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AI for Solar PV Forecasting, MPPT, and Energy Management: A Comprehensive Review

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Abstract: With sub-millisecond latency, 10 million devices per square kilometer of connectivity, and terabit Photovoltaic (PV) systems are becoming increasingly important in today's electricity networks. The fast growth of these installations is moving the focus from simply putting up the solar panels to ways to predict how much electricity they will produce in the future, ways to get the maximum generation from the panels (maximum power point tracking or MPPT), and ways to intelligently manage energy. At the same time, several different research articles demonstrate that artificial intelligence (AI) is becoming a fundamental part of three interrelated functions of PV: predicting future PV production, rapidly and stably extracting available power, and scheduling the interactions between PVs, batteries, loads, and the grid. The majority of reviews focus only on one of three areas: forecasting, MPPT, or energy management, while actual PV systems increasingly require those functions to be simultaneously optimized.

This review establishes a common technical framework across all three areas. It provides an overview of recent work on AI-based PV forecasting, smart and hybrid MPPT, and AI-enabled energy management; compares separate and hybrid approaches to all three processes; establishes a comprehensive benchmark and simulation framework from the literature reviewed; and identifies a number of key research areas needing attention, including benchmarks being established, quantifying uncertainties in the results, transferability of the results to other applications, battery aging considerations, explainability of the models being produced by the algorithms, and deployment based on digital twins.

The primary conclusion is that hybrid AI approaches currently represent a significant amount of the future direction for intelligent PV systems. In forecasting, applications of hybrid and physics-based deep-learning techniques lead to improved spatiotemporal characterizations of forecast uncertainty and improved robustness in their ability to forecast; in MPPT, the use of hybrid methods leads to better overall balancing of global vs. local searches for maximum power in partially shaded scenarios; and in energy management, the combination of forecast-based reinforcement learning methods and hybrid predictive control strategies provide the best overall balance between adaptability and operational constraints.

Keywords: Power Optimization; photovoltaic forecasting; maximum power point tracking; energy management; deep learning; reinforcement learning; hybrid intelligent systems.

1. Introduction

PVs have become one of the most rapidly expanding technologies of energy generation globally. The International Energy Agency's Photovoltaic Power System Programme Trends in Photovoltaic Applications (2025 Report) indicates global PV installations set yet again new highs and cumulative installed capacity continued its sharp rise confirming that photovoltaic (PV) will act as a fundamental building block in the transition of global electrical sources[1]. As such, this increased usage has led to two significant outcomes: (1) PV systems will need to operate more consistently across variable weather and grid conditions; and (2) PV intelligence will no longer be viewed as a single-task optimization issue, but will rather need to be viewed as several interacting layers within a common operational stack for forecasting, power extraction and energy management [1, 2].

AI has particular promise in the area of PVs due to the non-linear, time-varying, weather-dependent and often partially observable nature of the governing relationships. Forecasting models must be able to handle cloud movement, uncertainty in incoming irradiance, site-to-site variations, and multi-modal streams of input (e.g., historical energy production, weather variables, and images of the sky)[3, 4]. Maximum Power Point Tracker (MPPT) controllers must be able to find the optimum operating point where maximum energy production occurs during fast transient periods of changing irradiance, sensor noise, and partial shading conditions. Energy management systems (EMS) need to make continuous and sequential decisions with regard to storage, demand, and grid interactions in highly uncertain environments for both energy generation and load, frequently in real-time[5-9]. While literature has been published demonstrating the rapid growth in the field, there remains a tendency for researchers to treat these functions independently of one another. For example, forecasting research primarily focuses on maximizing predictive capabilities, frequently not addressing the subsequent value of control. MPPT studies typically focus on optimizing tracking efficiency and rate of convergence without regard to how the quality of the harvested energy will affect the harvesting and scheduling decisions. EMS literature typically makes assumptions about fixed forecast inputs and ideal converter response characteristics. This fragmentation creates gaps between how well the algorithms perform on a stand-alone basis as opposed to how much value they realize in a complete system[2, 5, 6]. The principal argument of this review is that the future of AI for PVs will reside with the development of hybrid, integrated, and hierarchical intelligence rather than in task specific models that operate independently[10] [2, 9].

1.1 Objectives and Contributions

The purpose of this review is to provide an integrated overview of AI in the context of solar photovoltaic (PV) forecasting, maximum power point tracking (MPPT), and energy management; examine both stand-alone and hybrid approaches to these areas; create a simulation-based benchmarking framework that synthesizes the literature; and identify future research directions for uncertainty-aware control, battery-age-aware EMS, physics-informed learning, and digital twin enabled operations.

1.2 Related Work and Research Gap

The recent reviews indicate that the number of publications related to AI for PV has increased greatly over the past three years. In addition, there are some recent forecasting review articles that discuss transformer architectures, multimodal inputs, transfer learning, and uncertainty estimation. MPPT review articles have become increasingly focused on differentiating between classical vs. intelligent, optimization-based vs. hybrid methods. EMS has shifted focus primarily to reinforcement learning, predictive control, and integration of PV and Battery Storage Systems in Buildings, and Homes [11-14].

For this review, recent peer-reviewed publications (2024-2026) have been prioritized, with a few foundational benchmark and dataset articles included as well when they were considered necessary [15-17]. In recent forecasting publications, the use of transformers, multimodal inputs, transfer learning, and uncertainty estimation is being emphasized, while there is an increased focus in MPPT literature on the differentiation between classical vs. intelligent, optimization vs. hybrid methods. In EMS analyses, there is a growing use of Reinforcement Learning, Predictive Control and Integration of PV and Battery Storage Systems in Buildings & Homes[18] [19, 20]. One of the significant gaps in the current literature is cross-layer fragmentation, which refers to how each layer is studied as a separate entity, when the performance of a real-world PV system is typically dependent upon the interaction of the three layers. Another major gap is weak standardization of benchmarks, whereby forecasting and MPPT methods are different based on both horizon and datasets; therefore, there are also significant differences in the benchmarking criteria used when comparing PV systems between MPPT and EMS research based upon the individual characteristics of those specific systems [2, 6, 9]. Table 1 shown a Summary of the Review Areas Reviewed.

