
**Scientific Journal of Engineering, and Technology (SJET)**
ISSN: 3007-9519 (Online)
Volume 2 Issue 2, (2025)
https://doi.org/10.69739/sjet.v2i2.1014
https://journals.stecab.com/sjet

Published by
**Stecab Publishing**

*Review Article*

# Stochastic Modeling for Wind–Solar Power Forecasting: Uncertainty-Driven Risk Decisions in Modern Grids

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## About Article

### Article History
**Submission**: July 19, 2025
**Acceptance** : August 25, 2025
**Publication** : September 18, 2025

### Keywords
*Power Forecasting, Power Generation, Stochastic Modeling, Wind–Solar*

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## ABSTRACT
The rapid rise of wind and solar capacity has transformed power generation but introduced severe forecasting uncertainty. Variable renewable production can swing from minutes to days, creating operational and economic risks for grids built around predictable dispatch. This narrative review surveys stochastic modeling techniques for wind and solar power forecasting published between 2015 and 2025, covering time-series, spatial–temporal, hybrid, and deep learning approaches. Comparative evidence shows that autoregressive and Kalman-filter models provide interpretable benchmarks yet struggle with non-linearities; copula and vine-copula schemes better capture spatial dependence; hybrid schemes that fuse numerical weather prediction with machine learning significantly reduce forecast errors; and emerging non-stationary Gaussian processes and generative models further improve probabilistic accuracy. Persistent gaps include limited cross-regional validation, short training periods, and inconsistent evaluation metrics. The review suggests that risk-aware scheduling can leverage these probabilistic forecasts for chance-constrained reserves and conditional-value-at-risk unit commitment, enabling more reliable and economical integration of wind and solar power.

**Citation Style:**

Odunlami, B., Arthur, C., & Udeagha, A. K. (2025). Stochastic Modeling for Wind–Solar Power Forecasting: Uncertainty-Driven Risk Decisions in Modern Grids. *Scientific Journal of Engineering, and Technology, 2*(2), 107-113. https://doi.org/10.69739/sjet.v2i2.1014

## 1. INTRODUCTION

Wind and solar generation now dominate the global renewable mix. Renewables contributed around 30 % of global electricity in 2023, with solar and wind alone rising from 0.2 % of electricity in 2000 to 13.4 % in 2023 (Ember, 2024). This expansion continues to outpace all other sources, driven by falling costs and climate policy. Yet meteorological dependence means output can change dramatically within hours; a passing cloud or wind lull may curtail gigawatts of capacity. Compared with load forecasts that typically have 1–3 % mean-absolute error, day-ahead wind forecasts routinely yield 15–20 % error (Lew & Milligan, 2011), forcing operators to procure more reserves and sometimes dispatch peaking units at high cost.

Forecast errors translate directly into operational, economic, and regulatory risks. Overforecasting unnecessarily commits conventional generation, resulting in curtailment or fuel waste, while underforecasting leaves insufficient capacity and triggers reserve shortfalls (Lew & Milligan, 2011). Large deviations jeopardize voltage and frequency stability, and regulated markets may penalize imbalance. Point forecasts alone are inadequate because they ignore uncertainty; probabilistic information is essential for robust scheduling and trading. For example, the rapid growth and correlation of wind speeds across regions can cause voltage fluctuations; modelling joint distributions rather than simple correlation coefficients is therefore vital (Chen *et al.*, 2019). The introduction of vine-copula functions, originally developed in finance and later adopted in power systems, has enabled flexible high-dimensional dependence modelling and has been applied to probabilistic power flow and risk assessment (Chen *et al.*, 2019).

