

Review

Recent Advances in Long-Term Wind-Speed and -Power Forecasting: A Review

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Abstract

This review examines advancements and methodologies in long-term wind-speed and -power forecasting. It emphasizes the importance of these techniques in integrating wind energy into power systems. Covering a range of forecasting timeframes from monthly to multiyear projections, this paper highlights the diversity of applications and approaches. These applications and approaches are essential for managing the inherent variability and unpredictability of wind energy. Various forecasting methods, including statistical models, machine-learning techniques, and hybrid models, are discussed in detail. The review demonstrates how these methods improve forecast accuracy and reliability across different temporal and geographical scales. It also identifies significant challenges such as model complexity, data limitations, and the need to accommodate regional variations. Future improvements in wind forecasting include enhancing model integration, employing higher resolution data, and fostering collaborative research to further refine forecasting methodologies. This comprehensive analysis aims to advance knowledge on wind forecasting, facilitate the efficient integration of wind power into global energy systems, and contribute to sustainable energy development goals.

Keywords: wind-speed forecasting; wind-power forecasting; forecasting methods; climate change; multi-timescale; renewable energy



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1. Introduction

Wind power has become a cornerstone of renewable energy strategies, owing to its abundance and low environmental impact. Integrating wind energy into power systems, however, remains challenging because wind speed and output are inherently variable and difficult to predict. Accurate forecasting is therefore essential to ensure grid stability, inform investment decisions, and guide policy. Early reviews by Madasthu et al. [1] and Soman et al. [2] examined forecasting techniques across horizons ranging from seconds to years, identifying key advances and persistent challenges. Subsequent surveys by Valdivia-Bautista et al. [3], Hanifi et al. [4], and Wang et al. [5] focused on improving forecasting accuracy through emerging technologies. They also noted issues such as wind intermittency and model complexity.

Although these reviews laid the groundwork for short-term wind forecasting, long-term perspectives spanning months, seasons, and years have received comparatively less attention. Yet, long-term forecasts are crucial for strategic planning, asset management, grid expansion, and policy formulation. Recent studies (summarized in Table 1) indicate that changing climate conditions are already altering wind-field patterns. This further

highlights the need for robust long-term models capable of capturing nonlinear interactions among atmospheric, geographical, and anthropogenic factors. Over the past two decades, publications on long-term wind forecasting have risen sharply (Figure 1), reflecting growing interdisciplinary interest. These data were retrieved from one of the largest academic search engines, Scopus, (collected using the search keywords ‘wind’ AND ‘forecasting’ AND ‘long-term’ AND ‘energy’ searched within the article title, abstract, and keywords). Figure 2 shows that Asia and Europe together account for most of these contributions, with North America also playing a major role.

Table 1. Summary of the recent studies addressing climatic influences on wind-field changes.

Focus of Study	Regions Covered	Applications
Changes in wind power linked to climate phenomena [6]	Northern Hemisphere, Tropics, Southern Hemisphere	Climate adaptation, energy policy, economic optimization
Impact of climate modes on wind variability [7]	Northern Europe, US Southern Great Plains	Energy planning, climate research, policy, cost management
Impact of climate change and tech on wind capacity [8,9]	North Sea, EU; Global	Energy efficiency, climate models, wind farm design
Seasonal wind-speed predictions [10]	Europe	Wind energy models, energy management
Long-term wind speeds using GCMs and downscaling [11]	Global	Infrastructure, agriculture, disaster risk management
Wind speeds in Europe using GCMs and downscaling [12–15]	Europe, North America, China	Climate adaptation, policy, renewable energy
Future wind energy under climate scenarios [16–19]	Europe, North America, offshore Northern Europe, China, UK, Australasia	Strategic planning, economic forecasting, education

