

SECTION 12.

ELECTRONICS AND TELECOMMUNICATIONS

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HYBRID FORECASTING OF PHOTOVOLTAIC GENERATION FOR POWER-SYSTEM BALANCING

Main text.

The rapid expansion of solar generation in Ukraine has shifted the operational focus from installed capacity growth to controllability of output. For modern PV operators, annual energy yield alone is no longer sufficient; consistent day-ahead and intraday schedule compliance is equally important. As the PV share increases, the balancing process becomes more sensitive to forecast deviations, particularly during morning and evening ramps. In this context, short-term forecasting is not only an analytical task but a core market and dispatch instrument. Forecast quality directly affects imbalance exposure, reserve requirements, and corrective-action costs, which makes forecasting performance a strategic factor for both portfolio profitability and grid reliability [2], [4].

Purely statistical models can perform well on stable historical distributions but degrade under rapidly changing cloud regimes and seasonal transitions. Conversely, purely physical models may not capture local nonlinear effects such as site-specific soiling patterns, inverter aging, tracker behavior, or export constraints at the grid connection point. Therefore, a hybrid approach is currently the most robust option in practice: a physical model defines a baseline trajectory, while a machine-learning component learns and corrects residual errors from plant-specific data. This combination preserves physical interpretability and adds adaptive power where deterministic assumptions fail [1], [3].

A production-grade architecture should include several layers. The first layer processes NWP weather data and local weather correction. The second computes physically expected power based on irradiance transformation and thermal effects. The third layer applies ML residual correction trained on SCADA history and contextual inputs. The fourth calibrates uncertainty intervals so that the final output includes P10, P50, and P90 estimates. This design provides both point accuracy and

risk-aware prediction ranges. In real balancing operations, uncertainty information is often as important as the point estimate itself because it supports reserve sizing and exposure control decisions under uncertain weather dynamics [3], [5].

Feature engineering is a decisive step for hybrid forecasting quality. Beyond direct weather variables, high-value features include cloud-change velocity, lagged forecast-error patterns, sun-angle regimes, maintenance event markers, and historical curtailment behavior. Such features help distinguish scenarios with similar irradiance but different effective AC output. Data quality governance is equally critical: missing values, timestamp misalignment, and sensor anomalies can silently degrade model performance and produce misleading evaluation results. In many utility-scale deployments, disciplined data hygiene contributes more to reliability than incremental model complexity, especially when multiple sites and equipment vintages are aggregated in one forecasting platform [1], [4], [5].

For Ukrainian portfolios, infrastructure heterogeneity is a practical barrier: different inverter generations, mixed communication protocols, inconsistent telemetry frequencies, and non-uniform operating procedures. A scalable rollout should therefore start with standardization: unified timestamp policy, explicit unit definitions, mandatory validation checks, and common data contracts for all sites. Without this layer, cross-site benchmarking becomes unreliable and model transferability remains weak. A standardized data backbone enables fair model comparison and faster replication of successful forecasting configurations from pilot plants to larger portfolios and balancing groups [2], [6].

Model assessment should combine statistical and economic metrics. MAE, RMSE, and MAPE are necessary for technical comparison, but they do not fully represent financial impact. Useful operational KPIs include imbalance cost per MWh, reserve activation frequency, magnitude distribution of forecast misses, and cost of corrective dispatch actions. In practice, a model with slightly higher RMSE can still outperform financially if it reduces tail-risk events during high-price or high-stress periods. This KPI-oriented perspective aligns forecasting development with real market outcomes and is especially relevant in systems with volatile balancing conditions [3], [4], [6].

A multi-level forecasting hierarchy is recommended for implementation. Level one predicts each PV plant independently with local feature tuning. Level two aggregates forecasts at node level with network constraints. Level three builds balancing-group forecasts for market submission and dispatch planning. This hierarchy reduces aggregate error, improves explainability of deviations, and allows targeted corrective actions. It also helps operators identify where uncertainty is introduced: at plant behavior level, network interaction level, or portfolio

aggregation level. Such transparency is essential for operational trust and continuous process improvement [2], [5].

Forecasting systems should be managed as continuous products, not one-time models. Seasonal shifts, equipment aging, firmware updates, and market-rule changes gradually alter data distributions and degrade model performance if left unmanaged. A robust MLOps framework should include drift detection, scheduled retraining, rolling out-of-sample validation, and alerting on quality deterioration. Governance processes should define fallback logic when model confidence drops below thresholds. This operational discipline prevents sudden performance collapse in critical periods and supports long-term reliability of market-facing forecasting services [1], [6].

Overall, hybrid PV forecasting should be viewed as a resilience instrument for both market operation and grid balancing. For Ukraine, where renewable integration and infrastructure modernization happen simultaneously, the combination of physical modeling and machine learning provides the necessary balance between interpretability, adaptability, and economic relevance. A phased deployment path—from representative pilots to portfolio-scale standardization and governance—can deliver measurable reductions in imbalance exposure and improved dispatchability of solar assets. With proper implementation, hybrid forecasting becomes a structural capability rather than an isolated analytics feature [1], [3], [6].

To move from pilots to industrial operation, forecasting must be embedded into a formal interaction protocol between trading teams, dispatch units, and plant operations. Forecast products should be delivered at multiple horizons: day-ahead, intraday, and short-term nowcasting. For each horizon, acceptable error ranges and escalation actions must be predefined. This prevents a common failure mode where technically strong models exist but do not influence operational decisions. In practice, process discipline around forecast consumption is as important as model architecture, because market exposure is reduced only when prediction outputs drive timely actions in balancing and schedule updates [2], [6].

Forecast value is also portfolio-dependent. If a balancing group combines different renewable technologies, optimization should account for cross-compensation effects between generation profiles. For example, wind output can partially offset morning PV deficits, reducing reserve stress and lowering imbalance costs. Under such conditions, model quality should be evaluated at portfolio level rather than plant level alone. This requires extending forecasting pipelines into co-optimization frameworks where prediction informs commercial bidding and risk-adjusted dispatch planning. A technically accurate single-site model may underperform economically if portfolio interactions are ignored [3], [4].

Future improvement paths include high-frequency satellite streams, local sky-camera systems, and physics-constrained deep learning architectures. These tools improve representation of fast cloud-motion dynamics, which remain a major source of short-horizon error. At the same time, interpretability must be preserved. Operators need to understand why forecast trajectories shift and which variables dominate model decisions. Therefore, state-of-practice development is not just about larger neural networks; it is about balancing explainability, robustness, and market usefulness under real operating constraints and accountability requirements [1], [5].

At national scale, a standardized certification framework for forecasting services would be highly beneficial. Such a framework can define minimum data requirements, mandatory evaluation metrics, independent validation rules, and uncertainty-audit procedures. Standardization would make supplier comparison transparent and reduce the risk of deploying unstable models in critical balancing contexts. It would also provide market participants with clear quality benchmarks and more predictable economic outcomes. In this way, forecasting quality governance becomes an enabling mechanism for large-scale integration of solar generation into a resilient and modernized power system [2], [3], [6].

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