Deterministic wind and solar forecasts provide a single expected value and are useful for long-term planning but cannot quantify uncertainty (Hatalis *et al.*, 2017; Xie *et al.*, 2022). Early statistical models such as autoregressive moving-average (ARMA) or ARIMA, offered point predictions and reduced error compared with persistence models, yet they require high orders and remain linear (Tyass *et al.*, 2022). Neural-network predictors capture non-linearity but still yield a single output and often ignore temporal causality. Probabilistic methods, by contrast, deliver predictive distributions or intervals (Hatalis *et al.*, 2017; Xie *et al.*, 2022). They combine calibration and sharpness, enabling decisions based on risk tolerance rather than expected value. Recent probabilistic studies emphasize that point forecasts are inadequate when weather volatility dominates; probabilistic outputs support secure, cost-effective operation and allow dynamic reserve sizing and market bidding (Henze *et al.*, 2020). Proper scoring rules, such as the continuous ranked probability score (CRPS), help assess both calibration and sharpness (Arnold *et al.*, 2023), providing a more reliable basis for model comparison.

This review traces the evolution of stochastic wind–solar forecasting models from early time-series techniques to modern deep generative networks. Its objective is to synthesize and critically evaluate the evolution of stochastic forecasting models for wind and solar power in grid-connected systems and to translate these technical advances into actionable implications for grid stakeholders. First, methods for data selection and synthesis are summarized. Next, the review outlines key findings about data characteristics, forecast horizons, and performance metrics. The main discussion compares six classes of models: time series, spatial-temporal and copula, hybrid and ensemble, uncertainty quantification and verification, risk-informed decision models, and emerging trends, highlighting merits and limitations. Finally, the review translates insights into implications for operators, market participants, and regulators; proposes research directions; critiques limitations; and concludes with forward-looking reflections.

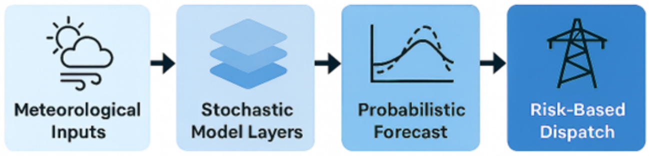


**Figure 1.** Conceptual pipeline: meteorological inputs ⟶ stochastic model layers ⟶ probabilistic forecast ⟶ risk-based dispatch.

## 2. LITERATURE REVIEW

Early stage (pre-2010): During the early years of wind-solar forecasting, deterministic point estimates dominated. Time-series models such as autoregressive (AR), ARMA, and ARIMA were popular owing to their simplicity and the limited availability of numerical weather prediction (NWP) data (Tyass *et al.*, 2022). These models reduced forecast errors compared with persistence yet assumed stationarity and linear relationships, which limited their accuracy under rapid weather changes. Seminal studies also applied Kalman filters to update forecasts in real time, but they remained largely linear and site-specific.

During the transitional period from 2010 to 2015, the literature shifted its focus toward probabilistic forecasting and dependence modeling. The introduction of copula methods allowed joint modelling of wind speeds or photovoltaic outputs across geographically dispersed sites, addressing spatial correlation. Gaussian random fields, regime-switching models, and vine-copula decompositions emerged to capture high-dimensional dependence (Chen *et al.*, 2019). Computational advances and open data led to the first probabilistic wind power forecasts using non-parametric approaches, although sample sizes remained limited. Researchers also began to combine NWP predictors with statistical models, bridging physical and data-driven paradigms.

Acceleration (2016–2025): The past decade saw rapid acceleration in modeling sophistication. Hybrid approaches integrated deep neural networks with NWP features, enabling non-linear capture of weather dynamics. Spatial–temporal models matured with vine-copula and Gaussian random field methods. Non-stationary Gaussian processes using spectral mixture kernels provided heteroscedastic uncertainty (Ladopoulou *et al.*, 2025), and generative adversarial networks (GANs) produced realistic power scenarios (Yuan *et al.*, 2021). Bayesian and physics-informed neural networks added interpretability and physically consistent constraints (Gijón *et al.*, 2023). Risk-aware optimization frameworks based on chance constraints and conditional value-at-risk (CVaR) were incorporated into dispatch and unit commitment models (Zhang & Giannakis, 2013). Viewed through this historical prism, present-day practice now centers on probabilistic models that integrate weather physics, machine learning, and risk metrics.

