

Recent Advances in Control, Power Management, and Forecasting for Grid-Connected Solar Photovoltaic Systems A Review (2020–2025)

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ABSTRACT

High penetration of grid-connected solar photovoltaic (PV) generation is reshaping distribution and transmission system operation. While PV contributes clean energy, its intermittency and inverter-based interfacing introduce challenges in voltage regulation, stability, and dispatchability. This review integrates three tightly linked domains: (i) inverter control for active/reactive power regulation and grid support, (ii) maximum power point tracking (MPPT) and DC-side voltage stability—especially critical in single-stage architectures, and (iii) solar generation forecasting using statistical, machine learning, and deep learning methods to support planning and real-time control.

Mathematical foundations of dq control, power decoupling, inverter capability limits, volt–var/volt–watt characteristics, and forecasting model formulations are presented. The paper emphasizes the operational co-design of forecasting and control to achieve reliable, cyber-resilient, high-PV grids and concludes with research directions for 2025-era smart inverters, probabilistic forecasting, and grid-forming control.

Keywords: Solar PV; smart inverter; volt–var control; volt–watt control; MPPT; DC-link stability; forecasting; XGBoost; Prophet; Transformer; probabilistic forecasting; grid-forming inverter.

INTRODUCTION

Solar photovoltaic (PV) deployment has expanded rapidly, driven by cost reductions and decarbonization policies. As penetration rises, PV plants are increasingly expected to behave as grid-supporting resources rather than passive energy injectors. Distribution feeders with significant PV commonly experience midday overvoltage, reverse power flow, and enhanced sensitivity to fast irradiance ramps. Unlike synchronous generators, PV systems are interfaced through inverters that can respond quickly but do not inherently provide rotational inertia. This shift motivates inverter functions such as reactive power support, voltage regulation, frequency response, and fault ride-through, which are now reflected in evolving interconnection standards and utility requirements [1]–[6].

A second operational driver is uncertainty. PV output depends on weather, so accurate forecasts are essential for reserve sizing, market bidding, battery scheduling, and proactive volt–var planning. Recent literature (2020–2025) shows that forecasting accuracy improves when models incorporate exogenous meteorological features and nonlinear learners such as gradient boosting and deep learning. At the same time, the strongest practical gains often come from integrating forecasting with control—translating predicted PV and load patterns into inverter setpoints, curtailment schedules, and adaptive volt–var rules [7]–[15].

This review is structured as follows: Section 2 summarizes PV system architectures and models. Section 3 elaborates inverter control for active and reactive power, including volt–var/volt–watt and grid-forming trends. Section 4 discusses MPPT and DC voltage stability with emphasis on single-stage PV systems. Section 5 reviews PV forecasting methods (statistical, ML, DL) with key equations. Section 6 outlines forecast-informed control and coordinated PV–storage operation. Section 7 highlights challenges and research opportunities (2025 perspective). Section 8 concludes.

2 Grid-Connected PV Architecture and Mathematical Modeling

2.1 PV array characteristics and maximum power condition

PV electrical behavior is nonlinear and varies with irradiance and temperature. The power–voltage (P–V) curve features a unique maximum under uniform irradiance, where incremental changes in operating voltage do not increase output power. This observation underpins most MPPT algorithms and also influences stability analysis because the PV incremental resistance changes rapidly near MPP. The maximum power condition is expressed by setting the derivative of PV power to zero [16]–[19].

$$P = V \cdot I \quad (1)$$

$$dP/dV = 0 \Rightarrow I + V \cdot (dI/dV) = 0 \quad (2)$$

2.2 Single-stage and two-stage PV conversion

In two-stage architectures, a DC–DC converter performs MPPT and DC voltage regulation, and the inverter performs grid synchronization and PQ control. This decoupling simplifies control and helps buffer DC-side disturbances. In single-stage systems, the PV array connects directly to the inverter DC link, improving efficiency and reducing component count. However, MPPT, DC voltage stability, and AC-side reactive power support become tightly coupled. Single-stage systems can exhibit PV/DC voltage collapse if inverter power demands and PV supply become mismatched during disturbances or aggressive reactive power control [20]–[22].