Table 1: Comparative summary of existing review focus areas

Review focus	Typical emphasis	Common limitation
PV forecasting	Accuracy, model class, horizon	Often disconnected from control value
MPPT	Tracking efficiency, PSC robustness	Limited EMS linkage
Energy management	Cost, self-consumption, RL/MPC	Often assumes exogenous perfect forecasts
Integrated PV intelligence	Emerging	Still underdeveloped

2. Problem Formulation

A modern PV intelligence stack can be represented as three coupled tasks. Let $P_{pv}(t)$be PV power, $G(t)$irradiance, $T(t)$temperature, $SOC(t)$battery state of charge, $L(t)$load, and $\pi(t)$tariff. Then:

$$\hat{P}_{pv}(t+\Delta) = f_\theta(x_t)$$

Models future PV output from data x_t, where $f_\theta$is a forecasting model.

$$u_m(t) = g_\phi(V_{pv}(t), I_{pv}(t), G(t), T(t))$$

Models the MPPT control law, where $u_m(t)$is typically the converter duty cycle and $g_\phi$may be classical, intelligent, or hybrid.

$$u_e(t) = h_\psi(\hat{P}_{pv}, SOC(t), L(t), \pi(t), \omega_t)$$

Models the energy-management policy, where $u_e(t)$determines battery action, load scheduling, or grid exchange under uncertainty ω_t[2], [5], [6].

A general EMS objective can be written as:

$$\min J = \sum_{t=1}^{H} [c_g(t)P_g(t) + \lambda_b D_b(t) + \lambda_u U(t) - \lambda_s S(t)]$$

Subject to power-balance, battery, inverter, and operational constraints. Here, $P_g(t)$is grid power, $D_b(t)$is a battery-stress or degradation proxy, $U(t)$is unmet demand or penalty, and $S(t)$is self-consumption reward. This formulation captures the multi-objective nature of PV-battery energy management and explains why RL and hybrid MPC/RL methods are attractive: they can handle nonlinear, time-coupled, and uncertain control problems more naturally than static rules [21-23].

The architecture of a multi-source data forecasted, maximum power point tracked and optimized energy management system for photovoltaic energy management is illustrated below in Figure-1. The forecasting component predicts photovoltaic generation with uncertainty bandings from both environmental and operational data. The forecasted output is used by both the MPPT controller to control the power converter and by the EMS for the optimum scheduling of battery storage, load demand, and grid interaction, thereby improving the overall performance of the PV system[24, 25].

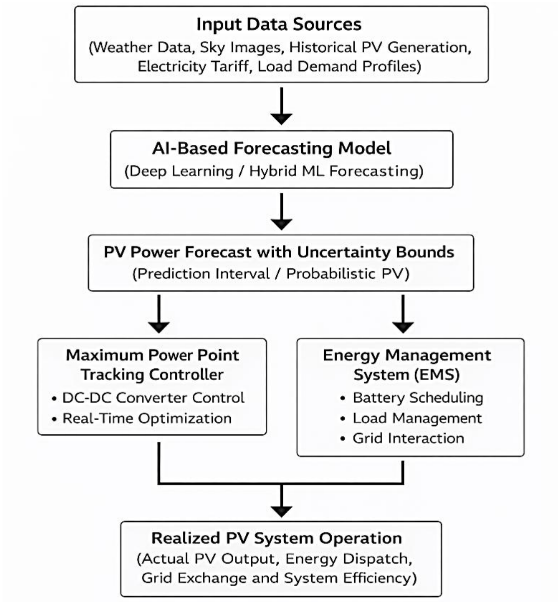

Figure 1: Integrated AI-based forecasting and control architecture

This block diagram clarifies that forecasting, MPPT, and EMS are linked layers in one control hierarchy[2, 3, 8, 9].

3. AI for Solar PV Forecasting

Several AI methods utilize for Solar PV forecasting, which can be summarized in:

3.1 Data Modalities and Forecast Horizons

The forecasting of PV (photovoltaic) output is multi-scale – from "nowcast" (very short time) to operational (1 hour ahead) to daily schedules (1-day ahead) to long-term planning. Factors that contribute to forecasting include past PV (photovoltaic) output, the amount of sunlight (irradiance), the temperature (temperature), numerical weather predictions (NWP) and recently published images taken from ground-based sky cameras (groundbased sky images)[26, 27]. Dataset papers such as SKIPP'D represent the continued trend toward multiple modes of forecasting and more realistic benchmark development in this field [28]. With respect to the latter, some of the recent studies show that model performance changes rapidly as the length of time until the forecast occurs increases, so it is essential to perform horizon aware evaluations [29].

3.2 Model Families

There are six primary models that can be used to create forecasts: persistence/statistical models, shallow machine learning, recurrent neural networks, hybrid CNN-LSTM architectures, transformer models, and physics-informed deep neural networks. Persistence and basic statistical models can serve as a baseline for most of the time spans covered by forecasts but are particularly good for very short time spans as baselines. In many contexts, tree-based machine learning models such as Random Forest and XGBoost continue to compete successfully with one another for tabular weather data. For more complex time series datasets (i.e., those that can benefit from additional temporal features or multiple input types), deep networks outperform shallow networks[30]. The use of transformer-based models was found to outperform other model types for hourly forecasts within a common evaluation framework (i.e., when evaluated using common data and models), especially when adaptive conformal inference was used to estimate uncertainty in the hour ahead forecast [31]. Physics-informed models such as RTI-Net are at the forefront of incorporating the physics of solar radiation into the learning pipeline as opposed to using black box techniques for feature extraction alone [32, 33].

