VedeniEnergy
Plugged Into The Energy Industry

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Advanced Forecasting

for Renewable-Dominated Power Systems

Technologies, Applications, and the Path to Grid Resilience

WHITEPAPER

VedeniEnergy
Plugged Into The Energy Industry

+1 463-266-4496
www.vedeni.energy
info@vedeni.energy
North Vernon, IN 47265, US

Introduction

The modern electric grid is undergoing a fundamental transformation. Across the United States and around the world, the rapid buildout of wind and solar generation is reshaping not only the composition of the resource stack but also the operational and planning requirements that keep electricity flowing reliably. In the U.S., installed utility-scale solar capacity has grown from negligible levels a decade ago to more than 150 gigawatts today, while wind capacity exceeds 145 gigawatts—together representing a substantial and rapidly expanding share of national generation. The North American Electric Reliability Corporation's (NERC) 2024 Long-Term Reliability Assessment projects that more than 122,000 megawatts of conventional dispatchable generation will retire over the next ten years, as variable, weather-dependent wind and solar resources dominate new capacity additions.

This structural shift introduces a category of operational challenge that conventional grid management was not designed to handle at scale: the inherent variability and uncertainty of renewable output. Unlike a natural gas peaker unit that can be started on command within minutes, a wind farm's output follows the wind and a solar array follows the sun—and neither aligns with the dispatch schedule. As renewable penetration increases, the accuracy of forecasts for wind and solar generation, transmission conditions, and electricity demand becomes increasingly consequential. Forecast errors translate directly into reserve shortfalls, unnecessary curtailment, inefficient unit-commitment decisions, and, in extreme cases, threats to grid reliability.

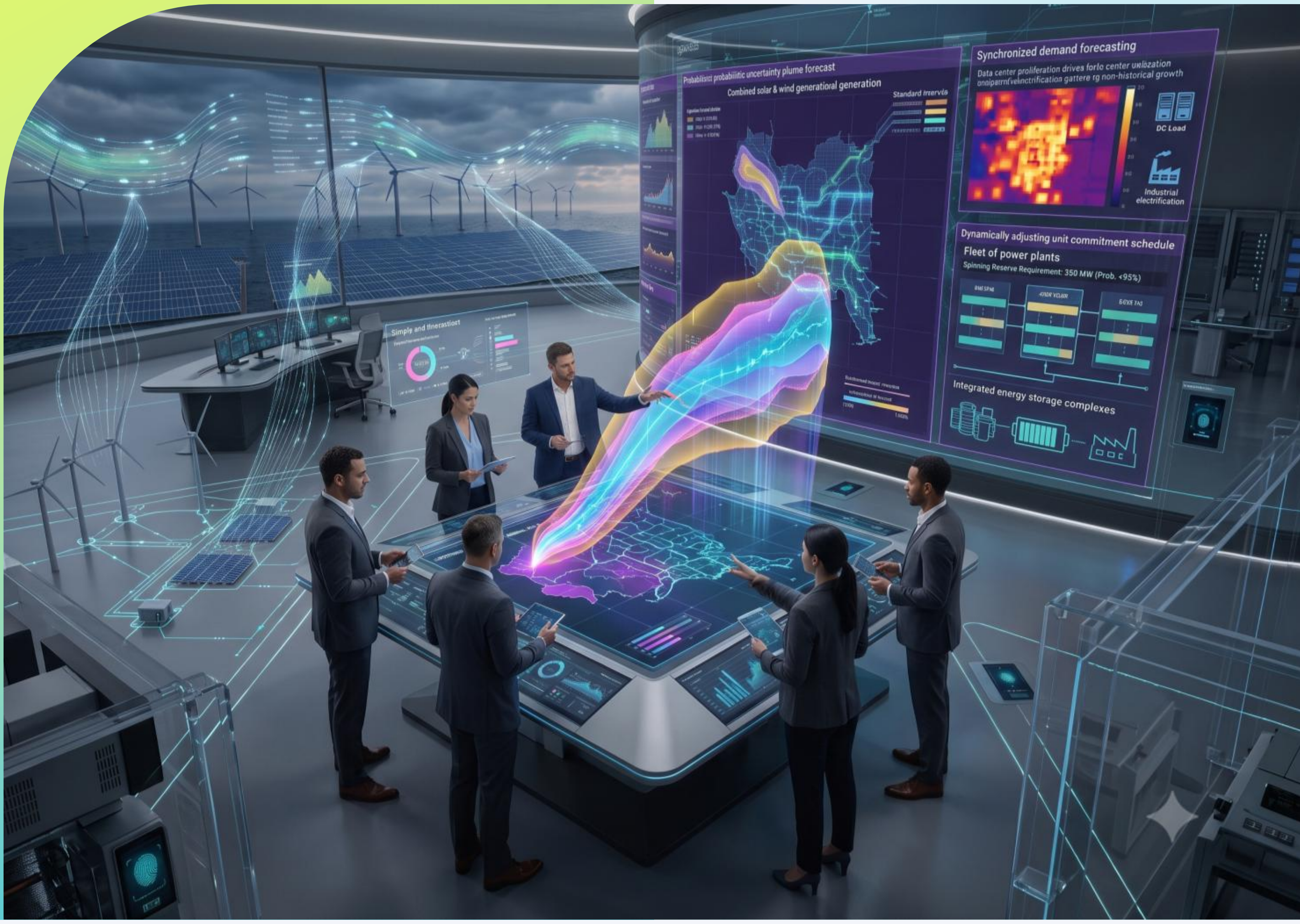
The importance of this challenge is no longer theoretical. In April 2025, a large-scale blackout in the Iberian Peninsula intensified scrutiny of reserve adequacy, inverter behavior, system inertia, and operational forecasting amid high renewable penetration. In the United States, CAISO curtailed 3.4 million megawatt-hours of utility-scale wind and solar output in 2024 alone—a 29 percent increase from the prior year—while ERCOT curtailed multiple terawatt-hours of renewable generation. These curtailments represent both economic waste and systemic inefficiency that better grid forecasting technology can help alleviate.

This white paper examines the state of the art in power system forecasting tools across three critical domains: weather-based renewable generation forecasting, probabilistic uncertainty quantification, and advanced electricity demand forecasting. It then explores how improved forecasts cascade through the operational stack, influencing unit commitment, transmission congestion management, and real-time electricity market operations. The analysis draws primarily on U.S. experience and incorporates relevant global examples. It is intended for industry professionals, grid operators, policymakers, and technology developers navigating this evolving landscape.