2.3 dq-frame inverter model and power decoupling

Most modern grid-connected inverters use synchronous reference frame (dq) control aligned with the grid voltage vector via a phase-locked loop (PLL). With ideal alignment, the q-axis grid voltage is near zero, and real and reactive power can be approximately controlled through d- and q-axis currents. This decoupling enables clear outer-loop design for P and Q (or voltage) regulation and fast inner current loops [2], [23]–[27].

$$P = (3/2) (v_d \cdot i_d + v_q \cdot i_q) \quad (3)$$

$$Q = (3/2) (v_q \cdot i_d - v_d \cdot i_q) \quad (4)$$

$$\text{If } v_q \approx 0: P \approx (3/2) v_d \cdot i_d, \quad Q \approx -(3/2) v_d \cdot i_q \quad (5)$$

3 Active and Reactive Power Control of PV Inverters

3.1 Power transfer intuition: angle and voltage magnitude

A useful physical interpretation of inverter power exchange is obtained by modeling the coupling impedance as mainly inductive. In that case, active power depends primarily on the phase angle difference between the inverter voltage and the grid voltage, while reactive power depends on the voltage magnitude difference. These relationships motivate controllers that regulate phase/angle for P and magnitude for Q or voltage support and remain conceptually helpful even when dq current control is used in practice [20], [21].

$$P \approx (V_t \cdot V_c / X) \cdot \sin(\delta) \quad (6)$$

$$Q \approx (V_t / X) \cdot (V_c \cdot \cos(\delta) - V_t) \quad (7)$$

3.2 PQ control using cascaded loops

In a standard cascaded architecture, outer loops compute current references from power commands and measured grid voltage, and inner loops regulate dq currents. With $v_q \approx 0$, the current references can be derived from the decoupled power expressions. In practice, saturation logic is needed to enforce inverter current limits and capability constraints under large disturbances, and anti-windup is required for PI controllers. This structure supports both MPPT-based operation (P follows available PV power) and dispatch/curtailment operation (P follows a setpoint) [2], [23]–[27].

$$i_d^* = (2/3) \cdot (P^* / v_d) \quad (8)$$

$$i_q^* = -(2/3) \cdot (Q^* / v_d) \quad (9)$$

3.3 Voltage regulation and Volt–Var control

Volt–var control maps local voltage measurements to reactive power references to mitigate voltage violations in distribution feeders. Standards commonly recommend piecewise-affine curves that inject reactive power when voltage is low and absorb reactive power when voltage is high. Recent 2024–2025 literature emphasizes distributed and sensitivity-aware volt–var policies to improve effectiveness and reduce unnecessary reactive circulation. Deep learning has also been used to design customized volt–var rules per node to better match feeder characteristics and reduce voltage fluctuations [11], [12], [28]–[31].

$$Q^* = f(V) \text{ (piecewise-affine Volt–Var rule)} \quad (10)$$

3.4 Volt–Watt control and combined strategies

When reactive power saturation is insufficient to prevent overvoltage, inverters may curtail real power using volt–watt control. Combined volt–var/volt–watt strategies reduce voltage excursions while limiting curtailment. Recent work addresses fairness and optimal contribution among many inverters so that voltage regulation is shared rather than concentrated on a few devices. Such settings can be optimized centrally or in distributed form, sometimes with reinforcement learning or online optimization frameworks [13], [32]–[35].

$$P^* = g(V) \text{ (Volt–Watt curtailment rule)} \quad (11)$$

3.5 Inverter capability limits and reactive headroom

Inverter apparent power rating limits simultaneous delivery of real and reactive power. At high real power output, reactive headroom shrinks; at low irradiance, reactive capacity may become available. Controller designs therefore require explicit enforcement of the PQ capability circle and careful interaction with volt–var policies, particularly during fast ramps and fault ride-through events.