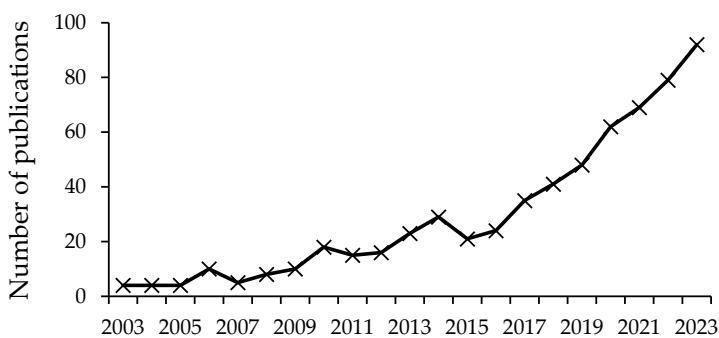


Figure 1. Number of long-term wind forecasting papers published each year from 2003 to 2023.

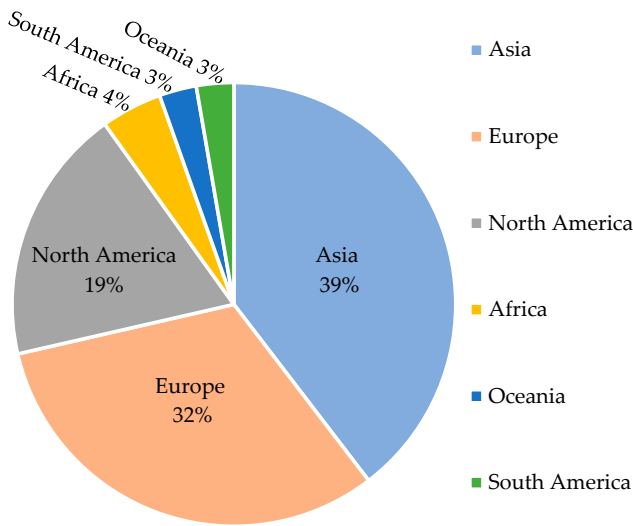


Figure 2. Proportion of papers published for each continental region from 2003 to 2023.

Considering this expanding literature, a dedicated review of long-term wind forecasting methods is timely. This paper synthesizes recent advances in monthly, seasonal, annual, and multiyear forecasting, categorizing approaches into purely statistical and hybrid (mixed) frameworks. We draw on both foundational and cutting-edge studies to assess model performance, underlying assumptions, and practical implications. This comprehensive review identifies gaps in existing research, and aims to guide future work toward more accurate, reliable forecasts under a shifting climate. Our ultimate objective is to advance wind energy forecasting and support the efficient and effective integration of wind power into global energy systems.

In particular, this review will

- i. Catalogue the key statistical, machine-learning, and hybrid methods developed for monthly, seasonal, annual, and multiyear wind forecasting.
- ii. Compare these methods on standardized criteria including data sources, forecast horizon, core parameters, and evaluation metrics to aid future research advancements.
- iii. Diagnose the main challenges, including data heterogeneity, model complexity, and climate nonstationarity that cut across forecasting horizons;
- iv. Recommend future directions for method development, data curation, and operational integration.

The remainder of this paper is organized as follows. Section 2 defines the time horizons relevant to long-term wind forecasting. Section 3 presents a detailed examination of forecasting methods for each horizon, grouping them into statistical and hybrid categories. Section 4 discusses cross-cutting challenges and outlines directions for future research. Section 5 offers concluding remarks.

2. Time Horizons for Long-Term Wind Forecasting

In this review, long-term wind forecasting is defined as the prediction of wind-speed or wind-power generation over horizons that extend beyond short-term (hourly to daily) intervals, specifically ranging from one month to multiple years. The primary objectives of such forecasts include informing operational planning, guiding market participation, and supporting strategic infrastructure development. Spanning multiple temporal scales, long-term forecasting addresses different aspects of wind energy management and planning. The studies reviewed here cover horizons ranging from one month to several years, highlighting a broad spectrum of applications and demonstrating the necessity for methodologies tailored to each forecast interval. In the following subsections, we break down these horizons by length and highlight how methodological choices evolve with each temporal scale. Additionally, the main forecasting parameters considered are highlighted and discussed in each subsection.