3.3 Hybrid Forecasting Methods

Hybrid deep architectures have become increasingly popular in recent years according to new studies that focus on this area of study. They utilize CNN layers to provide local spatial feature extraction from cloud images or multivariate inputs, while LSTM/BiLSTM layers model the temporal dependency between cloud images. Emerging hybrid models are incorporating physical constraint functions or decomposition modules for improvement on overall performance of hybrid hybrid architectures in different weather regimes[34]. Additionally, hybrid CNN-LSTM architectures continue to show robust practical performance, whereas continuing to develop robust models utilizing TCN/LSTM architecture and transformer-based Swin Hybrid CNN-LSTM and TCN/LSTM combinations have yet to be fully explored for even more demanding forecasting methods. Table-2, depicted a summary of some key aspects of hybrid forecasting methods such as TCNs, CNNs, Bi-LS, Transformers, LSTMs[1, 3, 4, 11].

Table 2: Comparative table: Hybrid forecasting methods

Hybrid method	Main idea	Strengths	Weaknesses	Best use case
CNN–LSTM	CNN extracts nonlinear/local features, LSTM models time dependence	Good accuracy, mature, easier to train than transformers	Can miss long-range dependencies; may need larger datasets	Short-term PV power forecasting
CNN–BiLSTM–Attention	Adds bidirectional temporal modeling and feature weighting	Better temporal context and interpretability than plain CNN–LSTM	Higher complexity and slower inference	Intra-hour and hour-ahead forecasting
Transformer–CNN–LSTM	Combines global attention, local feature extraction, and sequential modeling	Strong performance on complex multimodal data	Computationally heavy; hyperparameter-sensitive	Sky-image + sensor forecasting
Physics-informed TCN/LSTM	Combines learned features	Better generalization and	Harder to formulate; more	Multi-site and weather-shifted

hybrid	with physical relationships	physical consistency	design effort	deployment
Decomposition + deep learner	Decomposes signal into subcomponents before learning	Handles nonstationary signals well	Pipeline becomes complex and less end-to-end	Noisy irradiance and mixed weather regimes

The biggest benefit of hybrid forecast Models is that you can take out the compromise between local pattern extraction versus long-term sequence learning. The downside with using Hybrid forecasting techniques is that they usually require extensively tailored architecture tuning, and can prove challenging to implement on low energy-edge hardware. Hybrid forecasters have also shown the need for establishing parity benchmarks, estimation/determination of relative uncertainty, and establishing benchmarks & metrics for cost incurred during inference, see figure – 2 for examples of above.

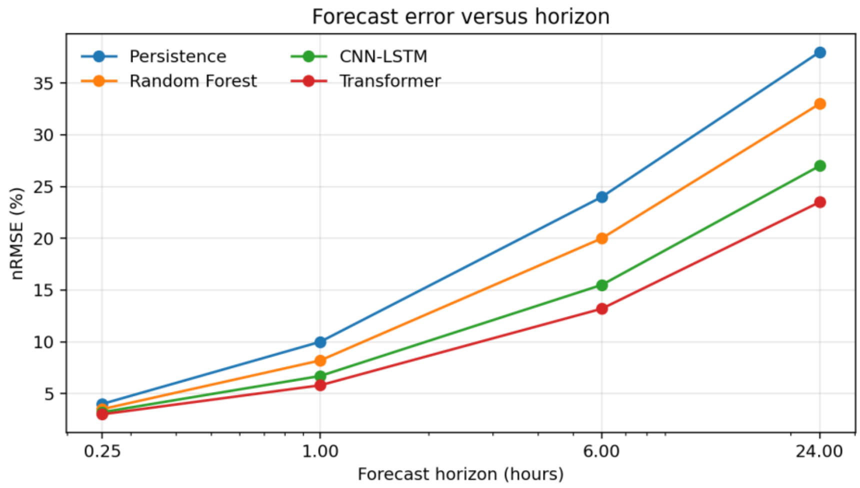

Figure 2: Forecast error versus horizon. Advanced hybrid and transformer models tend to degrade more gracefully as the forecast horizon increases.

Figure -3 shown Block diagram of a hybrid PV forecasting pipeline as simple baselines are competitive at short horizons, but advanced hybrid or transformer models degrade more gracefully as horizon increases[3, 4, 12].

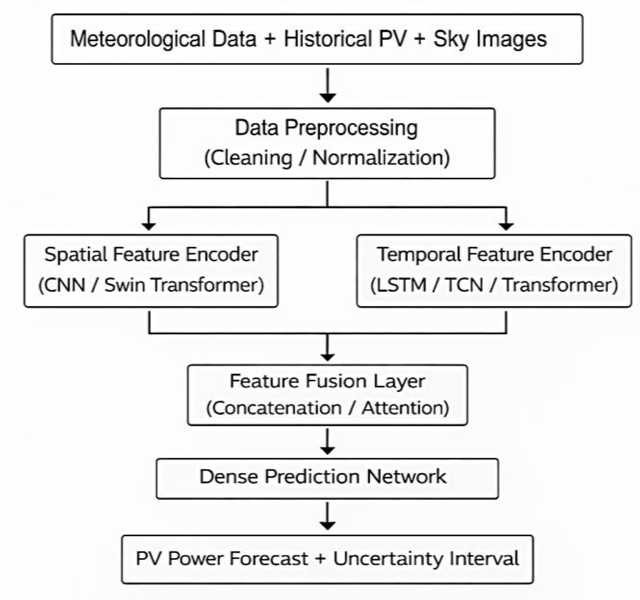

Figure 3: Block diagram of a hybrid PV forecasting pipeline [8], [13].