Renewable energy is transforming the power grid

Accurate forecasting is now essential for grid reliability

This paper explores next-generation forecasting technologies



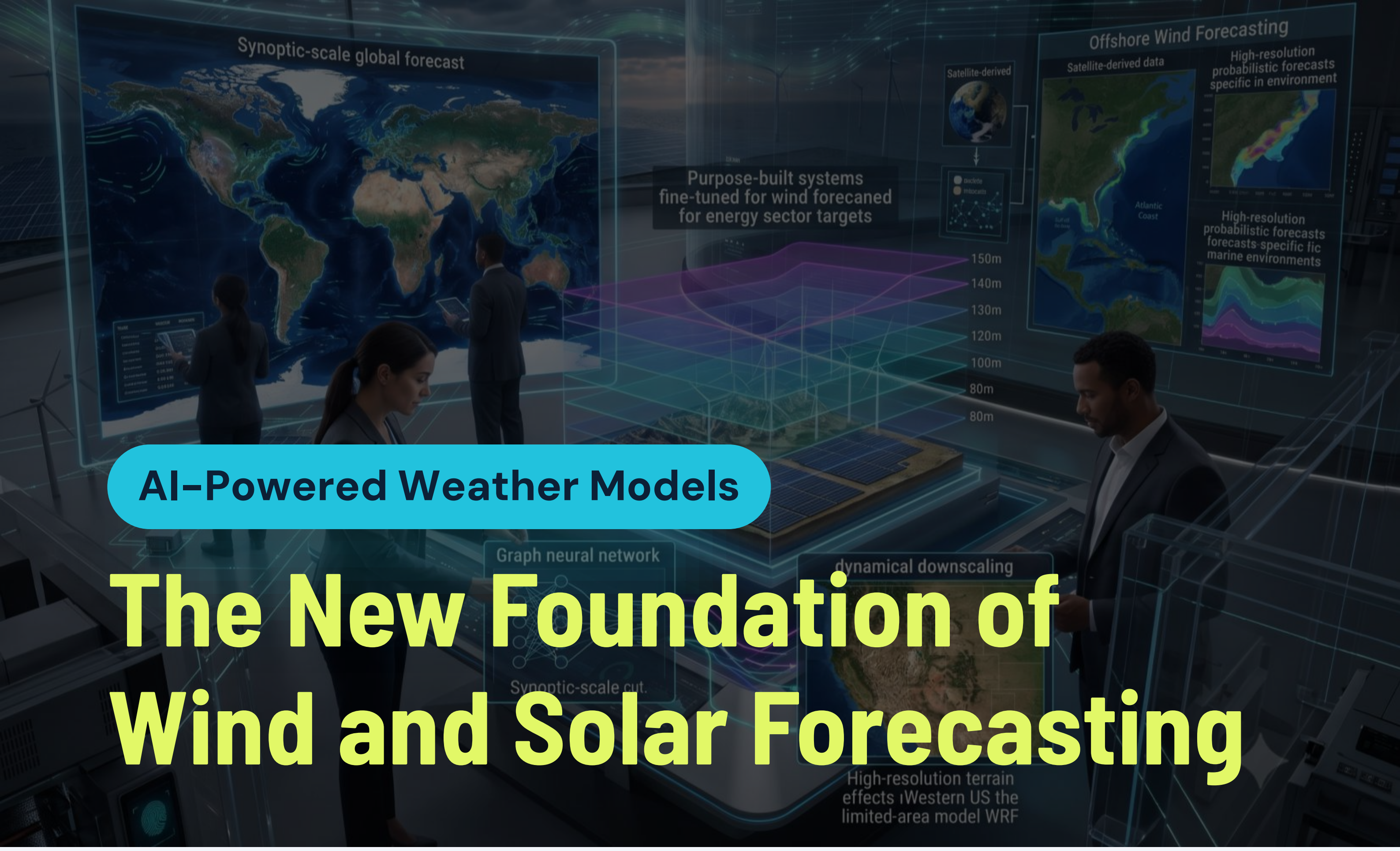
The Forecasting Imperative
in a Renewable-Dominated Grid

The relationship between forecast accuracy and grid efficiency is straightforward in principle but complex in practice. When a system operator or market participant schedules generation, procures reserves, or commits thermal units, the quality of the underlying forecasts determines the quality of those decisions. Point forecasts—single-valued estimates of expected generation or load—were adequate when the dominant sources of uncertainty were load variability and equipment outages. In a grid where wind and solar may supply 30, 50, or even 80 percent of instantaneous demand, uncertainty in the generation forecast becomes the dominant operational challenge.

The consequences of poor renewable energy forecasting appear across multiple timescales. In the day-ahead market, inaccurate wind and solar forecasts cause market participants and system operators to commit the wrong mix of thermal generation—too much, and capacity sits idle at cost; too little, and expensive real-time market purchases or reliability actions are required. In real-time operations, unexpected swings in renewable output require rapid deployment of regulation services and spinning reserves. Over longer planning horizons, systematic underestimation of renewable variability can lead to inadequate reserve margins and transmission congestion that limits the ability to deliver low-cost renewable energy to load centers. The scale of the problem in the United States is evident in curtailment data. In the Southwest Power Pool, curtailments exceeded 11,000 gigawatt-hours of wind energy in 2022, representing more than 10 percent of all wind energy produced in the region that year. CAISO's 29 percent increase in curtailments in 2024 reflects both growing solar capacity and the limitations of current balancing and trading mechanisms. The Western Energy Imbalance Market—a real-time balancing market spanning the western United States—averted more than 274,000 megawatt-hours of curtailments in 2024 through improved cross-regional coordination, but the fundamental cause of overgeneration—imperfect operational foresight—remains.

At the same time, U.S. electricity demand is entering a period of unprecedented growth after two decades of near-stagnation. The Brattle Group's 2024 analysis found that national five-year load forecasts are now five times higher than 2022 projections, driven by data center proliferation, industrial electrification, and electric vehicle adoption. The Electric Power Research Institute (EPRI) projects that data centers alone could consume between 9 and 17 percent of national electricity by 2030. NERC's 2025 Long-Term Reliability Assessment projects that summer peak demand will grow by 224 gigawatts over the next decade—a 69 percent increase over prior projections. Peak electricity demand in the United States is expected to increase by 128 gigawatts by 2029, roughly 13 times the amount of electricity New York City consumed at its peak in 2023. In this environment, electricity demand forecasting—traditionally a mature discipline—must contend with structural demand shifts that fall entirely outside historical patterns.