2.1. One-Month-Ahead Forecasting

The one-month-ahead interval aims to predict the average wind-speed or wind-power output for the month following the forecast date. This prediction is critical for aligning maintenance schedules, securing short-term power purchase agreements, and optimizing market participation. Different methodological approaches have been explored to enhance forecast accuracy at this time scale. Bou-Rabee et al. [20] developed a hybrid artificial intelligence model that combines machine-learning techniques with domain knowledge specific to coastal wind regimes. This model uses inputs such as monthly mean wind speed and wind direction at 10 m height, Weibull distribution parameters of shape k and scale c from empirical frequency histograms, and coastal regime indicators including land–sea temperature contrasts and surface roughness proxies. These inputs capture the key environmental drivers and statistical properties of coastal wind regimes for more accurate monthly

forecasts. Their results demonstrate that incorporating coastal meteorological features significantly reduces forecast error compared to conventional methods, underscoring the importance of location-specific modeling.

In contrast, Wang et al. [21] employed a combination method that integrates statistical dimension reductions, such as principal component (PC) analysis, yielding PC scores for the wind speed, air temperature, pressure, and humidity, curve-fitting procedures of regression coefficients mapping PCs to power output, and empirical distribution analyses including residual moments: mean, variance, and skewness. By fusing these techniques, their deterministic one-month-ahead wind-power predictions achieved lower bias and variance, which supports more reliable power scheduling under variable wind conditions.

Kritharas and Watson [22] evaluated both simple persistence (one-month and twelve-month) and more complex regression-based models, including ordinary least squares coefficients relating past wind speeds and optional seasonal dummy variables to next-month values, to establish baseline performance. Their comparison reveals that while persistence models offer a straightforward benchmark, hybrid and statistical combination methods consistently outperform persistence approaches in minimizing forecast mean absolute errors, particularly when historical wind patterns exhibit nonstationarity.

Together, these studies illustrate that one-month-ahead forecasting benefits from hybrid frameworks that either leverage machine learning to capture site-specific dynamics or combine statistical techniques to address underlying variability. The improved accuracy directly informs operational decisions by reducing uncertainty in maintenance timing and short-term energy procurement.

2.2. Multi-Month Forecasting

Moving beyond the one-month-ahead horizon, monthly forecasts project average wind-speed or -power generation for each month over a multi-month or multiyear period, therefore capturing broader temporal trends and supporting mid-range operational planning. Fei [23] proposed a hybrid framework combining empirical wavelet transform and relevance vector regression. The framework decomposes nonstationary wind-speed signals into frequency components, trains sparse probabilistic models on each component using sparsity-promoting priors and optimized relevance thresholds, and reassembles forecasts for subsequent months. The key parameters considered here included the number of wavelet decomposition levels corresponding to targeted frequency bands and the hyperparameters governing relevance vector sparsity. In a case study using eight years of hourly observations from a coastal site, this approach reduced the root-mean-square error by approximately 12% compared to an autoregressive baseline. As such, isolating high- and low-frequency fluctuations, the model better represented seasonal shifts and intermittent gusts, which is essential for scheduling quarterly maintenance and negotiating monthly energy contracts.

Similarly, Yin et al. [24] integrated large-scale climate model outputs (including geopotential height and sea-level pressure fields) into a long-short-term memory (LSTM) network to forecast monthly wind-power generation. Their method first downscaled general circulation model predictors to the site of interest through statistical bias correction and spatial interpolation. The multivariate inputs employed here included the downscaled geopotential height, sea-level pressure, wind speed, air temperature, and humidity, with the key LSTM design parameters comprising the number of memory cells per layer, number of hidden layers, learning rate, and dropout rate. The LSTM architecture was then trained on multivariate inputs that encapsulated synoptic patterns. Validation against three years of wind farm data demonstrated a 15% improvement in the mean absolute percentage error over conventional autoregressive and support vector regression benchmarks. The inclusion

of climate model indices enables the LSTM to capture inter-annual variability and seasonal persistence, which is critical for resource allocation and budget forecasting at the beginning of each quarter.