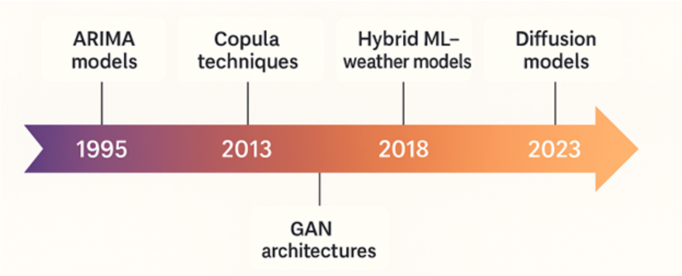


**Figure 2.** Timeline 1995–2025, highlighting milestones: adoption of ARIMA/ARMA.

The introduction of copula and spatio-temporal models, the entry of deep learning, the rise of hybrid and ensemble strategies, the emergence of generative adversarial models and CVaR-based risk methods, non-stationary Gaussian processes and quantile deep learning, and recent diffusion and physics-informed models.

## 3. METHODOLOGY

This narrative review synthesizes peer-reviewed evidence without applying systematic review or meta-analytic procedures. Searches covered Scopus, Web of Science, and IEEE Xplore on 27 August 2025 (Africa/Lagos). Keyword families included wind/solar/photovoltaic power; probabilistic/stochastic/uncertainty/quantile; forecast/prediction/scenario; copula/spatio-temporal/ensemble; and grid/power-system/unit-commitment/economic-dispatch/optimal-power-flow. The recency-first window targeted 2019–2025 (≥60% of citations), with reach-back to 2000–2018 for foundational or longitudinal context (≤30%) and pre-2000 only if strictly seminal (≤10%).

Inclusion required (i) grid-connected wind and/or solar forecasting or scenario generation; (ii) explicit stochastic/probabilistic outputs (quantiles, intervals, densities, or ensembles); (iii) empirical validation using proper metrics (CRPS, pinball, reliability) and/or decision-linked evaluation; and (iv) English, peer-reviewed journals or archival conference papers with full methods.

Exclusions: deterministic-only studies; synthetic-data results without real-world validation; non-electricity contexts; editorials, letters, and abstract-only records. Screening proceeded by title/abstract, then full text; duplicates were removed. Manual snowballs from reference lists captured additional studies. Quality emphasis favored multi-site or portfolio datasets, out-of-sample and cross-season validation, explicit calibration checks, and transparent code/data when available; low-information case reports and single-metric evaluations were deprioritized. Data fields extracted included data sources, forecast horizon, spatial scale, modeling class, verification metrics, and decision-use context. Findings were synthesized narratively by horizon and model family; no statistical pooling was undertaken.

## 4. RESULTS AND DISCUSSION

### 4.1. Data characteristics

High-quality probabilistic forecasts rely on datasets with appropriate temporal resolution, spatial coverage, and climate representation. Studies use resolutions from minutes to hours; high-frequency data capture intra-hour variability but suffer from sensor noise, whereas hourly or 15-minute data balance noise and computational cost. Spatial correlation of wind speeds or irradiance must be modeled: the correlation of wind across regions causes voltage fluctuations and cannot be represented by simple correlation coefficients (Chen *et al.*, 2019). Vine-copula and Gaussian random field approaches construct multivariate distributions by decomposing high-dimensional dependence into pair copulas (Chen *et al.*, 2019), enabling accurate joint forecasting across multiple turbines or solar sites. Climate regimes also influence model performance; models trained on temperate data may not generalize to tropical climates. Many studies still rely on short datasets (often less than five years), limiting the ability to capture extreme events or climate-driven non-stationarity.