The compound uncertainty from simultaneous supply and demand uncertainty creates new operational risk at a scale the U.S. grid has not previously encountered. The answer to this challenge is not, in the first instance, more dispatchable capacity—though dispatchable and flexible resources may be part of the solution—but more accurate, probabilistic, and operationally integrated forecasting. The imperative is not simply to forecast more accurately; it is to forecast in a manner that supports the decisions operators and market participants must make, on the timescales on which those decisions are made, and with sufficient characterization of uncertainty to enable risk-aware planning.



AI-Powered Weather Models

The New Foundation of Wind and Solar Forecasting

For decades, renewable energy forecasting relied on Numerical Weather Prediction (NWP) models—physics-based simulations of the atmosphere that solve partial differential equations on global or regional grids. Models such as the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecasting System and NOAA's Global Forecast System have provided the meteorological backbone for wind and solar generation forecasts. These systems are sophisticated, well-validated, and capable of producing ensemble forecasts that characterize uncertainty. They are also computationally expensive: a ten-day ECMWF forecast requires hours of supercomputing time on some of the world's most powerful machines.

The emergence of data-driven artificial intelligence weather models has fundamentally altered this landscape. Beginning with FourCastNet in 2022 and rapidly followed by DeepMind's GraphCast and Huawei's Pangu-Weather, a new generation of machine learning models trained on decades of reanalysis data has demonstrated the ability to produce medium-range global weather forecasts with skill comparable to—and, in some metrics, exceeding—the best NWP systems, at a fraction of the computational cost. GraphCast, built on a multi-scale graph neural network architecture that leverages multi-resolution atmospheric representations, can produce a 10-day global forecast in under 60 seconds on specialized accelerator hardware, compared with hours of supercomputing time for an equivalent NWP run. Pangu-Weather employs an innovative three-dimensional Earth-specific transformer architecture that better captures relationships among meteorological variables at different pressure levels—a capability directly relevant to hub-height wind speed forecasting, where atmospheric dynamics at 80 to 150 meters above ground differ significantly from surface-level conditions.

By 2025, these weather foundation models had moved beyond research demonstrations and were being evaluated or integrated alongside classical NWP systems by leading meteorological institutions and commercial forecasting providers. Their significance for power system forecasting is substantial. Wind power output scales approximately with the cube of wind speed, so even small improvements in wind speed forecast accuracy translate into meaningful reductions in generation forecast error and, consequently, in reserve requirements and balancing costs. Similarly, solar generation depends on cloud cover, solar irradiance, and atmospheric aerosol loading—variables that AI weather models capture with increasing fidelity by training on vast historical reanalysis datasets spanning multiple decades of global atmospheric observations.

A dedicated weather foundation model for power grid applications, described in research from 2025, represents the next step in this evolution. Rather than deploying a general-purpose atmospheric model and post-processing its output for energy applications, these purpose-built systems fine-tune large pre-trained atmospheric models on energy-sector-specific targets, including rime-ice formation on transmission lines, turbine-level wind speed forecasting at arbitrary hub heights, and generation forecasting under extreme weather conditions. The R^2Energy benchmark, published in 2026, specifically evaluates renewable energy forecasting under diverse and extreme meteorological conditions—a recognition that the edge cases most likely to challenge grid reliability are precisely those in which historical forecast accuracy has been weakest.

A hybrid forecasting paradigm is emerging as the practical optimum for near-term operational applications. This approach integrates AI-derived global-scale weather forecasts with high-resolution dynamical downscaling using limited-area models such as the Weather Research and Forecasting (WRF) system. The AI backbone provides fast, accurate synoptic-scale predictions; dynamical downscaling captures local terrain effects, sea breezes, orographic channeling, and other mesoscale phenomena that are critical for site-level resource assessment. Research published in 2025 in Artificial Intelligence for the Earth Systems demonstrates that this combined approach outperforms either technique in isolation for complex terrain environments—precisely the geography where much U.S. wind resource is concentrated, including the Great Plains wind corridor, Appalachian ridgelines, and mountainous western states.

For offshore wind forecasting—a domain of increasing strategic importance as the United States pursues deployment along the Atlantic and Gulf coasts—AI weather models offer particular advantages. Offshore environments lack the training-data density of land-based observing networks, and traditional NWP models have historically underperformed in these settings relative to their onshore skill. AI models trained on satellite-derived data, offshore buoy observations, and high-resolution reanalysis products are beginning to close this performance gap. Ensemble weather forecasting approaches provide high-resolution probabilistic forecasts specifically designed for renewable energy planning and operation, incorporating the uncertainty characterization that is essential for operational decision-making at offshore wind installations.

AI-powered weather forecasting models are transforming wind and solar prediction by delivering faster, more accurate, and energy-specific forecasts that improve grid reliability while reducing operational costs.

Probabilistic Forecasting

Quantifying Uncertainty to Enable Decisions

Even the most accurate deterministic forecast is, ultimately, a single scenario imposed on an uncertain future. For power system operators and market participants, what matters is not just the expected outcome but the distribution of possible outcomes—the range of conditions that reserve procurement, unit commitment, and transmission planning must accommodate. Probabilistic forecasting replaces the single-valued point forecast with a distribution of possible outcomes, expressed as prediction intervals, quantile forecasts, or full probability density functions. This shift from deterministic to probabilistic representations of the future is one of the most consequential methodological advances in the field of renewable energy forecasting.

The fundamental insight motivating probabilistic approaches to wind and solar forecasting is that different operational decisions require different representations of forecast uncertainty. A day-ahead unit commitment decision requires knowledge of the probability that solar output will fall below a certain threshold during the evening demand peak. A reserve adequacy assessment requires characterization of the joint probability that both wind and solar output will be simultaneously below forecast—a scenario that demands modeling the spatial and temporal correlations between these resources, not just their individual uncertainties. A transmission planning study requires understanding the joint distribution of renewable generation and load over a multi-year horizon under different climate scenarios. No single point forecast can serve all of these purposes.