Both studies highlight the value of combining signal-processing or climate-based inputs with advanced machine-learning techniques. These monthly forecasts bridge the gap between immediate one-month-ahead predictions and longer-range subseasonal or annual forecasts. Through accurately estimating average conditions one or more months in advance, operators can apply this to optimize blade inspection schedules, plan the plant's inventory for spare parts, and engage in more accurate power purchase agreements, therefore reducing financial risk associated with wind resource uncertainty.

2.3. Seasonal and Subseasonal Forecasts

While monthly forecasts capture trends over the course of several months and support mid-range operational planning, longer lead times require forecasts that resolve evolving weather patterns and seasonal variability. Seasonal and subseasonal forecasts extend from approximately two weeks to several months ahead and capture atmospheric signals that are not resolved by daily or monthly models. Seasonal predictions rely on coupled ocean–atmosphere models to estimate prevailing wind regimes over a season, while subseasonal forecasts bridge the gap between weather forecasts and seasonal outlooks by focusing on lead times of two to four weeks [25].

Lledó et al. [26] demonstrated that ensemble seasonal forecasts can effectively predict the seasonal mean wind-power generation. They achieved this by calibrating large-scale climate model outputs, such as sea-surface temperature anomalies, sea-level pressure fields, geopotential height at 500 hPa, and teleconnection indices against historical observations. The key parameters considered here included the ensemble size, bias-correction coefficients, and recalibration window length. Their study showed a 10 to 15% reduction in forecast error compared to climatology, indicating that seasonal signals such as shifts in the jet stream position are useful predictors for the turbine output. The Subseasonal-to-Seasonal (S2S) Prediction Project database [27] provides a comprehensive repository of real-time subseasonal forecast data from multiple international centers. This includes variables such as geopotential height (500 and 850 hPa), wind fields at 10 m and 850 hPa, zonal and meridional wind components, and temperature and humidity predictors at various lead times (two to four weeks). This database highlights efforts to develop and validate subseasonal models for energy applications.

Mariotti et al. [25] highlighted the necessity of coordinated community efforts to improve S2S forecast skills. They emphasized the integration of weather and climate research to reduce systemic biases such as the mean state drift in precipitation and wind and extend reliable predictability into the two-to-four-week range. Building on these foundations, Bloomfield et al. [28] applied S2S forecast products to energy variables, specifically wind power, solar power, and electricity demand, across twenty-eight European countries. The key parameters considered included the forecast lead time, selection of climate indices, and aggregation methods for national-scale output. Their results indicated that, compared to persistence and seasonal-climatology benchmarks, S2S forecasts reduced the mean absolute error by approximately 12% for wind power at a three-week lead time and by 8% for aggregate electricity demand.

Collectively, these studies demonstrate that seasonal forecasts complemented by subseasonal prediction systems using ensemble configuration parameters, calibrated climate model indices, and real-time forecast fields provide actionable information for grid operators. This enables more reliable risk management, reserve allocation, and market scheduling as renewable penetration increases.

2.4. One-Year-Ahead and Multiyear Forecasts

Forecast horizons extending beyond seasonal scales require consideration of annual and decadal variability. Year-ahead forecasts predict wind conditions over the next twelve months, and can be applied to support budgetary planning, market analysis, and maintenance scheduling on an annual cycle. Beyond this, multiyear forecasts evaluate climate-driven trends and long-term shifts in wind patterns and can provide pertinent information to guide infrastructure investment and policy development.