$$P^2 + Q^2 \leq S_{rated}^2 \quad (12)$$

3.6 Model predictive control and advanced regulation

Model predictive control (MPC) has become attractive for inverter regulation because it handles constraints explicitly and provides fast transient response. In finite-control-set MPC, candidate switching states are evaluated using a cost function that penalizes current tracking error and switching effort. MPC can be beneficial in weak grids where fast action is needed, but it requires accurate models and careful tuning to manage computation and switching ripple. Surveys from 2024–2025 highlight the increasing breadth of inverter control approaches and their alignment with grid-code requirements, power quality, and robustness [14], [36], [37].

$$J = w_i[(i_d^* - i_d(k+1))^2 + (i_q^* - i_q(k+1))^2] + w_u \cdot \Delta u^2 \quad (13)$$

3.7 Grid-forming control and inverter-dominated grids

As power systems move toward high shares of inverter-based resources, grid-forming (GFM) control is increasingly investigated to provide voltage and frequency establishment rather than only grid-following operation. GFM approaches include droop control, virtual synchronous machine emulation, and matching control. Reviews and roadmaps emphasize the need for universally valid models, robust fault behavior, and coordination among multiple GFM devices. Recent 2023–2025 publications provide a research landscape for GFM inverters and discuss how fast power control and virtual inertia can help stabilize low-inertia grids [6], [15], [38]–[40].

4 MPPT and DC-Side Voltage Stability

4.1 Perturb-and-observe MPPT

Perturb-and-observe (P&O) MPPT perturbs the PV operating voltage and observes the resulting power change. If power increases, the perturbation continues in the same direction; otherwise it reverses. P&O is popular due to simplicity but oscillates around the MPP and can mis-track during rapid irradiance changes because the power change may be driven by weather rather than by the perturbation. These effects can be material at high PV penetration where fast ramps are common [16], [18].

$$V(k+1) = V(k) + \text{sign}(\Delta P) \cdot \Delta V \quad (14)$$

4.2 Incremental conductance and adaptive MPPT

Incremental conductance (IC) uses the MPP condition that incremental conductance equals negative instantaneous conductance. Compared with P&O, IC can better distinguish irradiance-driven changes from control perturbations and can reduce steady oscillations when paired with variable step-size updates. Adaptive MPPT methods extend IC with gain scheduling, fuzzy logic, or metaheuristic search to improve performance under fast transients and partial shading [16]–[19], [41].

$$\text{At MPP: } \Delta I / \Delta V = -I / V \quad (15)$$

4.3 MPPT under partial shading and global search

Partial shading produces multiple local maxima on the PV P–V curve, making local search methods vulnerable to suboptimal convergence. Global MPPT methods incorporate periodic scanning, metaheuristic search (PSO, GA), or AI predictors to identify the global maximum. Recent 2025 reviews comprehensively classify MPPT into classical, adaptive, and hybrid categories, and highlight global MPPT approaches as essential for realistic PV installations that experience nonuniform irradiance [17], [19], [42]–[45].

4.4 DC-link dynamics and power balance

The DC-link capacitor integrates mismatch between PV-side power and inverter AC-side real power. In single-stage systems the inverter directly influences the PV operating point; therefore, rapid changes in AC commands or grid conditions can translate into unstable DC voltage behavior. A widely used energy-balance model expresses the DC voltage dynamics in terms of power mismatch. This model guides DC voltage regulators and stability monitors [20]–[22].

$$C_{dc} \cdot V_{dc} \cdot (dV_{dc}/dt) = P_{pv} - P_{ac} - P_{loss} \quad (16)$$

4.5 PV/DC voltage collapse in single-stage systems

Single-stage PV systems can suffer DC voltage collapse when the inverter demands power (or DC current) beyond what the PV array can supply at the current operating voltage, especially near the MPP where the slope of the I–V curve changes quickly. Under disturbances or aggressive reactive power injection, the PV operating point may drift into a region with insufficient voltage support, causing a rapid drop in PV/DC voltage. Dedicated studies show that stability can be improved by dynamic correction of inverter output power, limiting reactive demand during DC stress, and coordinating MPPT with AC-side control loops [20], [21].