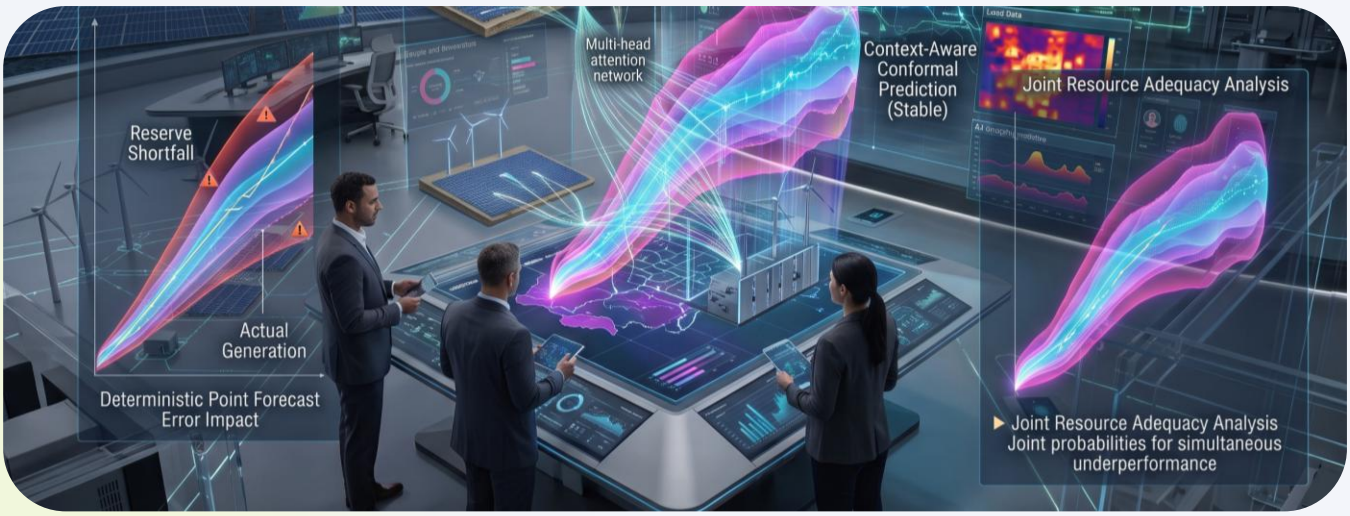
Several methodological frameworks have emerged as particularly promising for renewable energy probabilistic forecasting. Quantile regression models estimate conditional quantiles of the forecast distribution directly, without imposing a parametric distributional form, allowing the forecast to reflect the actual asymmetric, bounded, and multi-modal distributions that characterize renewable generation and electricity demand. Deep quantile regression architectures using temporal convolutional networks, long short-term memory networks, and multi-head attention mechanisms have demonstrated strong empirical performance on wind and solar datasets across diverse geographic and meteorological regimes.

Conformal prediction, a distribution-free framework rooted in statistical learning theory, has gained significant traction in energy applications for its ability to provide coverage guarantees without restrictive model assumptions. Conformalized quantile regression (CQR) and its ensemble variant (EnCQR) combine the flexibility of deep learning models with the statistical validity of conformal prediction theory, producing prediction intervals that are adaptive to local meteorological conditions—wider during periods of high atmospheric variability and narrower during stable, predictable weather regimes. A 2025 paper published in Sustainability demonstrates that a multi-network deep learning framework integrating temporal convolutional networks, convolutional neural networks, and attention mechanisms with quantile regression-based uncertainty quantification produces reliable joint probabilistic forecasts of wind and solar generation while capturing the spatiotemporal complementarity between these resource types.

Research published in 2025 and 2026 demonstrates the operational value of context-aware conformal prediction for renewable energy applications. By conditioning the conformal calibration procedure on meteorological regime, these methods produce tighter intervals during stable weather and appropriately wider intervals when atmospheric dynamics are uncertain—a property with direct operational value, as operators can be more confident acting on narrowly bounded forecasts. Recent work on nonparametric adaptive conformal inference for hour-ahead solar PV power forecasting has also shown how valid statistical coverage can be maintained while forecasts adapt dynamically to changing atmospheric conditions over the operating day.

Joint probabilistic forecasting—modeling the simultaneous uncertainty of wind and solar generation across multiple sites—represents a more challenging but operationally critical capability. Copula-based aggregation methods, which model the dependence structure between multiple uncertain variables independently of their individual marginal distributions, have been combined with context-aware conformal prediction to produce calibrated joint renewable forecasts for use in portfolio optimization and reserve procurement. The spatial and temporal complementarity of wind and solar resources means their joint distribution is not simply the product of their marginals: on overcast, low-wind days, both resources may simultaneously underperform, creating compound reliability risk that is systematically underestimated by independent, site-by-site forecasting.

The IEEE Hybrid Energy Forecasting and Trading Competition 2024 (HEFTCom2024) provided a practical demonstration of how probabilistic forecasting methods translate into operational and commercial value. The winning submission employed a hybrid strategy combining machine learning ensemble models, quantile regression, and Bayesian uncertainty quantification to produce accurate probabilistic forecasts for a wind-solar hybrid system, and it demonstrated that these forecasts—when integrated with optimal bidding strategies in the day-ahead electricity market—generated substantially higher trading revenue than deterministic forecast-based approaches. This result is directionally consistent with a broader body of research showing that probabilistic forecast information, when properly translated into operational decisions, reduces expected costs across a range of grid operating conditions. Despite this evidence, the translation of probabilistic forecast information into reserve procurement, unit commitment, and market pricing mechanisms in U.S. organized markets remains an area of active and incomplete development, representing a significant opportunity for grid reliability improvement.



Advanced Electricity Demand Forecasting
in an Era of Electrification

Electricity demand forecasting has long been among the most developed disciplines in power system analytics. Utilities and system operators have relied on statistical regression models, time series methods, and econometric approaches to predict demand across timescales from minutes to decades. These methods, calibrated against decades of historical data, achieved forecast accuracy sufficient for the relatively stable patterns that characterized the U.S. electricity sector from the 1990s through the 2010s. The current period of accelerating demand growth is challenging the assumptions embedded in conventional forecasting methodologies in ways that require fundamental rethinking of the tools and techniques employed.