Year-ahead forecasts aim to estimate monthly wind-power generation throughout the upcoming year. Cao, Li, and Yu [29] applied empirical mode decomposition to separate observed wind-power time series into intrinsic mode functions, then modeled each component with machine-learning or regression techniques before recombining them into monthly forecasts. In a case study of a coastal wind farm, this approach achieved roughly a 10% reduction in the root-mean-square error compared to an autoregressive baseline. In this study, the key parameters employed included the number of intrinsic mode functions, choice of modeling technique per mode such as support vector regression vs. neural network, and recombination weights. By isolating seasonal cycles and inter-annual fluctuations, their framework captures nonstationary behavior that is critical for aligning turbine maintenance schedules and negotiating annual power purchase agreements.

Al-Hamadi and Soliman [30] demonstrated a complementary approach by forecasting electrical load rather than wind generation. They used weekly simple linear regression on the previous year's data combined with an assumed annual growth rate to produce reliable twelve-month projections. In this study, the key parameters considered included the regression lag structure (weekly intervals) and the assumed percent growth rate per annum. Although focused on load, their methodology highlights the importance of combining short-term correlations with long-term trends in year-ahead energy forecasts. Moreover, this hybrid regression-plus-growth framework can be readily adapted to wind-power time series, where blending weekly wind-speed correlations with secular trend assumptions enhances forecast reliability. It also supports integrated net-load planning, reserve allocation, and maintenance scheduling [31].

Multiyear forecasts extend the horizon further to evaluate wind resource viability under evolving climate conditions. Yılmaz et al. [32] employed a multivariate adaptive regression spline (MARS) algorithm to predict wind-power potential for 2023–2052, incorporating both historical meteorological observations and downscaled climate model outputs. The key parameters considered in this study included the number of spline basis functions, interaction order, and selection of climate predictors. Their model outperformed traditional linear regression by about 15% in the mean absolute error during validation in 2000–2022 data, demonstrating MARS's capacity to adapt to nonlinear relationships between climate indicators and wind power.

On the other hand, Johnson and Erhardt [33] assessed changes in wind energy density across the continental United States by comparing historical (1968–2000) and future (2038–2070) periods using coupled general circulation model results. The study employed key parameters including the vertical resolution of layers, spatial grid spacing, and temporal aggregation period. They calculated wind energy density by integrating the cube of wind speed over vertical layers and spatial grids, finding a 5–20% decrease in central plains regions and a 10–15% increase along certain coastlines. These projections quantify how shifts in atmospheric circulation under climate change can alter regional wind resource availability, informing long-range site selection and policy decisions.

Together, year-ahead and multiyear studies demonstrate that decompositional methods, regression frameworks, and integration of climate model outputs are essential for capturing temporal scales from seasonal modulations to climate change signals. As such,

accurately forecasting wind-power availability over horizons of one to thirty years can enable stakeholders to optimize maintenance cycles, refine financial projections, and make informed decisions about long-term wind energy infrastructure.

2.5. Summary

Overall, the choice of forecasting horizon directly shapes the appropriate modeling framework. One-month and monthly forecasts rely on high-resolution meteorological inputs, such as Weibull parameters, PC scores, wavelet levels, and machine-learning techniques, to capture short-term variability and seasonal fluctuations. Seasonal and sub-seasonal predictions further incorporate coupled ocean–atmosphere models and ensemble approaches with defined ensemble size and recalibration procedures to resolve patterns at the two-week to multi-month scale. In contrast, year-ahead and multiyear projections draw on empirical signal decomposition, intrinsic mode functions, historical trend analysis, and downscaled climate models including spline basis functions, and climate indices to address inter-annual variability and long-term climate change. Across all horizons, a clear pattern emerges blending diverse data sources (for example, local observations, reanalysis fields, or climate model outputs) with hybrid modeling approaches that enhance forecast robustness and accuracy. Together, these studies illustrate that no single methodology can serve every temporal scale; instead, a spectrum of predictive models is required. Shorter horizons prioritize immediate decision support, such as maintenance scheduling and power market participation, while longer horizons inform strategic planning, policy development, and infrastructure investment. Stakeholders in the wind energy sector may, therefore, deploy tailored methodologies that meet both operational and strategic needs. In Section 3, we review long-term wind forecasting methods grouped first into statistical and hybrid frameworks, and then subdivided for each horizon: monthly, seasonal, and annual, comparing their key characteristics and reported performance metrics.