4. AI for Maximum Power Point Tracking (MPPT)

Photovoltaic (PV) panels have voltage-current and voltage-power characteristics that can change based on things like sunlight and temperature. When a PV panel is partially shaded, the voltage-power curve will often have two or more peaks, which will make finding maximum power point tracking (MPPT) difficult because it now will require tracking each peak globally instead of just tracking the maximum of each peak. Due to this fact, many researchers are focusing on developing advanced or hybrid techniques to track MPPTs since there is still not a consensus on how best to do this[35] [6, 11].

4.1 Method Families

Simple methods, like Perturb and Observe (P&O) and Incremental Conductance (IncCond), are often the most appealing MPPT techniques due to their ease of implementation and low computational cost. Using advanced techniques, like artificial neural networks (ANN), fuzzy logic or adaptive neuro fuzzy inference systems (ANFIS), will give instant adaptation for nonlinearity. Using optimization techniques, like particle swarm optimization (PSO), allows for greater efficiency in finding large or "global" search areas. Finally, hybrid methods are developed to use various combinations of these different method types, thus balancing between finding new search areas and refining already found search areas for maximum performance when shading occurs. For examples of hybrid MPPT methods[6, 11].

4.2 Hybrid MPPT Methods

Hybrid algorithms combine the fast response time of conventional controllers with the global reach of either metaheuristic or learning algorithms. This has led to a large amount of interest in ANN-PSO, fuzzy-PSO, and traditional controller-based ANN methodologies due to their hybrid properties. Similarly, this conclusion is also found when looking at the broader MPPT literature, where researchers suggest that newer MPPT methodologies should also be compared based upon the following metrics: efficiency, ripple, speed of convergence, computational complexity, and robustness to realistic variations of the solar array. The primary benefit of hybrid MPPT methods is that they allow for tracking to avoid (i.e., not to be misled by) local maxima, while maintaining reasonably fast dynamic response times; however, the main challenges associated with implementing hybrid MPPT methods include implementation complexity, training/tuning time, and the significant amount of simulation-based evidence that exists for most studies, with limited material present for large-scale field verification in relation to hybrid MPPT methodology[6, 11]. A table-3, comparing the different hybrid MPPT methods is shown in Table-3.

Table 3: Comparative table: Hybrid MPPT methods

Hybrid method	Main idea	Advantages	Disadvantages	Best use case
P&O–Fuzzy	Classical perturbation with fuzzy adaptation	Faster settling than plain P&O; reduced oscillation	Still may struggle with severe multi-peak curves	Mild shading, low-cost systems
ANN–PSO	ANN estimates region; PSO performs global search	Strong under partial shading; good global MPP finding	Higher computation; training required	Variable irradiance and complex shading
ANFIS-based hybrid	Neuro-fuzzy inference for nonlinear adaptation	Smooth control, better rule flexibility	Rule design and tuning can be difficult	Dynamic irradiance with noisy measurements
Fuzzy–DDPG	Fuzzy membership improves RL state/action handling	Strong adaptive behavior and convergence under PSC	High design and training complexity	Advanced intelligent converters
Metaheuristic + classical local refinement	Global search then fast local tracking	Good balance of exploration and stability	Can be slower at startup if poorly tuned	Harsh shading with real-time constraints

Hybrid Maximum Power Point Tracking (MPPT) methods have a major benefit in that they possess both a global search capability and a high-speed local convergence capability; however, the significant drawback of hybrid methods is the high level of implementation complexity when utilizing embedded processing devices with limited memory and low timing margins. Several reviews published from 2025 to 2026 showed that hybrid AI MPPT methods have the highest potential for use in partial shade; however, at this time, the level of real-time experimental validation of hybrid AI MPPT methods is significantly lower than the level of validation through simulation. Although hybrid methods may incur somewhat more computational complexity for the same decision, hybrid methods will converge closer to the global optimal point with lower steady-state ripple when subject to partial shading conditions (see Figures 4 and 5) than other methods.

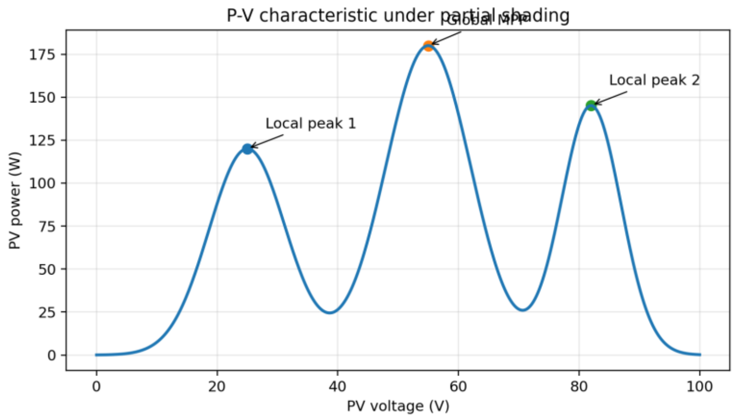

Figure 4: P-V characteristic under partial shading, illustrating multiple local maxima and the need for global-search-capable MPPT.

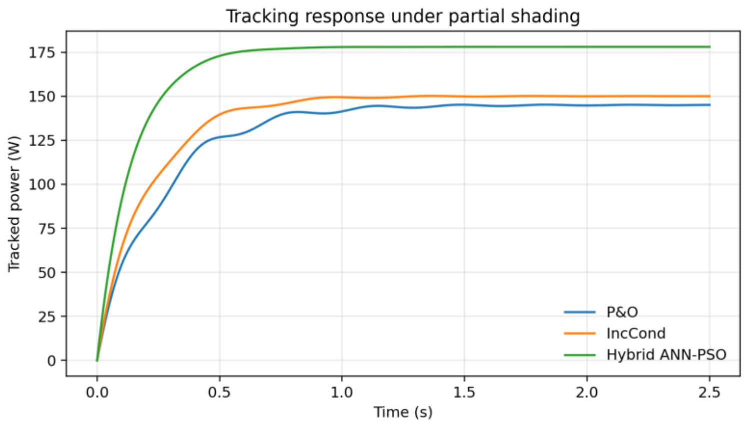

Figure 5: Tracking response under partial shading. Hybrid tracking typically converges nearer the global optimum with lower ripple.