### 4.2. Forecast horizons

Forecast horizons range from seconds to weeks, each with distinct challenges. Very-short-term (seconds to minutes) forecasts leverage autoregressive filters, persistence, and machine vision of cloud movement; these are vital for inverter control and frequency regulation. Short-term (minutes to hours) forecasts rely on NWP ensembles augmented by machine learning to correct systematic biases; models such as Kalman filters and vector autoregression (VAR) update predictions in real time (Wang, 2023). Day-ahead to week-ahead forecasts depend heavily on NWP; hybrid models and non-stationary Gaussian processes improve uncertainty quantification (Ladopoulou *et al.*, 2025). Performance deteriorates with horizon length, and the ensemble spread often underestimates uncertainty. Benchmark studies indicate that sparse VAR models exploiting turbine layout and wind direction outperform simple AR models for multi-site prediction (Ahmed *et al.*, 2024). Across horizons, the challenge remains to balance sharpness and calibration while avoiding overconfidence.

### 4.3. Performance metrics

Probabilistic forecasts are assessed by proper scoring rules that reward calibration and sharpness. The continuous ranked probability score (CRPS) integrates the squared difference between the predictive and empirical cumulative distributions; lower values indicate better accuracy and sharpness (Leutbecher, 2023). Decomposition of the CRPS reveals components related to reliability, resolution, and uncertainty (Arnold *et al.*, 2023). Pinball loss evaluates quantile forecasts by penalizing deviations above and below the predicted quantiles; it is robust to noise and heavy-tailed data (Deng *et al.*, 2024). The Winkler score measures prediction interval quality by combining interval width and coverage (Deng *et al.*, 2024). Reliability diagrams graphically compare forecast quantiles with observed frequencies; points on the diagonal indicate perfect calibration (Ait Mouloud *et al.*, 2025). Combining CRPS with reliability diagrams provides a comprehensive assessment of calibration and sharpness and has been applied to seasonal solar forecasts (Ait Mouloud *et al.*, 2025). However, many studies use non-standardized metrics, complicating cross-paper comparison.

**Table 1.** Mini-comparative table of metrics

| Uncertainty metric | Reserve sizing | Intraday trading | Outage planning |
|---|---|---|---|
| Continuous ranked probability score (CRPS) – integrates squared difference between forecast and empirical CDF, evaluates calibration and sharpness (Leutbecher, 2023) | Suitable for reserve sizing because it penalises large deviations, ensuring adequate but not excessive reserves. | Useful for intraday trading to compare competing probabilistic models under high uncertainty. | Less commonly used; can inform maintenance scheduling by assessing distribution tails. |
| Pinball loss – quantile-based loss function that penalises under- and over-estimates, robust to noise (Deng *et al.*, 2024). | Allows tuning of reserve levels through choice of quantiles; provides asymmetric penalties reflecting operator risk preferences. | Widely used for intraday price and volume forecasts where quantiles matter for bids. | Helps plan outages by predicting extreme low-production periods. |
| Reliability diagram – graphical tool comparing forecast probabilities with observed frequencies; points on the diagonal imply perfect calibration (Ait Mouloud *et al.*, 2025). | Assists operators in verifying that reserve policies align with forecast reliability. | Supports trading strategies by revealing systematic bias or overconfidence. | Applicable when scheduling outages during periods of high reliability. |