The structural drivers of this growth—large-scale data center construction, industrial electrification under federal incentive programs, widespread adoption of electric vehicles, and heat pump deployment in the residential sector—do not appear in historical load data and cannot be captured by extrapolating historical trends. Grid Strategies LLC's 2025 National Load Growth Report found that load growth forecasts were revised upward for the third consecutive year, with data centers dominating near-term growth expectations. Data center demand is projected to rise 22 percent in 2025 alone, potentially tripling by 2030. The spatial concentration of this demand—data centers cluster in geographic zones based on land availability, water access, fiber infrastructure, and power pricing—creates localized grid stress that aggregate national or regional forecasts obscure. High-resolution, location-specific electricity demand forecasting is increasingly essential for transmission planning, interconnection studies, and localized reserve adequacy assessment.

Advanced machine learning methods are being applied to these challenges with increasing sophistication. Transformer architectures, temporal convolutional networks, and hybrid deep learning frameworks have demonstrated improved accuracy for short-term load forecasting by capturing complex nonlinear relationships among demand, temperature, time-of-day patterns, calendar effects, and behavioral covariates. Recent reviews of machine learning approaches to load forecasting show that the

combination of smart grid sensor data and AI-based forecasting systems can outperform traditional statistical methods in capturing the nonlinear dynamics of modern demand portfolios that include large shares of temperature-sensitive heating and cooling loads, flexible industrial demand, and distributed generation.

Electric vehicle charging represents a particularly challenging load forecasting problem because it combines high power density (a single DC fast charger can draw several megawatts), high temporal variability (charging events are discrete and stochastic), and strong spatial concentration (charging hubs at highway interchange locations can create demand spikes on distribution circuits not designed for such loads). Location-based probabilistic EV charging demand forecasting using multi-quantile temporal convolutional networks with deep transfer learning, as described in a 2024 paper, illustrates how granular demand-side uncertainty can be quantified for specific infrastructure elements and used to inform distribution planning decisions. The emerging EV-STLLM framework, applying spatio-temporal large language models with multi-frequency and multi-scale information fusion, represents the frontier of AI-native approaches to this forecasting challenge.

Very short-term load forecasting (VSTLF), covering horizons from minutes to an hour, has particular operational importance in a high-renewable grid. VSTLF errors propagate directly into real-time balancing decisions, and their magnitude relative to available regulation capacity determines whether the system can continuously balance supply and demand. As behind-the-meter solar penetration increases, the effective net load seen by system operators—total consumption minus distributed generation—becomes more volatile and more difficult to forecast, because the behavior of individual customers' solar panels is not directly observable by the operator. The development of advanced net load forecasting methods that simultaneously account for distributed solar, demand response, and storage dispatch represents a near-term priority for system operators navigating high distributed energy resource environments.

Analyses of electricity demand forecasting for future grid states highlight the importance of incorporating forward-looking structural assumptions—about electrification rates, building stock turnover, industrial capacity additions, and policy trajectories—into long-term load forecasting frameworks. These scenario-based approaches, which explicitly model alternative futures rather than extrapolating a single expected trajectory, are better suited to the policy-driven and technology-driven demand growth now underway. The integration of high-resolution spatial demand forecasting with transmission planning processes is a particularly valuable application, enabling planners to identify localized transmission constraints before they materialize rather than after expensive congestion management actions have already been required.

Unit Commitment Under Uncertainty

From Deterministic to Stochastic Optimization

Unit commitment—the decision of which generating units to bring online for each operating period, typically covering a day-ahead planning horizon with hourly or sub-hourly resolution—is one of the most consequential operational decisions in power system management. The unit commitment problem balances the cost of starting and operating thermal generators against the reliability risk of having insufficient generation available to meet demand. In conventional grids dominated by dispatchable thermal resources, this optimization is computationally tractable and reasonably well understood. Renewable energy forecasting uncertainty fundamentally complicates unit commitment by introducing correlated uncertainty across the generation portfolio.

A deterministic unit commitment based on the expected wind and solar forecast may leave insufficient reserves when generation falls below expectations; a risk-averse commitment that assumes poor renewable conditions may unnecessarily commit expensive peaking units. The ideal approach is stochastic unit commitment—an optimization framework that explicitly represents the probability distribution of renewable generation outcomes and minimizes expected total cost across a realistic set of scenarios. Stochastic unit commitment models represent uncertain renewable generation through scenario trees, where each scenario corresponds to a possible trajectory of wind and solar output over the planning horizon, weighted by its probability. The optimization selects generator commitment decisions that minimize expected costs across scenarios while satisfying reliability constraints in each scenario.

A 2024 hybrid data-driven and model-based approach to stochastic unit commitment and economic dispatch, documented in the Department of Energy's OSTI repository, demonstrates that machine learning-based scenario generation combined with physics-based grid simulation can achieve computational efficiency sufficient for operational use. By training surrogate models to approximate the feasible operating region of the power system and using those surrogates to accelerate scenario evaluation, the hybrid approach achieves cost savings relative to deterministic unit commitment without sacrificing reliability, while remaining tractable for near-real-time decision-making. A separate 2024 study addressing inertia constraints in unit commitment under renewable uncertainty demonstrates that, as synchronous generators are displaced by power-electronics-coupled wind and solar resources, unit commitment models must explicitly account for the system's frequency response characteristics to prevent under-frequency events following generation loss.

Risk-aware extensions of stochastic unit commitment, including chance-constrained formulations and conditional value-at-risk (CVaR) optimization, provide additional flexibility in characterizing and managing reliability risk. Chance-constrained formulations ensure that reliability standards are met with a specified probability across the scenario distribution, rather than in expectation; CVaR formulations minimize expected cost in the worst tail of the outcome distribution, providing explicit protection against low-probability, high-consequence events. Risk-aware scheduling can leverage probabilistic forecasts to determine chance-constrained reserves—ensuring with high probability that sufficient flexibility is available to balance the system even under adverse renewable generation scenarios—without the systematic over-commitment that results from worst-case robust approaches.

The practical implementation of stochastic unit commitment in U.S. organized markets has been incremental. MISO, PJM Interconnection, and CAISO have implemented versions of stochastic or robust unit commitment for specific reliability-critical applications, particularly reserve procurement. The challenge lies in computational tractability: accurate stochastic optimization over realistic scenario trees with thousands of generating units and complex network constraints requires substantial computational resources and sophisticated solution algorithms. Academic and national laboratory research is actively addressing this gap through decomposition methods, machine learning accelerators, and the development of operational-scale stochastic software platforms. As computational costs decline and algorithmic capabilities improve, broader deployment of stochastic unit commitment in day-ahead and intra-day market operations is an achievable near-term goal.