Figure-6 illustrates the hybrid M.P.P.T. control structure that is designed for PV systems. This structure can work in both fully illuminated and partially shaded areas. The control architecture uses various environmental and electrical parameters (such as PV voltage, I, temperature, and irradiance) to determine if the system is stable, or if it has had some type of shading occurrence or other instability occur. It applies a hybrid control method which utilizes both a global optimization control method (including PSO, A.N.N., or reinforcement learning) to identify the global maximum power point (M.P.P.), and a local tracking control method (including perturb-and-observe or incremental conductance) for faster convergence. Once a control method has completed its calculations, the duty-cycle will be changed on the D.C.-D.C. converter, and the two control methods will be continuously monitored in a feedback loop.

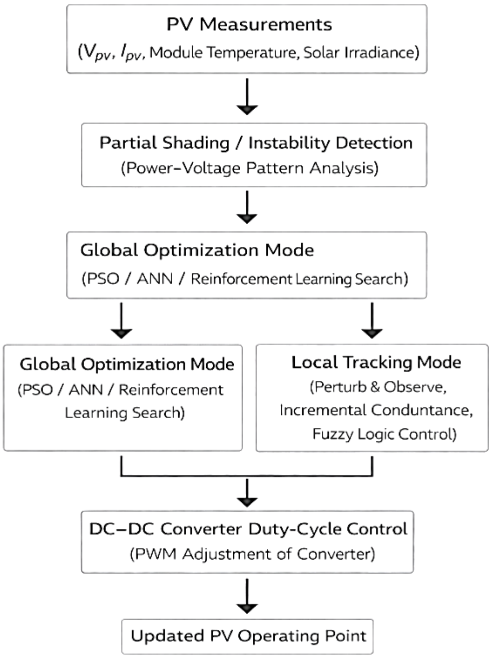

Figure 6: Hybrid maximum power point tracking (MPPT) control architecture for photovoltaic systems operating under partial shading conditions

5. AI for Energy Management

Management of energy usage is the means by which photovoltaic (PV) energy is distributed between grid systems, storage and loads throughout any given facility (e.g., housing, commercial, or microgrid). This includes the need to manage various relationships among cost, self-consumption, comfort, peak load reduction, battery cycle, and in some cases, carbon emissions or are influenced by the connected electrical distribution system within that facility. The most current reviews of integration of PV energy storage systems within buildings indicate that mathematical modeling and operational optimization will be significant components of the total benefits associated with distributed PV systems [7].

5.1 Reinforcement Learning and Hybrid Control

HEMS (Home Energy Management Systems) has come to rely heavily on deep reinforcement learning (DRL). DRL will allow for real time adaptations to demand and generation in an ever-changing environment with smart appliances/load and renewable energy generation. In work by Latoń et al. (2019) they provided a comparison of numerous RL strategies/methods as applied to demand response (DR), scheduling and storage coordination/loss management. They rank DRL as one of the leading methodologies/strategies for adaptive home energy management – next to model-based (MB) agents, which were evaluated as one of the least effective strategies/methodologies for this application. In research conducted by Real et al. (2019), they show that coupling DRL with CNN-LSTM generated load forecasts results in 35% lower total electrical usage (based on reduced electrical costs) and <10 second runtime solutions for a seven days solution. Additionally, they have a PV-battery 2 stage implementation – which helps create additional (6%-12%) energy savings.

The articles demonstrate that any future HEMS (Home Energy Management Systems) initiatives will increasingly utilize a combination of both forecasting, as well as control, rather than separating these areas of focus into different silos (e.g., HEMS = load forecasting; HEMS = load control).

5.2 Hybrid Energy-Management Methods

Hybrid energy management systems combine multiple methods, resulting in an architecture that offers the ability to plan ahead, adapt to changing conditions, and abide by operational constraints. However, these hybrid architectures are often much more complex than traditional architectures and require tuning and testing across multiple modules; this can lead to less interpretable final decision-making processes than either rule-based or optimization-only control systems [6, 7, 9]. The main advantage of artificial intelligence-based energy management systems is adaptability in unpredictable environments. Artificial intelligence-based energy management systems are also often able to respond to forecasting information, floating rates, and changing user behaviors in ways that static control systems cannot [6, 7]. A summary of hybrid energy management methods can be found in table-4.

Table 4: Comparative table for Hybrid energy-management methods

Hybrid method	Main idea	Advantages	Disadvantages	Best use case
Forecasting + MPC	Forecasts feed a model predictive controller	Strong constraint handling; transparent optimization	Needs accurate model and forecasts	Grid-connected PV-battery systems
Forecasting + RL	Forecasts inform RL state and policy	Adaptive and good for uncertainty	Training can be unstable; explainability issues	Dynamic tariffs and changing load patterns
RL + rule-based safety layer	RL optimizes, rules enforce hard limits	Safer deployment and easier acceptance	May reduce optimality	Residential HEMS and microgrids
Optimization + RL	Optimization gives baseline, RL refines in real time	Good balance of reliability and adaptability	More modules and tuning effort	Complex multi-objective EMS
Multi-agent RL + forecasting	Distributed agents coordinate PV, storage, and loads	Scalable for communities and microgrids	High training and communication complexity	Building clusters and local energy communities

Hybrid EMS methods are advantageous because they provide solutions for adaptability as well as meeting operational constraints which is something typically reserved for either stand-alone controller. They are disadvantageous in that they can have a very large state-space (making them more difficult to work with) and are thus very much dependent on the quality of their forecasts and therefore have poor interpretability for operators[9]. For example, figure-7, provides an illustration of the daily power flow associated with a PV battery system. Figure-8 shown how the costs and stresses associated with battery systems vary across alternative approaches to energy management.