3. Long-Term Wind Forecasting Methods

Before examining the specific forecasting techniques, it is essential to acknowledge that national wind-speed archives differ in reporting height, temporal aggregation, and the suite of auxiliary measurements they provide. Despite this heterogeneity, the methods reviewed here draw on a consistent set of core inputs: wind speed recorded as instantaneous or aggregated values at one of the standard reference heights (10 m, 30 m, 50 m, 80 m, or 100 m), typically sampled at ten-minute or hourly intervals. They also include complementary predictors such as wind direction, air temperature, pressure, and relative humidity, either used directly or to compute statistical moments and distribution parameters; where spatial context is required, geographic coordinates (latitude, longitude, and elevation). Through the standardization of these climatic and statistical parameters, long-term forecasting frameworks remain adaptable to diverse data formats and ensure comparability across regions [34,35].

Building on the time horizons outlined in Section 2, we now examine the methods developed for each temporal interval, transitioning from the classical applied methods to more emergent technologies. Accurate long-term forecasts support reliable grid integration, optimized maintenance scheduling, and strategic planning. Shorter horizons rely on detailed meteorological inputs, while longer horizons require climate projections and trend analysis. As a result, this literature includes a review of classical methods, purely statistical techniques, machine-learning algorithms, and hybrid frameworks that combine both. In the subsections that follow, we first discuss classical wind-speed and wind-power forecasting methods. We then group the emerging methods by horizon (monthly, seasonal, annual, and

multiyear) and highlight how each approach addresses challenges such as nonstationary wind behavior, limited historical data, and uncertainty in future climate.

3.1. Classical Methods

At the beginning of this century, long-term wind forecasting relied on statistical distribution fitting, climatological baseline consideration, exponential smoothing, and simple trend extrapolation. Fitting two-parameter distributions, most commonly Weibull (shape k , scale c) and Rayleigh (scale σ), were widely applied to monthly wind-speed data. The parameters in such studies were commonly estimated through method-of-moments or maximum-likelihood techniques to characterize frequency behavior and derive probabilistic forecasts.

Carta et al. [36] reviewed a comprehensive set of probability distributions, including Weibull (shape k , scale c), Rayleigh (scale σ), lognormal (mean μ , standard deviation σ), and gamma distributions (shape α , scale β), across six Canary Islands sites. The study evaluated three parameter-estimation methods, including method-of-moments, maximum likelihood, and least squares, alongside goodness-of-fit tests (Kolmogorov–Smirnov, chi-squared), to identify the optimal model for each wind regime. Their key finding was that the Weibull model with maximum-likelihood-estimated parameters consistently yielded the lowest average K–S statistic (≈ 0.05) and chi-squared error, demonstrating robust performance across both moderate- and high-wind regimes. Lognormal and gamma distributions occasionally matched Weibull in moderate regimes but showed larger deviations in extreme-wind tails. The strengths of this study include its systematic parameter-method comparison and multi-site analysis; weaknesses lie in its geographic focus, which may limit transferability to non-island climates, as these distribution-based models directly yield expected monthly wind speeds and energy estimates over seasonal to annual horizons. Their parameters and fit metrics constitute a classical long-term forecasting approach that provides the probabilistic baseline for subsequent time-series, machine-learning, and hybrid methods.