Stochastic unit commitment improves grid reliability and reduces costs by optimizing generator schedules across multiple renewable generation scenarios instead of relying on a single deterministic forecast, with machine learning accelerating real-time decision-making.

Risk-aware optimization techniques—including chance-constrained and CVaR methods—help balance reliability and cost under renewable uncertainty, and are increasingly being adopted by major U.S. grid operators despite ongoing computational challenges.

Transmission Congestion Management and Dynamic Line Ratings

The integration of large-scale wind and solar generation with load centers separated by significant distances requires transmission infrastructure that can accommodate both the magnitude and variability of renewable power flows. Transmission congestion—the condition in which power flow on a line or interface exceeds its rated capacity, requiring costly redispatch or curtailment—is increasingly driven by renewable generation patterns rather than demand patterns alone. In the United States, transmission infrastructure expansion has not kept pace with the growth of renewable capacity.

Grid Strategies LLC reported that only 888 miles of new high-voltage transmission were completed in the United States in 2024, a fraction of the approximately 5,000 miles per year that analysts estimate are needed to fully integrate the renewable capacity currently in the interconnection queue. The backlog of interconnection requests, the complexity of multi-state transmission siting, and the time required for permitting and construction—typically seven to 12 years—mean that transmission constraints will remain a binding limitation on renewable integration for the foreseeable future. In this constrained environment, the optimization of existing transmission assets through improved forecasting is a near-term mechanism for extracting additional renewable energy delivery capacity from the current network.

Dynamic line ratings (DLR) and the related concept of ambient-adjusted ratings (AAR) represent this near-term opportunity. Conventional static line ratings conservatively assume worst-case ambient conditions—high air temperatures, low wind speeds, and maximum solar heating—that rarely materialize simultaneously. In practice, transmission lines can safely carry substantially more power when actual conditions are favorable. DLR systems use real-time sensor data on conductor temperature, tension, and sag, combined with high-resolution meteorological forecasts, to compute actual available thermal capacity on a sub-hourly basis. FERC Order 881, finalized in 2021 and requiring compliance by 2025, mandates that transmission providers adopt AARs, incorporating ambient temperature forecasts on a 10-day-ahead, hourly basis into their line rating calculations. This regulatory requirement has made wind and solar forecasting directly relevant to transmission operations: the accuracy of meteorological forecasts now directly determines the rated capacity of transmission paths serving renewable generation.

Forecasting-based congestion management extends beyond line ratings. Anticipatory redispatch—in which system operators proactively adjust the generation dispatch schedule in advance of a predicted congestion event—requires reliable forecasts of both renewable generation and transmission conditions. Germany's experience with high renewable penetration illustrates both the challenge and the cost: redispatch and congestion-management costs have reached multibillion-euro annual levels in recent years, driven in part by the need to manage renewable generation that cannot always be delivered to load centers. Transmission network congestion is also increasingly visible at the distribution level, where decentralized solar generation is creating new localized constraints. Stochastic optimal power flow models that incorporate probabilistic renewable generation forecasts have been shown in the academic literature to reduce curtailment and redispatch costs relative to deterministic approaches by pre-positioning the system to handle a range of renewable output scenarios rather than optimizing for a single expected outcome.

The connection between improved forecasting and reduced transmission congestion also has implications for renewable energy investment economics. Curtailment risk—the probability that a generation asset's output will be constrained by transmission limitations—is a material factor in project financing, offtake agreement structuring, and risk assessment. Accurate curtailment forecasting tools, which combine grid topology models with probabilistic renewable generation forecasts, enable project developers, financiers, and offtakers to better characterize and price this risk. Research published in 2024 specifically addresses the challenge of predicting curtailment events to unlock the full economic potential of renewable generation, demonstrating that machine learning-based curtailment prediction substantially improves upon heuristic approaches and supports more accurate project revenue modeling.

Transmission congestion is becoming a major barrier to renewable energy integration, and with new transmission expansion lagging behind demand, technologies like Dynamic Line Ratings (DLR) and Ambient-Adjusted Ratings (AAR) use real-time weather and sensor data to safely increase existing grid capacity.

Accurate renewable and weather forecasting enables proactive congestion management, reduces curtailment and redispatch costs, improves transmission efficiency, and provides better curtailment risk predictions that support renewable project financing and revenue planning.

Real-Time Market Operations and the Role of Improved Forecasts

Electricity markets in the United States operate on multiple timescales, from year-ahead capacity markets to five-minute real-time balancing markets, and each timescale has distinct forecasting requirements. The day-ahead energy market—in which participants submit generation offers and load bids for the following operating day, and the market operator clears the market to minimize total cost—is particularly sensitive to renewable generation forecasts. If system operators and market participants use different forecasts, or if both use inaccurate forecasts, the resulting commitment and dispatch schedule may be inefficient, requiring costly real-time adjustments. When renewable generation substantially underperforms or overperforms the day-ahead forecast, the real-time market must make up the difference through emergency purchases, demand response activations, or, in the worst case, reliability actions.

CAISO provides a practical illustration of how improved forecasting integrates with market operations. The California ISO provides market participants with hourly variable energy resource forecasts and updated scheduling information to facilitate timely position management. As renewable penetration has grown—with projections showing solar generation capacity approaching and exceeding 12,000 megawatts in the CAISO footprint—the accuracy of these forecasts has taken on increasing operational significance. The 3.4 million megawatt-hours of renewable curtailment in 2024, a 29 percent increase year-over-year, reflects in part the mismatch between renewable generation patterns and the available flexibility of the dispatch portfolio—a mismatch that more accurate and timely forecasting can help operators address proactively rather than reactively.

Intra-day and real-time markets are where forecast errors have their most immediate operational consequences. As the operating hour approaches, improved forecasts based on updated weather observations, satellite-derived cloud cover imagery, and high-frequency SCADA data from operating renewable assets allow market participants and operators to update their positions. The Living Forecast concept, described in a 2025 paper, proposes continuously updating probabilistic forecasts as new information becomes available—transforming forecasting from a batch process into a real-time data stream that continuously informs dispatch decisions as the gap between forecast and reality narrows with each passing hour. This approach is conceptually aligned with the evolution of organized market structures toward more frequent clearing intervals: CAISO's 15-minute market, MISO's real-time pricing intervals, and the emerging extension of intra-hour trading in other organized markets reflect a growing recognition that traditional hour-ahead scheduling is too coarse to efficiently manage renewable variability.