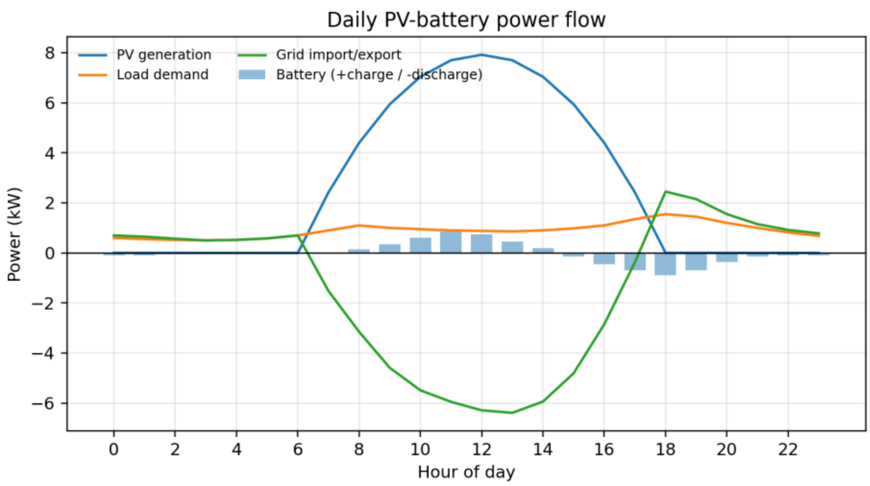

Figure 7: Daily PV-battery power flow showing midday charging, evening discharge, and reduced grid import under a forecast-informed EMS.

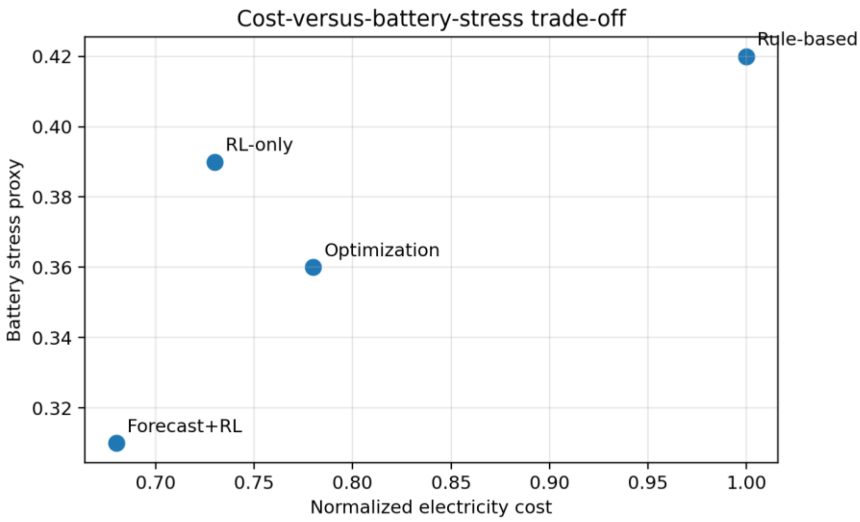

Figure 8: Cost-versus-battery-stress trade-off across representative EMS strategies.

The framework of an intelligent energy management system (EMS) integrates photovoltaric-battery based integrated energy systems and is shown in figure 9. Inputs to the decision engine include predicted photovoltaic generation, load demand, tariff rates, storage state of charge (SOC) and constraints for the end user. Advanced control techniques such as Reinforcement Learning (RL), Model Predictive Control (MPC), and hybrid optimization provide optimal energy dispatch decisions for use by the EMS. The EMS then controls battery charge and discharge, flexible load schedules and grid interaction to enhance overall system performance as measured by operating cost, comfort level of the user, peak demand on a distribution grid and degradation of the battery.

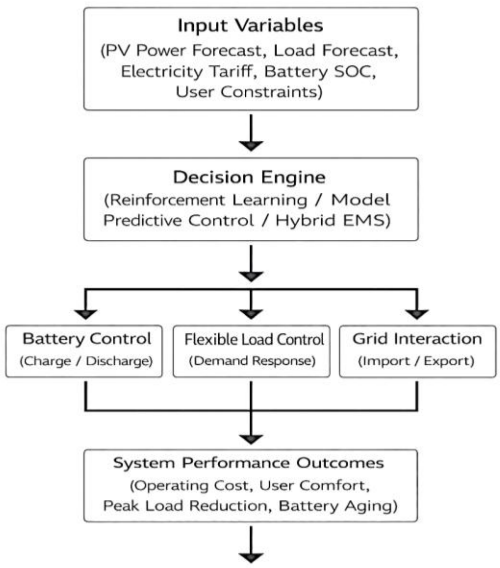

Figure 9: Hierarchical EMS block diagram

5.4 Cross-Section Comparative

Table-4 in the article presents a complete hybrid AI methodology comparison for three different perspective types (forecasting, Maximum Power Point Tracking, and energy Management), enabling an integrated review of hybrid AI because hybrid AI contains no single family of methodologies; rather, it identifies hybrid AI as a design approach/methodology whereby each methodology combines complementary methodologies to effectively manage nonlinear behaviors, uncertainty, and operational requirements compared to independent or unintegrated methodologies.