Similarly, Celik [37] conducted an analogous analysis for Turkey, applying both the Weibull and Rayleigh fits to ten-minute wind-speed measurements at 15 Turkish stations. The distribution parameters were estimated through the method-of-moments, and then the speeds were converted into the power density, and the normalized root-mean-square error (NRMSE) for both variables was computed. The Weibull model achieved an average NRMSE of 7.8% for wind speed and 10.2% for power density, compared to Rayleigh's 12% and 14% respectively, confirming Weibull's superior accuracy across diverse terrains. Celik's strength is the demonstration of distributional forecasting's utility in varied climates. Its limitation is the exclusion of other potential distributions, such as gamma or lognormal, and the lack of an extreme-value tail analysis.

Building on these distributional foundations, Bremnes [38] introduced probabilistic wind-power forecasting using local quantile regression. This method employs a moving historical window of the length L of months weighted by a Gaussian kernel with bandwidth h to fit quantile regression models that minimize the asymmetric loss function for target quantile levels τ ; for example, 5%, 50%, and 95%, respectively. This was applied to European wind-farm datasets, spanning 10 years of monthly generation. This approach produced median ($\tau = 50\%$) forecasts with a mean absolute percentage error (MAPE) of approximately 11% and 90% prediction intervals, whose empirical coverage closely matched nominal bounds of approximately 92%. The key forecasting parameters considered in this study included the quantile level τ , window length L , kernel bandwidth h , and choice of covariates, such as lagged power and climatological indices. This demonstrates how quantile regression enables explicit uncertainty quantification and adapts to nonstationarity through a moving-window estimation.

Additionally, Kavasseri and Seetharaman [39] applied autoregressive integrated moving-average (ARIMA) models to monthly mean wind-speed series data from 1995 to 2005 at a coastal site. They selected model orders (p,d,q) and seasonal parameters (P,D,Q) via the Akaike information criterion, ultimately fitting an ARIMA(2,1,2)(1,0,1) [12] model that captured both short-term autocorrelation and annual seasonality. The parameters were estimated by maximum likelihood, including autoregressive coefficients ϕ_1, ϕ_2 , and seasonal Φ_1 , moving-average coefficients θ_1, θ_2 , and seasonal Θ_1 , as well as residual variance σ^2 . The one-month-ahead forecasts achieved a root-mean-square error (RMSE) of 0.58 m/s and MAPE of 9.5%, reducing errors by approximately 12%, relative to simple persistence. This study highlights the critical role of ARIMA order selection, seasonal differencing, and the training-window length as forecasting parameters for long-term horizons.

Collectively, Bremnes’s quantile-regression framework and Kavasseri and Seetharaman’s ARIMA models complement the earlier distribution-based methods by adding explicit uncertainty quantification and temporal autocorrelation modeling. These classical approaches establish a robust set of parameters, including the distribution shape and scale, quantile levels, window and bandwidth settings, ARIMA orders, and seasonal components that bolster subsequent machine-learning and hybrid forecasting techniques.

Table 2 summarizes these four studies, comparing application contexts, geographic regions, methodologies, key forecasting parameters, evaluation metrics, and principal findings. The table highlights how distribution fitting, quantile regression, and ARIMA models each address distinct aspects of long-term wind forecasting, balancing data requirements, uncertainty quantification, and temporal dependence to provide a robust foundation for subsequent machine-learning (ML) and hybrid approaches.

Table 2. Comparative overview of classical forecasting methods.