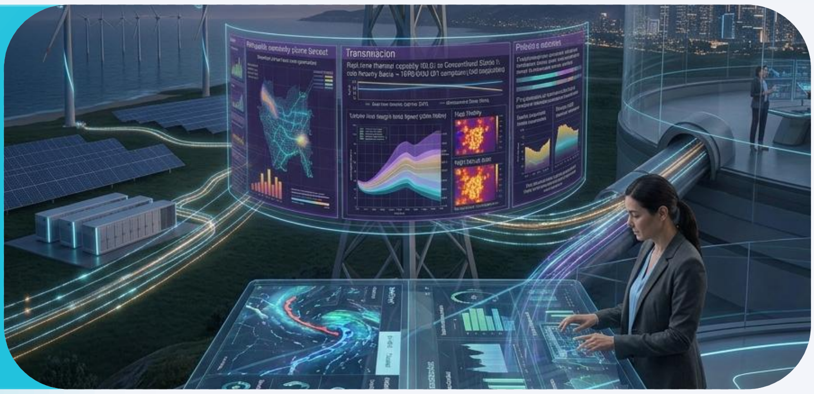
The market design implications of improved renewable energy forecasting extend to ancillary services procurement. Operating reserves—frequency regulation, spinning reserves, and non-spinning reserves—are procured in advance to ensure that sufficient flexible capacity is available to respond to unexpected deviations from the dispatch schedule. Probabilistic forecasting enables reserve requirements to be set dynamically based on forecast uncertainty in the specific operating period, rather than at fixed levels derived from historical average variability. When forecast uncertainty is low—a clear, stable high-pressure day with predictable solar output across a well-observed footprint—reserves can be reduced; when uncertainty is high—a frontal passage with rapidly changing wind speeds and cloud shadows—reserves should be augmented. Research demonstrates that dynamic probabilistic reserve procurement reduces system costs without compromising reliability relative to static reserve requirements calibrated to worst-case conditions.

The integration of forecasting improvements with market mechanisms requires sustained regulatory engagement and institutional adaptation. Recent market reforms and regulatory approvals related to real-time co-optimization of energy and ancillary services in organized markets reflect a broader trajectory toward more dynamically efficient market designs that can leverage improved forecast information. For regional transmission organizations and independent system operators, the computational and data infrastructure required to operationalize probabilistic forecasting at market scale—including scenario-based reserve procurement, forecast-conditioned dispatch optimization, and real-time uncertainty communication to market participants—represents a substantial investment with correspondingly substantial returns in reduced system costs and improved reliability outcomes.

Improved real-time and probabilistic renewable energy forecasting enables electricity markets to optimize dispatch, dynamically allocate reserves, reduce operating costs, and enhance grid reliability amid increasing renewable energy integration.

Global Perspectives and Lessons for the United States

International experience demonstrates that advanced renewable forecasting, flexible electricity market designs, and real-time coordination are essential for integrating high levels of wind and solar power while maintaining grid reliability.



Case studies from Germany, Denmark, the UK, Spain, and Australia provide valuable lessons for the U.S. on improving forecasting, balancing operations, grid resilience, and market reforms as renewable energy penetration continues to grow.

While this paper is primarily focused on the U.S. power system, international experience with renewable integration and forecasting offers instructive perspectives. European power systems, which have operated at high renewable penetration for longer than most U.S. regions, have developed forecasting practices and market mechanisms from which U.S. stakeholders can draw valuable lessons. The IEA Renewables 2025 report confirms that the global expansion of renewable capacity continues to accelerate, with Europe, the United States, and China collectively accounting for the majority of new installations and each facing distinct but related forecasting and integration challenges.

Germany's experience with high wind and solar penetration—and the associated challenge of grid congestion and renewable curtailment—has driven the development of sophisticated forecasting-based redispatch systems. The country's public grid congestion management frameworks, combined with electricity market reforms that enable intraday trading up to 30 minutes before delivery, provide a template for how market design can accommodate renewable variability through improved information flows. Denmark, with wind energy routinely supplying more than 50 percent of national electricity demand, has developed real-time balancing arrangements with neighboring Nordic and German markets that rely heavily on short-term renewable forecasting for cross-border scheduling decisions. The Danish experience demonstrates that accurate, shared renewable generation forecasts are a prerequisite for the cross-border coordination that enables small, highly interconnected power systems to manage high renewable variability without excessive reserve requirements.

The United Kingdom's experience with offshore wind integration is particularly relevant as the U.S. develops its Atlantic and Gulf Coast offshore wind pipeline. The UK operates some of the world's largest offshore wind installations and has invested significantly in ensemble weather models and probabilistic forecasting systems tailored to North Sea meteorological conditions. Europe's offshore wind capacity is projected to double toward 140 gigawatts by 2030, with the UK and Germany leading installation programs. The spatial aggregation of multiple offshore wind projects across a wide geographic footprint provides natural diversification of generation variability but requires sophisticated multi-site joint forecasting frameworks that capture the meteorological correlations among sites operating within the same synoptic weather systems.

The April 2025 Iberian Peninsula blackout represents a consequential recent example of the operational risks that can arise in power systems with high renewable penetration and increasingly complex balancing requirements. Post-event discussions have examined the roles of reserve adequacy, inverter behavior, system inertia, voltage control, and operational forecasting, but official findings and technical interpretations have continued to evolve. The incident has accelerated European discussions about minimum synchronous generation requirements, grid-forming inverter standards, and the design of inertia markets—discussions with direct relevance for U.S. grid planning as renewable penetration increases in ERCOT, CAISO, and other regions operating with diminishing shares of synchronous thermal generation.

Australia's National Electricity Market, where solar penetration in South Australia intermittently supplies more than 100 percent of regional demand, has been a proving ground for advanced power system forecasting tools and real-time market adaptations. The Australian Energy Market Operator has developed a suite of forecasting tools, including five-minute-ahead solar generation forecasts and probabilistic wind generation forecasts, that inform real-time dispatch and voltage management. These tools have been cited by U.S. system operators as practical models for near-term development.

Policy, Regulatory, and Investment Dimensions

The translation of advanced forecasting capabilities from research settings into operational power systems requires not only technological development but also supportive policy, regulatory frameworks, and sustained investment. In the United States, several regulatory and policy developments are shaping the environment for power system forecasting and grid integration.