Table 5: Unified comparison of hybrid AI methods across forecasting, MPPT, and energy management

Application	Representative hybrid methods	Main benefit	Main limitation	Recommended evaluation metrics
Forecasting	CNN–LSTM, Transformer–CNN–LSTM, physics-informed hybrids	Better spatiotemporal learning and robustness	High computation, benchmark inconsistency	RMSE, MAE, nRMSE, MAPE, CRPS, interval coverage
MPPT	ANN–PSO, P&O–fuzzy, fuzzy–DDPG, ANFIS hybrids	Better global MPP search and reduced oscillation	Embedded implementation burden	Tracking efficiency, settling time, ripple, GMPP success rate
Energy management	Forecasting + MPC, forecasting + RL, optimization + RL	Better cost-flexibility trade-off	Harder interpretability and policy tuning	Cost, self-consumption, peak reduction, battery throughput, comfort violation

Overall, hybrid AI methods represent the most promising direction for intelligent PV systems because they align naturally with the layered structure of real solar installations. In forecasting, they improve feature fusion across spatial and temporal data. In MPPT, they balance global exploration with fast local convergence. In energy management, they connect prediction with constrained real-time control.

6. Literature-Synthesized Benchmarking and Simulation Protocol

In order to present an accurate picture of the state of knowledge in forecasting/dynamic tracking, maximum power point tracking (MPPT), and intelligent energy-management systems, and therefore provide a basis for future research and advancement, this paper uses a dual evaluation framework. The first is to produce a seasonal standard simulation environment that can be used as a basis for reproducible inter-domain benchmarking for all future researchers. The second is to produce a synthesized literature inter-domain benchmark, which will contain only those metrics that are clearly explicitly note and/or published by a limited number of peer-reviewed publications. Both recent reviews of the state-of-the-art in PV forecasting and those in RL-HEMS have indicated that the fragmentation of datasets and the inconsistencies in how the data is evaluated continue to be the major barriers to establishing reliable basis for inter-domain comparisons.

6.1 Suggested parameter ranges

The most justifiable protocol for the forecasting process is at least one hour ahead benchmarking and short-term benchmarking, as the forecast horizon has a very major impact on the ranking of models, and recent benchmarking documents have shown this to be accurate. The benchmark for MPPT will require uniform irradiance, step changes of irradiance as well as partial shading, and should be evaluated under both simulation conditions and remuneratively when possible. The energy management benchmark will require battery SOC constraints, efficiency of charging/discharging, demand variation based on time of day, and at least one week for the rolling of decision making to capture the practicality of operations.

The following is a compact parameter block suitable for this work:

- Forecasting parameters: sampling interval = 5–60 min; forecast horizon = 1 h and 24 h; train/validation/test split = 70/15/15; rolling-origin evaluation enabled; normalization = z-score or min max.
- MPPT parameters: irradiance = 200–1000 W/m²; temperature = 15–55°C; scenarios = uniform, fast ramp, partial shading; converter = boost or buck–boost; switching step recorded.
- EMS parameters: battery SOC range = 20–90%; round-trip efficiency = 90–95%; decision interval = 15–60 min; tariff = fixed and time-of-use; horizon = 24 h receding horizon or 7-day rolling horizon. These parameter ranges are not claims about one single published benchmark; they are a review-derived protocol that aligns with the operating ranges and task formulations used across the recent literature.

6.2 Metrics

The paper distinguishes between functions and metrics:

1. For forecasting, the most relevant metrics are RMSE, MAE, nRMSE, SMAPE, R^2, and where possible calibrated uncertainty metrics such as interval coverage or conformal prediction validity. Recent PV forecasting benchmark work explicitly reports MSE, MAE, RMSE, R^2, and SMAPE, and newer studies are increasingly emphasizing uncertainty-aware evaluation.
2. For MPPT, the benchmark should report tracking efficiency, settling time, oscillation or ripple around the MPP, global-MPP success under partial shading, and computational burden. Recent MPPT reviews explicitly frame the comparison around speed, stability, and efficiency, and newer hybrid methods increasingly include complexity-aware benchmarking.
3. For energy management, the key metrics are electricity cost, self-consumption ratio, battery throughput or degradation proxy, peak grid import, unmet load or comfort violation, and solver/runtime cost. Recent PV-battery RL work highlights cost reduction and runtime as deployment-relevant indicators, while RL reviews emphasize adaptive management across demand response and renewable integration.

7. Results & Comparative Synthesis

This paper categorizes the results and the comparative synthesis according to:

7.1 Forecasting Results

Based on recent benchmarking studies on forecast accuracy, hybrid models and transformer models have been evaluated and determined to be the best performers for forecasting. For example, when benchmarking 1 Hour ahead PV Forecast accuracy for 2025, the SL-Transformer had a solar forecasting SMAPE of 4.22% and R2=0.9674, outperforming numerous forecasting techniques, including ARIMA/SVM/LSTM/N-BEATS/vanilla-Transformer forecasting methods. In addition, other studies have demonstrated that hybrid CNN-Transformer models produced over a 20% RMSE reduction compared to LSTM/GRU forecasting techniques and achieved over an R2=0.98 for short-term PV forecasting. An area of intense research interest is continuing to develop techniques using physics-informed forecasting because it builds upon purely black-box images of the sky and improves the physical consistency of the forecasts obtained from them.

Overall, the leading-edge forecasting techniques reviewed reveal that the best forecasting methods tend to combine different types of local feature extraction with longer-term temporal features. In addition, they also have the ability to combine physical priors during the forecasting process for even higher performing forecast estimates. However, due to these combinations, the resulting forecasts tend to be more computationally complex than their more traditional counterparts, and may have a greater level of sensitivity to the setup of the benchmarking that is used for comparison with their performance. Table-6 contains a compilation of the literature published for the most recent comparative study of PV forecasting results.

