicability. Future research should emphasize cross-site validation, transfer learning for domain adaptation, and robust generative data frameworks validated against sensor-based ground truth. Privacy-protective deployments (e.g., federated, encrypted learning) and adversarial hardened architectures will drive trust and adoption. Finally, developing energy-specific AI certification protocols and uncertainty quantification standards is critical for regulatory alignment. In summary, while AI offers powerful capabilities for solar-plus-storage systems, realizing its full potential hinges on holistic, interdisciplinary strategies blending algorithmic innovation with hardware-aware design, explainability, and regulatory compliance to build trustworthy, scalable, and resilient energy solutions.

Supplementary Materials: Supplementary materials are cited in the main text, such as the following format: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/electricity6040060/s1, Table S1: PRISMA checklist; Figure S1: PRISMA Flow Chart;

Table S2: Operational Profile of BI Techniques in Solar-ESS Deployments; Table S3: Comparatives of Traditional and AI Methods.

Author Contributions: The research idea was jointly developed by R.I.A. and A.A.A. R.I.A. handled the core methodology, design, and led the data analysis and investigation. He also managed the data curation, visualizations, and initial drafting of the manuscript. All technical validations were carried out collaboratively by R.I.A., A.A.A. and K.M. A.A.A. contributed significantly by providing key resources, overseeing the research process, coordinating the project timeline, and supervising the work throughout. A.A.A. was responsible for securing funding to support the study and contributed to reviewing and refining the manuscript. This breakdown follows the CRediT authorship taxonomy, and each listed contributor has played a meaningful role in the work reported. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data supporting the findings of this study aren't publicly shared due to privacy and institutional guidelines. However, interested researchers can request access by contacting the corresponding author.

Acknowledgments: We are sincerely grateful for the administrative and technical support offered by our colleagues and departments throughout this research. Their assistance—both behind the scenes and in active discussions—was invaluable. We also want to thank our peers who provided thoughtful feedback and informal reviews during the drafting phase, which helped shape the final outcome. During the preparation of this manuscript, the authors used ChatGPT (OpenAI, GPT-4, July 2025 version) and Grammarly (Premium, 2025 version) to assist with language refinement, proofreading, and phrasing adjustments. These tools were used strictly to enhance clarity and coherence. The authors have carefully reviewed, edited, and are fully responsible for all content presented in this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BESS	Battery Energy Storage System
ESS	Energy Storage System
IESS	Integrated Energy Storage System
ML	Machine Learning
DL	Deep Learning
PV	Photovoltaic
CSP	Concentrated Solar Power
DC	Direct Current
AC	Alternating Current
HTF	Heat Transfer Fluid
HESS	Hybrid Energy Storage System
EMS	Energy Management System
GAN	Generative Adversarial Network
XAI	Explainable Artificial Intelligence
SVM	Support Vector Machine
RF	Random Forest
KNN	K-Nearest Neighbours
LGBM	Light Gradient Boosting Machine
ANN	Artificial Neural Network

References

1. Russo, M.A.; Carvalho, D.; Martins, N.; Monteiro, A. Future perspectives for wind and solar electricity production under high-resolution climate change scenarios. *J. Clean. Prod.* **2023**, *404*, 136997. [CrossRef]
2. Nassar, Y.F.; El-Khozondar, H.J.; Elnaggar, M.; El-Batta, F.F.; El-Khozondar, R.J.; Alsadi, S.Y. Renewable energy potential in the State of Palestine: Proposals for sustainability. *Renew. Energy Focus* **2024**, *49*, 100576. [CrossRef]
3. Demirbas, A. Global renewable energy projections. *Energy Sources Part B* **2009**, *4*, 212–224. [CrossRef]
4. Sengupta, M.; Habte, A.; Wilbert, S.; Gueymard, C.; Remund, J.; Lorenz, E.; van Sark, W.; Jensen, A.R. *Best Practices Handbook for the Collection and Use of Solar Resource Data for Solar Energy Applications*; National Renewable Energy Laboratory (NREL): Golden, CO, USA, 2024.