### 4.4. Discussion

#### 4.4.1. Time-series stochastic models

How can classical time-series models represent wind and solar uncertainty? Autoregressive (AR), ARMA, and ARIMA models remain common benchmarks. They model linear correlations in wind speed or irradiance time series and are computationally inexpensive. Early studies found that ARMA models reduce forecast error relative to persistence and that ARIMA models offer better sensitivity to wind speed adjustment (Tyass *et al.*, 2022). However, they require high model orders when capturing complex dynamics and assume stationarity, which may not hold under changing weather regimes. The Kalman filter extends these models by updating forecasts recursively as new observations arrive. In nonlinear settings, sigma-point Kalman filters approximate state distributions via deterministic samples but are sensitive to model mismatch (Wang, 2023). Extreme-learning Kalman filters combine neural networks with sigma-point filtering to improve nonlinear modeling (Wang, 2023). Vector autoregression (VAR) generalizes autoregression to multivariate time series, capturing cross-correlations among multiple turbines or solar sites. Sparse VAR models, which utilize turbine layout and wind direction, improve day-ahead accuracy (Ahmed *et al.*, 2024). Regime-switching and Markov models further account for weather-driven state transitions and can capture sudden changes. Despite interpretability, time-series models struggle with long lead times and often underestimate extreme events, prompting the shift toward more flexible methods.

#### 4.4.2. Spatial–temporal and copula methods

How can spatial dependence and non-Gaussian joint distributions be captured? Wind and solar power outputs exhibit strong spatial correlations due to mesoscale weather systems. Traditional two-dimensional copulas capture dependence between pairs but cannot scale to multiple locations; vine-copula decompositions assemble high-dimensional distributions from bivariate copulas, overcoming the "curse of dimensionality" (Chen *et al.*, 2019). Vine-copula models originated in finance and have been applied to power systems for probabilistic power flow and risk assessment (Chen *et al.*, 2019). Gaussian random fields treat the wind or irradiance field as a continuous stochastic process defined by a covariance function; asymmetry due to prevailing wind direction can be incorporated via convex combinations of symmetric and asymmetric kernels (Ezzat *et al.*, 2019). Spatial–temporal Kalman filters track evolving wind fields using state-space models, while spatio-temporal copulas model joint distributions across time and space. These methods allow simulation of power scenarios for multiple sites, enabling regional reserve pooling and risk assessment. Limitations include computational complexity for large networks and the need for careful kernel selection or copula family choice.

#### 4.4.3. Hybrid and ensemble strategies

How can physical and data-driven methods be synthesized? Hybrid models combine NWP outputs with statistical or machine-learning models to exploit physical knowledge while correcting systematic errors. For short-term horizons, NWP features (wind speed, irradiance, temperature) feed into deep neural networks such as convolutional–gated recurrent units (CNN-GRU) or extreme learning machines, extracting spatial–temporal patterns (Zhu *et al.*, 2022). Quantile regression (QR) models relate inputs to conditional quantiles; combining QR with kernel density estimation yields full distributions, though traditional QR is linear and struggles with non-linearity (Zhu *et al.*, 2022). Neural-network QR models, quantile regression forests, and gradient boosting overcome this challenge by learning non-linear quantile functions. Ensemble methods, including Bayesian model averaging and stacking, aggregate multiple forecasts to improve robustness. For instance, probabilistic wind prediction based on Bayesian neural networks yields both point estimates and uncertainty by sampling from posterior distributions (Deng *et al.*, 2024). Hybrid decomposition approaches use empirical mode decomposition or variational mode decomposition to separate signal components before modeling; these decomposition-hybrid models often outperform monolithic deep networks. Challenges remain in choosing decomposition levels, preventing over-fitting and managing computational costs.

#### 4.4.4. Uncertainty quantification and verification

Which methods quantify forecast uncertainty and verify probabilistic outputs? Prediction intervals can be constructed using bootstrapping, quantile regression, or quantile regression forests. Winkler scores evaluate interval forecasts, balancing interval width against coverage (Deng *et al.*, 2024). Reliability calibration techniques adjust predictive distributions to ensure that nominal coverage matches empirical coverage. Reliability diagrams plot predicted quantiles against observed frequencies; points near the diagonal indicate well-calibrated forecasts (Ait Mouloud *et al.*, 2025). CRPS, as described earlier, is widely used because it rewards both calibration and sharpness and can be decomposed to assess resolution (Arnold *et al.*, 2023). Pinball loss evaluates quantile forecasts; by choosing quantiles reflecting operator risk tolerance, one can tailor the penalty for under- or over-prediction (Deng *et al.*, 2024). The selection of metrics affects how models are ranked; it is therefore recommended to report multiple metrics. Sample sizes must be sufficient to produce reliable reliability diagrams; consistency bars are used to account for serial correlation (Ait Mouloud *et al.*, 2025). Cross-validation across seasons and climates is also crucial, as model performance can vary by season (Ait Mouloud *et al.*, 2025).