5 Solar Power Forecasting (2020–2025): Methods and Equations

5.1 Operational role of forecasting in high-PV grids

Forecasting is now a core requirement for operating PV-rich systems. Day-ahead forecasts support unit commitment and market bids; hour-ahead forecasts support dispatch and battery scheduling; and ultra-short-term forecasts support ramp-rate mitigation and voltage management. In distribution networks, forecasts can also be used to tune volt–var settings proactively to reduce midday overvoltage or to plan coordinated curtailment [7], [10], [46]–[48].

5.2 ARIMA/ARIMAX and seasonal models

ARIMA models capture autocorrelation structure in time series after differencing, while ARIMAX includes exogenous regressors such as irradiance or temperature. These models are computationally light and remain useful baselines and interpretable tools, particularly for aggregated monthly or weekly forecasting. A 2023 IEEE study comparing ARIMAX, ARIMA, and SARIMA for PV output highlights that exogenous variables improve accuracy and that time-series models may perform best for monthly horizons compared with daily horizons [10].

$$\phi(B)(1-B)^d y_t = \theta(B)\epsilon_t \quad (\text{ARIMA}) \quad (17)$$

$$\phi(B)(1-B)^d y_t = \beta \cdot x_t + \theta(B)\epsilon_t \quad (\text{ARIMAX}) \quad (18)$$

5.3 Prophet additive decomposition

Prophet models a time series as the sum of trend, seasonality, holiday effects, and noise. It is robust to missing data and outliers and is easy to configure for strong seasonal patterns. Comparative studies on solar generation forecasting report that Prophet often performs reasonably well but may be outperformed by gradient boosting methods when nonlinear relationships are dominant [7].

$$y(t) = g(t) + s(t) + h(t) + \epsilon(t) \quad (19)$$

5.4 Gradient boosting (XGBoost) for PV forecasting

XGBoost builds an additive ensemble of regression trees optimized by gradient boosting with regularization. It models nonlinear interactions among time indices, lag features, and meteorological variables and often yields strong performance on tabular PV datasets. A 2022 IEEE case study comparing Prophet and XGBoost for solar generation concluded that XGBoost provided better fitting and accuracy in their experimental setting [7].

$$L(t) = \sum_i \ell(y_i, \hat{y}_i(t-1) + f_t(x_i)) + \Omega(f_t) \quad (20)$$

5.5 Deep learning and Transformer-based forecasting

Deep learning models (LSTM/GRU/TCN) learn temporal dependencies and nonlinear dynamics directly from data and have shown strong performance for short-term forecasting. Recent 2024 research emphasizes hybrid deep learning (e.g., CNN–LSTM–Transformer) to capture both local patterns and longer-range dependencies. Transformer-based approaches using attention mechanisms are increasingly applied to PV forecasting, including minimalist feature transformers that aim to reduce data requirements while maintaining accuracy. 2025 publications also emphasize probabilistic forecasting using deep models to quantify uncertainty, which is crucial for risk-aware operations and reserve scheduling [9], [49]–[54].

5.6 Deterministic and probabilistic evaluation metrics

Forecast evaluation commonly uses RMSE, MAE, and MAPE for point predictions. Probabilistic forecasting evaluates the calibration and sharpness of prediction intervals and uses scoring rules such as pinball loss or CRPS. The shift toward probabilistic PV forecasting in 2024–2025 is motivated by operational needs: system operators require not only expected PV output but also uncertainty bounds for decision-making [9], [52], [55].