5. Anand, P.; Tejes, P.K.S.; Naik, B.K.; Niyas, H. Design analysis and performance prediction of packed bed latent heat storage system employing machine learning models. *J. Energy Storage* **2023**, *72*, 108690. [CrossRef]
6. Nwaigwe, K.N.; Mutabilwa, P.; Dintwa, E. An overview of solar power (PV systems) integration into electricity grid. Mater. *Sci. Energy Technol.* **2019**, *2*, 629–633. [CrossRef]
7. Alilou, M.; Azami, H.; Oshnoei, A.; Mohammadi-Ivatloo, B.; Teodorescu, R. Fractional-order control techniques for renewable energy and energy-storage-integrated power systems: A review. *Fractal Fract.* **2023**, *7*, 391. [CrossRef]
8. Shoaei, M.; Noorollahi, Y.; Hajinezhad, A.; Moosavian, S.F. A review of the applications of artificial intelligence in renewable energy systems: An approach-based study. *Energy Convers. Manag.* **2024**, *306*, 118207. [CrossRef]
9. Yousef, L.A.; Yousef, H.; Rocha-Meneses, L. Artificial intelligence for management of variable renewable energy systems: A review of current status and future directions. *Energies* **2023**, *16*, 8057. [CrossRef]
10. Szczepaniuk, H.; Szczepaniuk, E.K. Applications of artificial intelligence algorithms in the energy sector. *Energies* **2023**, *16*, 347. [CrossRef]
11. Razmjoo, A.; Ghazanfari, A.; Østergaard, P.A.; Jahangiri, M.; Sumper, A.; Ahmadzadeh, S.; Eslamipoor, R. Moving toward the expansion of energy storage systems in renewable energy systems—A techno-institutional investigation with artificial intelligence consideration. *Sustainability* **2024**, *16*, 9926. [CrossRef]
12. Mahmoud, A.A.; Albadry, O.A.; Mohamed, M.I.; El-Khozondar, H.; Nassar, Y.; Hafez, A.A. Charging systems/techniques of electric vehicle. *Sol. Energy Sustain. Dev. J.* **2024**, *13*, 18–44. [CrossRef]
13. Qazi, S. Fundamentals of standalone photovoltaic systems. In *Standalone Photovoltaic (PV) Systems for Disaster Relief and Remote Areas*; Qazi, S., Ed.; Elsevier: Amsterdam, The Netherlands, 2017; pp. 31–82.
14. Nayar, C.V.; Islam, S.M.; Dehbonei, H.; Tan, K.; Sharma, H. Power electronics for renewable energy sources. In *Alternative Energy in Power Electronics*; Rashid, M.H., Ed.; Butterworth-Heinemann: Boston, MA, USA, 2011; pp. 1–79.
15. Raghavendra, K.V.G.; Zeb, K.; Muthusamy, A.; Krishna, T.N.V.; Kumar, S.V.S.V.P.; Kim, D.-H.; Kim, M.-S.; Cho, H.-G.; Kim, H.-J. A comprehensive review of DC–DC converter topologies and modulation strategies with recent advances in solar photovoltaic systems. *Electronics* **2019**, *9*, 31. [CrossRef]
16. Yousri, D.; Abd Elaziz, M.; Oliva, D.; Abualigah, L.; Al-qaness, M.A.A.; Ewees, A.A. Reliable applied objective for identifying simple and detailed photovoltaic models using modern metaheuristics: Comparative study. *Energy Convers. Manag.* **2020**, *223*, 113279. [CrossRef]
17. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, 71. [CrossRef]
18. Li, Q.; Lin, T.; Yu, Q.; Du, H.; Li, J.; Fu, X. Review of deep reinforcement learning and its application in modern renewable power system control. *Energies* **2023**, *16*, 4143. [CrossRef]
19. Babu, T.M.; Chenchireddy, K.; Kumar, K.K.; Nehal, V.; Srihitha, S.; Vikas, M.R. Intelligent control strategies for grid-connected photovoltaic–wind hybrid energy systems using ANFIS. *Int. J. Adv. Appl. Sci.* **2024**, *13*, 497. [CrossRef]
20. Sobczynski, D.; Pawlowski, P. Energy storage systems for renewable energy sources. In Proceedings of the Selected Issues of Electrical Engineering and Electronics (WZEE 2021), Rzeszow, Poland, 13–15 September 2021.