#### 4.4.5. Risk-informed operational decisions

How can probabilistic forecasts inform grid operation and market participation? Chance-constrained optimization introduces probabilistic constraints that ensure violations occur with low probability. A chance-constrained economic dispatch problem for renewable-rich portfolios was proposed by Sandia researchers; it ensures that the scheduled wind energy meets portfolio requirements with high probability and uses sample average approximation to handle uncertainty (Cheng *et al.*, 2018). Weighted chance constraints generalize this concept by using a weight function to penalize larger violations more heavily, preserving convexity and enabling tractable optimal power flow (OPF) formulations (Roald *et al.*, 2016). Conditional value-at-risk (CVaR)–based formulations regularise objective functions with a risk term reflecting the expected shortfall beyond a specified value-at-risk; this yields convex optimization problems and allows distribution-free sample average approximations (Zhang & Giannakis, 2013). CVaR is preferred over value-at-risk because it is subadditive and easier to optimize. CVaR-based unit commitment and robust OPF frameworks have The system demonstrated improved performance on test networks, including the IEEE 30-bus network. In practice, operators should choose risk levels consistent with reliability criteria; overly conservative settings inflate costs, whereas lax settings risk violations. Integrated energy-storage dispatch can further mitigate uncertainty by providing flexible reserves.

#### 4.4.6. Emerging trends

What frontiers are shaping the next generation of stochastic forecasting? Non-stationary Gaussian processes using spectral mixture kernels accommodate time-varying periodicities and heteroscedastic noise, outperforming stationary kernels on short-term wind power data (Ladopoulou *et al.*, 2025). Generative adversarial networks (GANs) and progressive growing techniques generate realistic wind power scenarios that capture temporal dynamics and reduce scheduling costs (Yuan *et al.*, 2021). Physics-informed neural networks enforce physical laws (e.g., conservation of mass or turbine power curves) during training and provide uncertainty estimates via evidential learning (Gijón *et al.*, 2023). Diffusion models and diffusion probabilistic models are being explored for scenario generation, offering advantages in modelling multi-modal distributions. Emerging hybrid deep learning frameworks incorporate graph neural networks to model grid topology and meteorological relationships. On the operational side, integrated risk models that combine CVaR, weighted chance constraints, and stochastic ramping costs are being tested for real-time energy markets. Open testbeds that emulate realistic grid dynamics under high renewable penetration have been proposed to benchmark new models, emphasizing that they require reproducibility and standardized datasets.

### 4.5. Implications

Stochastic forecasting influences a range of stakeholders. Grid operators should adopt reserve procurement strategies that account for risk and are informed by probabilistic forecasts: chance-constrained dispatch and CVA-based OPF can ensure reliability while minimizing costs (Bienstock *et al.*, 2014). Operators could also use probabilistic ramp-rate smoothing strategies to coordinate battery storage and demand response, reducing wear on conventional units (Olivares *et al.*, 2014). Market participants, including traders, aggregators, and plant owners, can design bidding strategies using quantile forecasts, hedging instruments, and scenario generation to manage price risk (Nowotarski & Weron, 2018). Probabilistic forecasts enable dynamic portfolio rebalancing and encourage investment in flexible assets (Idema *et al.*, 2013). Regulators should encourage disclosure of forecast accuracy and uncertainty using proper scoring metrics such as CRPS and pinball loss, which have been widely validated in probabilistic energy forecasting literature (Gneiting & Raftery, 2007). They could set minimum reliability requirements for forecast providers and incentivize adoption of probabilistic bids. Introducing standardized probabilistic benchmarks and leaderboards would allow fair comparison and spur innovation (Hong *et al.*, 2014). Regulators may also need to adapt market rules to accommodate stochastic bids and risk-priced reserves. Overall, the integration of probabilistic forecasts into dispatch, trading, and regulation could enhance security of supply, lower balancing costs, and accelerate renewable penetration.