Table 6: Literature-synthesized comparison of recent PV forecasting results

Study / method	Task	Reported metric	Reported finding
SL-Transformer	Hour-ahead PV forecasting	SMAPE	4.22%
SL-Transformer	Hour-ahead PV forecasting	R^2	0.9674
CNN–Transformer hybrid	Short-term PV forecasting	RMSE reduction vs LSTM/GRU	>20%
CNN–Transformer hybrid	Short-term PV forecasting	R^2	>0.98
RTI-Net	Sky-image PV forecasting	Qualitative finding	Improves physical interpretability by modeling radiation transmission

7.2 MPPT findings

As evident by many of the recent reviews of MPPT, there appears to be a consensus that traditional methods (e.g., P&O & Incremental Conductance) will always remain viable because of their low cost and ease of use; however, hybrid (i.e., Intelligent) methods have been increasing in popularity because of their ability to adapt quickly to rapid environmental changes (e.g., in shading or cloudy weather) or rapidly-changing light levels. In fact, several papers have described hybrid MPPT methods that combine both classical and smart techniques to achieve a better balance between responsivity and stability.

In addition to highlighting this 'hybrid' approach, one paper reported 99.94% efficiency (standard test conditions), 99.21% (experimental data), and up to 7.8% efficiency improvement in partial shading conditions as a result of the system being initialized. Another paper reported an 11.8% improvement in power output and 62% reduction in time to track using a fuzzy plus shading adaptive particle swarm optimizer (PSO) compared to classical tracking methods. These results further support the conclusion obtained from the literature review that hybrid techniques provide the best overall solution for simultaneous global-MPP search and stability requirements; however, this does not hold in all studies due to the differences in hardware and the extent of shading conditions. A summary of this hybrid MPPT review can be found in Table-7 below:

Table 7: Literature-synthesized comparison of recent hybrid MPPT results

Study / method	Scenario	Reported metric	Reported finding
Adaptive gradient + P&O hybrid	STC	Tracking efficiency	99.94%
Adaptive gradient + P&O hybrid	Experimental data	Tracking efficiency	99.21%
Adaptive gradient initialization	Partial shading	Efficiency improvement	Up to 7.8%
Fuzzy + shading-aware PSO	Dynamic shading faults	Power improvement	Up to 11.8%
Fuzzy + shading-aware PSO	Dynamic shading faults	Tracking time reduction	62%

7.3 Energy-management findings

Energy management is seeing the strongest evidence in the increased use of predictive modeling with dynamic adaptive logic via reinforcement learning. A recent study analyzing the ability of using CNN-LSTM load forecasting in conjunction with deep reinforcement learning to develop versatile PV-battery solutions demonstrated the cost-effectiveness of implementing a deep reinforcement learning (RL) agent; specifically, an RL agent achieved 35% less total electricity cost (compared to an optimization agent) with sub-10 second runtime on developing a schedule for a week. This is one of the most definitive signs since hybrid predictive-control pipelines are considered operational as opposed to simply theoretical. In addition to PV-battery applications, reinforcement learning (RL) has been increasingly cited as an effective means to activate Demand Response (DR), load scheduling and facilitate the integration of renewable resources through the Internet of Things (IoT) in smart homes and buildings. Table-8 summarizes the comparison of a variety of recent EMS literature synthesized into common results.

Table 8: Literature-synthesized comparison of recent EMS results

Study / method	Scenario	Reported metric	Reported finding
DRL + CNN-LSTM load forecasting	Residential PV-battery HEMS	Electricity cost reduction	35% vs optimization-based agent
DRL + CNN-LSTM load forecasting	Residential PV-battery HEMS	Runtime	<10 s for 7-day solution
RL-for-HEMS review	Smart home / HEMS	Qualitative finding	RL supports adaptive management, demand response, and renewable integration

8. Discussion

This review's primary conclusion is that artificial intelligence (AI) for photovoltaic (PV) systems is on a path towards a hybrid model of hierarchical Intelligence. On the one hand, incoming forecast models are being developed increasingly from single stream predictors into greater complexity through the integration of multimodal, uncertainty-aware, and physics-based systems. On the other hand, methods for Maximum Power Point Tracking (MPPT) have transitioned from using local perturbation rules to being a hybrid control mechanism by combining search strategies, adaptive techniques, and robustness. Finally, methods of Energy Management Systems (EMS) have also evolved from being purely static schedules to being forecast aware, adaptable to change, and capable of making multiple-objective decisions.

The second critical finding from this review is that hybrid methods for accomplishing various tasks work better than conventional independent methods do, in terms of their overall performance, not simply their raw performance as compared with conventional independent methods. For example, in making forecasts, hybrid methods produce better overall forecasts than by using only local pattern matching and/or temporal modeling or physical consistency to base such forecasts.

The third noteworthy finding of this review is that deployment considerations have overtaken other factors as the primary driver of whether current AI techniques developed for PV will be transferred from the prototype stage of development into proven systems capable of being deployed in the PV space. These deployment-related factors include benchmark inconsistency, the transferability of the techniques, the quantification of uncertainty in the applied technique, constraints placed on the performance of edge computing systems, the impacts of lithium-ion battery ageing, and the need for the ability to explain how an AI technique arrives at its solution. Therefore, the rapid growth of interest in digitalization of PV and the concurrent introduction of PV digital twins reflects this overall transition from algorithm-driven intelligence to operational-driven approaches.

9. Conclusion

Across three highly linked operating tiers of PV systems, AI is progressing to increasingly impact the following: forecasting, MPPT, and energy management. The papers examined in this review provide considerable evidence of recent advances in transformer forecasting, hybrid intelligent MPPT using PSC, and forecast-aware reinforcement-learning based EMS systems. The overall trajectory of the field is moving toward the combination of IDLPs (i.e., isolated), hierarchical, hybrid, and deployment-aware types of PV intelligence.

This review illustrates that the next level of advancement will not occur from merely improving the accuracy of the former IDLPs but rather through better educating engineers and researchers in terms of existing standard operating procedures, appropriate benchmarking protocols, trustworthy deployment mechanisms, and lifecycle-aware decision-making. As a result, future PV research should place greater emphasis on integrated assessment of multiple operating tiers, uncertainty management, battery aware optimization, and digital operational intelligence in order to maximize the impact of AI in real-world PV installations.

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