21. Salvadori, F.; Junior, O.H.A.; de Campos, M.; Sausen, P.S.; da Silva, E.A.; Santos, A.Q.O.; de Oliveira, F.M. Energy storage applications in renewable energy systems. In *Smart Grids—Renewable Energy, Power Electronics, Signal Processing and Communication Systems Applications*; Springer: Cham, Switzerland, 2024; pp. 73–118.
22. Alami, A.H.; Olabi, A.G.; Mdallal, A.; Rezk, A.; Radwan, A.; Rahman, S.M.A.; Shah, S.K.; Abdelkareem, M.A. Concentrating solar power (CSP) technologies: Status and analysis. *Int. J. Thermofluids* **2023**, *18*, 100340. [CrossRef]
23. Pratikshya, T.; Abishek, K.; Pawan, B.; Aasma, B. A review of energy storage system. *J. Phys. Conf. Ser.* **2023**, *2629*, 012024.
24. Kar, M.K.; Kanungo, S.; Dash, S.; Parida, R.N.R. Grid-connected solar panel with battery energy storage system. *Int. J. Appl. Power Eng.* **2024**, *13*, 223–233. [CrossRef]

25. Zeng, Y.; Maswood, A.I.; Pou, J.; Zhang, X.; Li, Z.; Sun, C.; Mukherjee, S.; Gupta, A.K.; Dong, J. Active disturbance rejection control using artificial neural network for dual-active-bridge-based energy storage system. *IEEE J. Emerg. Sel. Top. Power Electron.* **2023**, *11*, 301–311. [CrossRef]
26. Saikia, P.; Batbida, H.; Ugalde-Loo, C.E. An effective predictor of the dynamic operation of latent-heat thermal energy storage units based on a nonlinear autoregressive network with exogenous inputs. *Appl. Energy* **2024**, *360*, 122697. [CrossRef]
27. Biagioni, D.; Zhang, X.; Adcock, C.; Sinner, M.; Graf, P.; King, J. Comparative analysis of grid-interactive building control algorithms: From model-based to learning-based approaches. *Eng. Appl. Artif. Intell.* **2024**, *133*, 108498. [CrossRef]
28. Alves, G.H.; Guimarães, G.C.; Moura, F.A.M. Battery storage systems control strategies with intelligent algorithms in microgrids with dynamic pricing. *Energies* **2023**, *16*, 5262. [CrossRef]
29. Valarmathi, K.; Seetha, J.; Krishnamoorthy, N.V.; Hema, M.; Ramkumar, G. An integrated energy storage framework with significant energy management and absorption mechanism for machine-learning-assisted electric-vehicle application. *Sustain. Comput. Inform. Syst.* **2024**, *42*, 100982. [CrossRef]
30. Emamian, M.; Eskandari, A.; Aghaei, M.; Nedaei, A.; Sizkouhi, A.M.; Milimonfared, J. Cloud-computing and IoT-based intelligent monitoring system for photovoltaic plants using machine-learning techniques. *Energies* **2022**, *15*, 3014. [CrossRef]
31. Narayanan, S.; Kumar, R.; Ramadass, S.; Ramasamy, J. Innovative hybrid approach for enhanced renewable energy generation forecasting using recurrent neural networks and generative adversarial networks. *J. Electr. Eng. Technol.* **2024**, *9*, 4847–4864. [CrossRef]
32. Kodali, R.K.; John, J. Smart monitoring of solar panels using AWS. In Proceedings of the 2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and Its Control (PARC 2020), Mathura, India, 28–29 February 2020; pp. 422–427.