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_t (y_t - \hat{y}_t)^2} \quad (21)$$

$$\text{MAE} = \frac{1}{N} \sum_t |y_t - \hat{y}_t| \quad (22)$$

$$\text{MAPE} = \frac{100}{N} \sum_t |(y_t - \hat{y}_t)/y_t| \quad (23)$$

6 Forecast-Informed Control and Coordinated PV–Storage Operation

6.1 Forecast-informed curtailment and off-MPPT operation

When voltage or thermal constraints limit allowable PV injection, forecast-informed curtailment can be scheduled to minimize unnecessary energy loss. A simple policy caps PV output to the minimum of available PV power and the predicted feeder limit. Implementing this cap stably requires MPPT methods that can operate off MPP without causing DC instability. Modified incremental conductance approaches were proposed specifically to enable stable active power limiting while still supporting reactive power control [2].

$$P^*(t) = \min(P_{\text{avail}}(t), P_{\text{max}}(t)) \quad (24)$$

6.2 Forecast-informed volt–var parameter adaptation

Static volt–var curves may be suboptimal across seasons and load conditions. With forecasts of PV and load, inverter volt–var parameters can be selected (within allowable limits) to reduce tap operations, prevent voltage violations, and reduce reactive circulation. Recent work uses voltage sensitivity analysis and learning-based approaches to design customized rules per node. These approaches are promising but require stability-aware constraints to avoid adverse interactions among many inverters [11], [12], [28], [31].

6.3 PV–battery coordination for smoothing and voltage support

Co-located storage enables PV smoothing, ramp-rate control, and reduced curtailment. Forecasts schedule battery charge/discharge to maintain a target net injection profile and preserve feeder voltage margins. Coordinated optimization typically includes battery state-of-charge constraints, inverter capability limits, and voltage objectives. Distributed and event-triggered control methods have been proposed for voltage regulation using virtual energy storage resources in PV-rich feeders [56].

7 Open Challenges and Future Directions (2025 Perspective)

7.1 Stability and protection in inverter-dominated grids

As grids approach high inverter penetration, stability and protection must be rethought. Grid-forming controls provide voltage and frequency establishment but introduce new interactions and require robust fault behavior. Research roadmaps emphasize coordinated modeling, standardized test protocols, and controller designs that remain stable across a wide range of grid strengths and operating points [6], [38], [39].

7.2 Cybersecurity and remote access risk

Smart inverters rely on communications for monitoring, updates, and advanced functions. This increases cyber exposure, including risks from undocumented or poorly secured communication interfaces. Recent analyses and industry reporting have intensified focus on supply-chain transparency, secure update mechanisms, and segmentation of inverter communications from critical utility control networks [57].

7.3 Forecasting generalization and explainability

Forecasting models must generalize across sites and seasons and remain explainable enough for operator trust. Transfer learning, domain adaptation, and minimalist feature sets are actively studied to reduce data demands for new plants. Probabilistic forecasts with interpretable uncertainty bounds are likely to be adopted more widely as utilities integrate renewables into reliability frameworks [51], [52], [54].

CONCLUSION

This review synthesized PV inverter control, MPPT/DC stability, and forecasting as an integrated operational stack for high-penetration PV grids. Mathematical foundations of dq control, PQ decoupling, volt–var/volt–watt functions, and inverter capability constraints were presented alongside recent control trends such as MPC and grid-forming operation. MPPT methods were reviewed with emphasis on single-stage PV stability and practical curtailment needs. Forecasting methods from ARIMAX and Prophet to gradient boosting and deep probabilistic/Transformer approaches were elaborated, highlighting the growing importance of uncertainty quantification. Future PV systems will increasingly coordinate forecasts, inverter setpoints, and stability monitors to deliver reliable energy and ancillary services simultaneously.

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