FERC Order 881's requirement for ambient-adjusted transmission line ratings represents the most direct regulatory mandate for improved meteorological forecasting in grid operations. By requiring transmission providers to incorporate hourly ambient temperature forecasts into line rating calculations on a ten-day-ahead basis, the order creates structured demand for high-quality weather forecasting services and establishes a regulatory baseline for forecast-based transmission capacity assessment. Compliance, required by 2025, has driven investment in sensor networks, data integration platforms, and forecasting services across the transmission sector—a demonstration that targeted regulatory requirements can effectively accelerate the operational adoption of improved forecasting tools.

FERC Order 1920, which requires transmission providers to conduct long-term scenario-based transmission planning, has created additional demand for long-range renewable resource forecasting as an input to transmission expansion studies. Identifying high-value transmission projects in a future grid dominated by wind and solar requires understanding where those resources will be located, at what capacity factors, and with what correlation structure across regions—questions that are fundamentally forecasting questions requiring probabilistic scenario analysis rather than single-trajectory projections. At the federal agency level, NOAA's investments in next-generation NWP systems and the Department of Energy's funding of research into AI-based weather models for energy applications are building the public-good scientific infrastructure on which commercial forecasting products depend. Federal reliability and grid-security analyses also emphasize improved forecasting as a near-term, cost-effective mechanism for improving grid reliability relative to the capital-intensive alternatives of new generation and transmission construction.

State-level renewable portfolio standards and clean energy commitments are driving the pace of renewable deployment that creates the forecasting challenge, while also driving regulatory attention to grid integration planning. California, Texas, and a growing number of states in the Southeast and Midwest are grappling with the operational consequences of high renewable penetration and are beginning to incorporate advanced forecasting requirements into their grid planning and market design frameworks. At the market level, investment in renewable energy forecasting services—including commercial wind and solar forecasting platforms, probabilistic market intelligence products, and AI-enhanced meteorological services—has grown substantially, reflecting the economic value of forecast accuracy in competitive electricity markets where energy prices are highly correlated with renewable generation levels.

THE PATH FORWARD

Priorities For Progress

Several near- and medium-term priorities emerge from the foregoing analysis as particularly consequential for the advancement of forecasting capabilities in renewable-dominated power systems. Progress on each of these fronts will require collaboration across research institutions, system operators, technology developers, market participants, and regulatory agencies.

The maturation and operational deployment of AI weather models—specifically foundation models fine-tuned for power system applications—represents perhaps the most transformative near-term opportunity. The computational cost advantage of AI models over NWP systems, combined with their demonstrated skill at global scales and their capacity for rapid retraining on new observational data, makes them strong candidates for integration into the operational forecasting chains of system operators and market participants. The adaptation of these models to produce reliable, calibrated uncertainty estimates—not just improved point forecasts—is a research priority that the energy forecasting community is actively pursuing, and one in which progress over the next two to three years is realistic and consequential.

The development of standardized probabilistic forecasting benchmarks and evaluation frameworks, illustrated by initiatives such as the R²Energy benchmark and the IEEE HEFTCom competition series, is important for accelerating methodological progress and facilitating reproducible comparisons among forecasting approaches. These benchmark initiatives bridge academic research and operational deployment by articulating the specific forecast products—quantiles, scenarios, prediction intervals, and joint distributions—that operational decision-making requires, and by providing standardized datasets on which diverse methodologies can be evaluated under common conditions.

Investment in data infrastructure—advanced metering networks, distribution management system upgrades, sub-hourly SCADA data from renewable assets, and expanded meteorological monitoring through surface stations, atmospheric profilers, and satellite-based remote sensing—is a prerequisite for the advanced forecasting methods discussed in this paper. Machine learning models are only as good as their training data, and the spatial and temporal granularity of available observational data largely determines the achievable forecast accuracy, particularly at the site-specific and distribution-network levels where the operational impact of forecasting improvements is most immediate.

The integration of forecasting improvements into market design and operational protocols requires sustained institutional commitment from system operators, regulators, and market participants. The academic literature on probabilistic unit commitment, dynamic reserve procurement, and forecast-informed ancillary services markets has matured to the point where pilot programs and regulatory proceedings can translate these concepts into operational practice. The Western Energy Imbalance Market's demonstrated reduction in renewable curtailment through improved real-time coordination provides a practical proof of concept for the value of this integration—and points toward the broader market design reforms, including expanded real-time markets, intraday trading, and cross-regional balancing arrangements, that will be necessary to fully realize the value of improved renewable energy forecasting.

Conclusion

The transition to a renewable-dominated power system is not only a question of resource adequacy—although adequate resources, transmission, and flexibility remain essential. It is also a question of operational intelligence: the ability to predict, in advance and with appropriate characterization of uncertainty, what the wind and sun will provide, what customers will demand, and what the transmission system can accommodate. Advanced forecasting—spanning wind and solar forecasting, electricity demand forecasting, probabilistic uncertainty quantification, and transmission condition assessment—is the operational intelligence that makes renewable integration efficient, reliable, and economical.

The technologies reviewed in this paper—AI-powered weather models including GraphCast and Pangu-Weather, probabilistic uncertainty quantification methods including conformalized quantile regression and copula-based joint forecasting, and advanced load forecasting architectures incorporating deep learning and scenario-based structural modeling—represent a genuine step change in forecasting capability relative to methods that were standard practice a decade ago. Their translation from research into operations is underway but incomplete, and the gap between the state of the art and current operational practice in U.S. power markets remains significant. Closing that gap requires sustained investment in technology, data infrastructure, computational platforms, and market design, as well as regulatory frameworks that create incentives for forecasting improvement and operational adoption.

The stakes are clear. NERC's 2024 and 2025 reliability assessments document a power system under compounding stress from rapid renewable deployment, conventional generator retirements, and surging electricity demand driven by data center growth and electrification. Forecasting improvements will not substitute for needed transmission investment or resource adequacy planning, but they represent a relatively near-term, cost-effective, and high-leverage intervention that can improve the performance of the existing system while the infrastructure investments required for the long-term energy transition are being planned and built. For grid operators, market participants, technology developers, and policymakers, advanced forecasting for renewable-dominated power systems is not an optional enhancement—it is a core operational requirement of the energy transition itself.

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