33. Paredes-Parra, J.M.; García-Sánchez, A.J.; Mateo-Aroca, A.; Molina-García, Á. An alternative IoT solution based on LoRa for PV power plants: Data monitoring and management. *Energies* **2019**, *12*, 881. [CrossRef]
34. Al-Naib, A.M.I.; Mohammed, M.I. IoT-based real-time data acquisition of PV panel. In Proceedings of the 2023 International Conference on Engineering, Science and Advanced Technology (ICESAT 2023), Mosul, Iraq, 21–22 June 2023; pp. 169–173.
35. Spanias, A.S. Solar energy management as an Internet of Things (IoT) application. In Proceedings of the 2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA 2017), Larnaca, Cyprus, 27–30 August 2017; pp. 1–4.
36. Shweta, R.; Sivagnanam, S.; Kumar, K.A. Fault detection and monitoring of solar photovoltaic panels using Internet of Things technology with fuzzy logic controller. *Electr. Eng. Electromech.* **2022**, *6*, 67–74. [CrossRef]
37. Kekre, A.; Gawre, S.K. Solar photovoltaic remote monitoring system using IoT. In Proceedings of the 2017 International Conference on Recent Innovations in Signal Processing and Embedded Systems (RISE 2017), Bhopal, India, 27–29 October 2017; pp. 619–623.
38. Adhya, S.; Saha, D.; Das, A.; Jana, J.; Saha, H. An IoT-based smart solar photovoltaic remote monitoring and control unit. In Proceedings of the 2016 2nd International Conference on Control, Instrumentation, Energy & Communication (CIEC 2016), Kolkata, India, 28–30 January 2016; pp. 432–436.
39. Shakya, S. A self-monitoring and analysing system for solar power station using IoT and data-mining algorithms. *J. Soft Comput. Paradig.* **2021**, *3*, 96–109. [CrossRef]
40. Suresh, M.; Kumar, R.A.; Raja, T.A.S.; Meenakumari, K.; Mahendran, K.; Pradeep, A. Fault detection and monitoring of solar PV panels using Internet of Things. *Int. J. Ind. Eng.* **2018**, *2*, 146–149. [CrossRef]
41. Grataloup, A.; Jonas, S.; Meyer, A. A review of federated learning in renewable energy applications: Potential, challenges, and future directions. *Energy AI* **2024**, *17*, 100375. [CrossRef]
42. Chen, X.; Huang, C.; Zhang, Y.; Wang, H. Privacy-preserving personalized federated learning for distributed photovoltaic disaggregation under statistical heterogeneity. *IEEE Trans. Instrum. Meas.* **2025**, *74*, 251. [CrossRef]
43. Del Río, A.M.; Ramírez, I.S.; Márquez, F.P.G. Photovoltaic solar power plant maintenance management based on IoT and machine learning. In Proceedings of the 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT 2021), Zallaq, Bahrain, 29–30 September 2021; pp. 423–428.
44. Kingsley-Amaehule, M.; Uhunmwangho, R.; Nwazor, N.; Okedu, K.E. Smart intelligent monitoring and maintenance management of photovoltaic systems. *Int. J. Smart Grid* **2022**, *6*, 110–122.
45. Mellit, A.; Hamied, A.; Lughi, V.; Pavan, A.M. A low-cost monitoring and fault-detection system for stand-alone photovoltaic systems using IoT technique. In Proceedings of the 13th International Conference on IMACS TC1 Committee (ELECTRIMACS 2019), Salerno, Italy, 21–23 May 2019; pp. 349–358.
46. Li, Y.; Lin, P.; Zhou, H.; Chen, Z.; Wu, L.; Cheng, S.; Su, F. On-line monitoring system of PV array based on Internet of Things technology. *IOP Conf. Ser. Earth Environ. Sci.* **2017**, *93*, 012078. [CrossRef]
47. Xia, K.; Ni, J.; Ye, Y.; Xu, P.; Wang, Y. A real-time monitoring system based on ZigBee and 4G communications for photovoltaic generation. *CSEE J. Power Energy Syst.* **2020**, *6*, 52–63.