## 5. CONCLUSION

Renewable forecasting has matured from single values to probabilistic signals that inform risk. The path forward is to turn those signals into routine, verifiable practice. To make "open testbeds" concrete rather than aspirational, a risk-aware forecasting testbed should include: (1) Data layer: multi-site wind/solar, NWP ensembles, satellite/sky-cam feeds, and metadata (turbine/panel specs, curtailments), with rolling windows for at least three climate regimes; (2) Horizon × scale grid: standardized tasks spanning 5-minute nowcasts to week-ahead forecasts at site, portfolio, and control-area levels; (3) Benchmark suite: strong baselines (persistence, climatology, ARIMA), physics-only, ML-only, and hybrid references with frozen versions; (4) Verification & risk metrics: CRPS and pinball for sharpness, reliability diagrams for calibration, plus tail-focused VaR/CVaR and outage-probability checks; (5) Decision-in-the-loop simulators: stochastic unit-commitment, probabilistic reserve sizing, and trading backtests that turn forecast skill into cost, reliability, and emissions deltas; (6) Extreme-event protocol: stress tests for ramps, widespread cloud fronts, calm spells, and sensor dropouts, with red-team adversarial scenarios; (7) Reproducibility & audit: public code, fixed seeds, dataset cards, versioned APIs, and submission checklists (data splits, rolling-origin evaluation, cross-season tests); (8) User-facing artifacts: fan charts, probability-of-exceedance curves, and succinct risk dashboards with plain-language summaries.

Such a testbed converts model progress into operational value, anchors comparisons across sites and horizons, and makes risk communication as standard as the forecast itself—toward steadier, smarter grids.

## RECOMMENDATIONS

Climate-scale inputs. Researchers should couple sub-seasonal and seasonal climate outlooks with intra-day models to capture large-scale patterns such as El Niño–Southern Oscillation that modulate wind and solar availability (Springenberg *et al.*, 2025). Multi-resolution models could propagate uncertainty from climate to operational timescales, yielding more robust forecasts (Liu *et al.*, 2025).

Verification standardization. A common set of benchmark datasets and proper scoring rules is needed. A CRPS-based leaderboard similar to Kaggle competitions would allow transparent comparison of models across horizons and climates (Gneiting & Raftery, 2007; Hong *et al.*, 2014). Reliability diagrams and pinball loss should accompany CRPS to reveal calibration and tail behavior.

Testbeds. Open-access testbeds, perhaps named "Grid-Lab," should be developed to stress-test stochastic models under synthetic yet realistic scenarios (Pacific Northwest National Laboratory, n.d.). These platforms could simulate grid physics, market rules, and weather events, enabling researchers to assess performance under extreme ramp events, curtailments, and storage constraints. Collaboration between academia, industry, and system operators would promote adoption and ensure that models address practical challenges.

## LIMITATIONS

This review synthesizes narrative rather than systematic evidence, so selection bias may persist. The heterogeneity of modeling approaches and performance metrics hampers direct comparisons and may overstate improvements. Many cited studies focus on single regions or short data sets, limiting generalizability across climates or longer temporal scales. Emerging methods such as diffusion models remain speculative with few validation studies. The review emphasizes technical literature and may underrepresent market or policy perspectives. Future meta-analyses with standardized datasets would provide more rigorous comparisons.

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