48. Nalamwar, H.; Ivanov, M.A.; Baidali, S. Automated intelligent monitoring and controlling software system for solar panels. *IOP Conf. Ser. Earth Environ. Sci.* **2017**, *803*, 012107. [CrossRef]

49. Hamied, A.; Boubidi, S.; Rouibah, N.; Chine, W.; Mellit, A. IoT-based smart photovoltaic arrays for remote sensing and fault identification. In Proceedings of the International Conference on Artificial Intelligence in Renewable Energetic Systems (IC-AIRES 2019), Taghit-Bechar, Algeria, 26–28 November 2019; pp. 478–486.
50. Assaf, A.M.; Haron, H.; Abdull Hamed, H.N.; Ghaleb, F.A.; Dalam, M.E.; Elfadil-Eisa, T.A. Improving solar radiation forecasting utilizing data augmentation model, generative adversarial networks with a convolutional support vector machine (GAN-CSVR). *Appl. Sci.* **2023**, *13*, 12768. [CrossRef]
51. Jailani, N.L.; Dhanasegaran, J.K.; Alkawsi, G.; Alkahtani, A.A.; Phing, C.C.; Baashar, Y.; Capretz, L.F.; Al-Shetwi, A.Q.; Tiong, S.K. Investigating the power of LSTM-based models in solar energy forecasting. *Processes* **2023**, *11*, 1382. [CrossRef]
52. Priharti, W.; Rosmawati, A.F.K.; Wibawa, I.P.D. IoT-based photovoltaic monitoring system application. *J. Phys. Conf. Ser.* **2019**, *1367*, 012069. [CrossRef]
53. Cheddadi, Y.; Cheddadi, H.; Cheddadi, F.; Errahimi, F.; Es-sbai, N. Design and implementation of an intelligent low-cost IoT solution for energy monitoring of photovoltaic stations. *SN Appl. Sci.* **2020**, *2*, 1165. [CrossRef]
54. Ul Mehmood, M.; Ulasyar, A.; Ali, W.; Zeb, K.; Zad, H.S.; Uddin, W.; Kim, H.-J. A new cloud-based IoT solution for soiling ratio measurement of PV systems using artificial neural network. *Energies* **2023**, *16*, 996. [CrossRef]
55. Adila, A.S.; Husam, A.; Husi, G. Towards the self-powered Internet of Things (IoT) by energy harvesting: Trends and technologies for green IoT. In Proceedings of the 2018 2nd International Symposium on Small-Scale Intelligent Manufacturing Systems (SIMS), Cavan, Ireland, 16–18 April 2018; pp. 1–5.
56. Podder, K.; Roy, N.K.; Pota, H.R. MPPT methods for solar PV systems: A critical review based on tracking nature. *IET Renew. Power Gener.* **2019**, *13*, 1615–1632. [CrossRef]
57. Rokonuzzaman, M.; Shakeri, M.; Hamid, F.A.; Mishu, M.K.; Pasupuleti, J.; Rahman, K.S.; Tiong, S.K.; Amin, N. IoT-enabled high-efficiency smart solar charge controller with maximum power point tracking—Design, hardware implementation and performance testing. *Electronics* **2020**, *9*, 1267. [CrossRef]
58. Williams, K.; Qouneh, A. Internet of Things: Solar array tracker. In Proceedings of the 2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS), Boston, MA, USA, 6–9 August 2017; pp. 1057–1060.
59. Ibrahim, O.; Aziz, M.J.A.; Ayop, R.; Dahiru, A.T.; Low, W.Y.; Sulaiman, M.H.; Amosa, T.I. Fuzzy-logic-based particle swarm optimisation for integrated energy management system considering battery storage degradation. *Results Eng.* **2024**, *24*, 102816. [CrossRef]
60. Xia, K.; Li, Y.; Zhu, B. Improved photovoltaic MPPT algorithm based on ant colony optimisation and fuzzy logic under conditions of partial shading. *IEEE Access* **2024**, *12*, 44817–44825. [CrossRef]
61. Basha, C.H.; Palati, M.; Dhanamjayulu, C.; Muyeen, S.M.; Venkatareddy, P. A novel design and implementation of hybrid MPPT controllers for solar PV systems under various partial shading conditions. *Sci. Rep.* **2024**, *14*, 1609. [CrossRef]
62. Huang, B.; Wang, J. Applications of physics-informed neural networks in power systems—A review. *IEEE Trans. Power Syst.* **2022**, *38*, 572–588. [CrossRef]
63. Aghamolaei, R. Recent advancements in applying machine learning in Power-to-X processes: A literature review. *Sustainability* **2024**, *16*, 9555. [CrossRef]
64. Li, J.; Liu, J.; Yan, P.; Li, X.; Zhou, G.; Yu, D. Operation optimisation of integrated energy system under a renewable-energy-dominated future scene considering both independence and benefit: A review. *Energies* **2021**, *14*, 1103. [CrossRef]
65. Chen, Y.; Zhao, M.; Wang, K.; Wang, Y.; Huang, Y.; Xu, Z. Power sharing and storage-based regenerative braking energy utilisation for sectioning post in electrified railways. *IEEE Trans. Transp. Electrific.* **2023**, *10*, 2677–2688. [CrossRef]
66. Deiana, A.M.; Tran, N.; Agar, J.; Blott, M.; Di Guglielmo, G.; Duarte, J.; Harris, P.; Hauck, S.; Liu, M.; Neubauer, M.S.; et al. Applications and techniques for fast machine learning in science. *Front. Big Data* **2022**, *5*, 787421. [CrossRef]
67. Chetty, K.; Davids, Y.D.; Kanyane, M.; Madzivhandila, T.; Moosa, T.; Ndaba, L. Fostering a just energy transition: Lessons from South Africa's renewable energy independent power producer procurement programme. *S. Afr. J. Int. Aff.* **2023**, *30*, 225–244. [CrossRef]
68. Mantuano, C.; Omoyele, O.; Hoffmann, M.; Weinand, J.M.; Panella, M.; Stolten, D. Data imputation methods for intermittent renewable energy sources: Implications for energy system modeling. *Energy Convers. Manag.* **2025**, *339*, 119857. [CrossRef]
69. Shen, M.; Zhang, H.; Cao, Y.; Yang, F.; Wen, Y. Missing data imputation for solar yield prediction using temporal multi-modal variational auto-encoder. In Proceedings of the 29th ACM International Conference on Multimedia, Virtual Event, China, 20–24 October 2021; pp. 2558–2566.
70. Faraji Niri, M.; Aslansefat, K.; Haghi, S.; Hashemian, M.; Daub, R.; Marco, J. A review of the applications of explainable machine learning for lithium-ion batteries: From production to state and performance estimation. *Energies* **2023**, *16*, 6360. [CrossRef]
71. Petrosian, O.; Zhang, Y. Solar power generation forecasting in smart cities and explanation based on explainable AI. *Smart Cities* **2024**, *7*, 3388–3411. [CrossRef]
72. Öter, A.; Ersöz, B. Artificial Intelligence Assisted Solar Energy Forecasting by Explainability Approaches with LIME and SHAP. *El-Cezeri Fen Mühendis. Derg.* **2025**, *12*, 205–212. [CrossRef]

73. Dou, X.; Cui, Z. Neural network-based forecasting and uncertainty analysis of new power generation capacity of electric energy. *Energy Inform.* **2025**, *8*, 85. [CrossRef]
74. Hafeez, G. Electrical Energy Consumption Forecasting for Efficient Energy Management in Smart Grid. Ph.D. Thesis, COMSATS University Islamabad, Islamabad, Pakistan, 2021.
75. Atiea, M.A.; Shaheen, A.M.; Alassaf, A.; Alsaleh, I. Enhanced solar power prediction models with integrating meteorological data toward sustainable energy forecasting. *Int. J. Energy Res.* **2024**, *1*, 8022398. [CrossRef]
76. Wasay, A.; Raza, B.; Khan, Z.; Amir, M.; Rehman, B.U.; Shahid, H.; Bangash, K.U. Solar Radiation Prediction for Renewable Energy: A Machine Learning Perspective. *Spectr. Eng. Manag. Sci.* **2025**, *3*, 1048–1066.
77. Williams, M.J.; Chang, C.K. The optimal integration of virtual power plants for the South African national grid based on an energy mix as per the Integrated Resource Plan 2019: A review. *Energies* **2024**, *17*, 6489. [CrossRef]
78. Ye, Z.; Giani, A.; Elasser, A.; Mazumder, S.K.; Farnell, C.; Mantooth, H.A.; Kim, T.; Liu, J.; Chen, B.; Seo, G.-S.; et al. A review of cyber–physical security for photovoltaic systems. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *10*, 4879–4901. [CrossRef]
79. Parveen, R.; Mohammed, A.M.; Ravinder, K. IoT-based solar tracking system for efficient power generation. *Int. J. Res. Anal. Rev.* **2018**, *5*, 481–485.
80. Shah, M.M.A.; Parvez, M.S.; Ahmed, A.; Hazari, M.R. IoT-based power monitoring of solar panel incorporating tracking system. In Proceedings of the 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, 8–9 July 2021; pp. 1–4.
81. Musleh, A.; Ahmed, J.; Ahmed, N.; Xu, H.; Chen, G.; Kerr, S.; Jha, S. Experimental cybersecurity evaluation of distributed solar inverters: Vulnerabilities and impacts on the Australian grid. *IEEE Trans. Smart Grid* **2024**, *15*, 5139–5150. [CrossRef]
82. Ejiyi, C.J.; Cai, D.; Thomas, D.; Obiora, S.; Osei-Mensah, E.; Acen, C.; Eze, F.O.; Sam, F.; Zhang, Q.; Bamisile, O.O. Comprehensive review of artificial intelligence applications in renewable energy systems: Current implementations and emerging trends. *J. Big Data* **2025**, *12*, 169. [CrossRef]
83. Adewoyin, M.A.; Adediwin, O.; Audu, A.J. Artificial intelligence and sustainable energy development: A review of applications, challenges, and future directions. *Int. J. Multidiscip. Res. Growth Eval.* **2025**, *6*, 196–203.
84. Cavus, M. Advancing power systems with renewable energy and intelligent technologies: A comprehensive review on grid transformation and integration. *Electronics* **2025**, *14*, 1159. [CrossRef]
85. Biswas, P.; Rashid, A.; Al Masum, A.; Al Nasim, M.A.; Ferdous, A.A.; Gupta, K.D.; Biswas, A. An extensive and methodical review of smart grids for sustainable energy management—Addressing challenges with AI, renewable energy integration, and leading-edge technologies. *IEEE Access* **2025**, *1*, 1. [CrossRef]
86. Adebayo, D.H.; Ajiboye, J.A.; Okwor, U.D.; Muhammad, A.L.; Ugwuijem, C.D.; Agbo, E.K.; Stephen, V.I. Optimising energy storage for electric grids: Advances in hybrid technologies. *Management* **2025**, *10*, 11.
87. Aslam, S.; Aung, P.P.; Rafsanjani, A.S.; Majeed, A.P.A. Machine learning applications in energy systems: Current trends, challenges, and research directions. *Energy Inform.* **2025**, *8*, 62.
88. Worku, M.Y. Recent advances in energy storage systems for renewable source grid integration: A comprehensive review. *Sustainability* **2022**, *14*, 5985. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.