Aspect	Distribution Fitting (Parametric Distribution)	Distribution Fitting (Two-Parameter)	Quantile Regression	ARIMA Models
Authors	Carta et al. [36]	Celik [37]	Bremnes [38]	Kavasseri and Seetharaman [39]
Application	Estimating monthly wind speed and energy distributions	Predicting monthly power density	Probabilistic wind-power forecasting with prediction intervals	One-month-ahead wind-speed forecasting
Location	Six Canary Islands sites	Fifteen Turkish stations	Multiple European wind farms	Coastal site (1995–2005), North Dakota
Methodology	Parametric distribution fitting (Weibull, Rayleigh, lognormal, gamma) with goodness-of-fit tests	Two-parameter distribution fits (Weibull, Rayleigh) for speed and power	Local quantile regression with moving-window and Gaussian kernel	ARIMA(p,d,q)(P,D,Q) modeling short-term autocorrelation and seasonality
Data Used	Monthly wind-speed records (20+ years)	Ten-minute wind-speed measurements aggregated to monthly	Ten years of monthly power generation	Hourly wind-speed records from four North Dakota sites
Key parameters	Distribution family; shape k , scale c ; goodness-of-fit thresholds	Shape k , scale c (Weibull); scale σ (Rayleigh); NRMSE	Quantile level τ ; window length L ; kernel bandwidth h ; covariate selection	ARIMA orders p,d,q ; seasonal orders P,D,Q ; coefficients ϕ, θ, Φ ; differencing and variance parameters
Evaluation metrics	Kolmogorov–Smirnov D ; χ^2 error	Normalized RMSE (NRMSE) for speed and power	Mean absolute percentage error (MAPE) for median; interval coverage accuracy	Root-mean-square error (RMSE); mean absolute percentage error (MAPE)
Findings	Weibull provides the best fit	Weibull gives lower error	Median error $\approx 11\%$ with accurate intervals	ARIMA reduces RMSE by $\approx 12\%$ vs. persistence
Strengths	Systematic multi-distribution comparison; robust across regimes	Demonstrates distributional forecasting in diverse climates	Explicit uncertainty quantification; adapts to nonstationarity	Captures temporal autocorrelation and seasonality; tuned via AIC
Limitations	Geographic specificity; excludes nonparametric methods	Limited to two distributions; no tail analysis	Requires selection of window and kernel parameters; computational overhead	Assumes linear relationships; may struggle with nonstationary trends beyond seasonality

3.2. Statistical Methods

3.2.1. Monthly

- Statistical analysis and empirical data approaches
- Combined statistical, probabilistic, and pattern recognition methods
- LSTM neural networks (Machine learning)
- Gaussian mixture copula model (Multivariate analysis)

A monthly wind energy estimation requires methods that balance data availability, computational complexity, and forecast accuracy. García-Bustamante et al. [40] compared three empirical approaches using five wind farms in Northeast Spain from June 1999 to June 2003. By examining intra- and inter-annual variability, the authors assessed how different representations of the wind-speed-to-power relationship influence monthly energy estimates. Their first method combined hourly wind-speed frequency distributions considering histogram bins and Weibull's fit shape k and scale c with corresponding power output data, evaluating how various empirical curves (through power-curve parameters including cut-in, rated, and cut-out speeds) affect estimation error. The second method interpolated monthly wind values along a theoretical power curve with the curve coefficients mapping the wind speed to power, providing a simplified estimate when high-resolution data are lacking. The third method applied a straightforward linear regression (slope and intercept) between observed monthly wind speeds and power values, effectively approximating the global power curve at monthly time scales. The study found that even this simple linear-regression approach can reliably estimate monthly energy production, highlighting its usefulness in contexts with limited high-resolution power data. These findings carry important implications for electricity system operators and planners working under medium- and long-term frameworks, where data scarcity often precludes more complex models.

In another study, Lin et al. [41] addressed the challenge of medium- and long-term forecasting by introducing a cumulative-distribution-function (CDF)-based model for monthly wind farm generation in northern Hebei Province. Instead of predicting power curves directly, their method fits a beta distribution with the parameters α and β to monthly wind-power data, with the parameters determined by observed periodic patterns. First, historical wind data were classified into abundance categories according to a multi-scale periodicity, capturing seasonal and shorter-term cycles. The alpha parameter of the beta distribution is assigned based on these categories, while the beta parameter is derived from the average of the previous two months. The study found that by incorporating multi-scale periodic patterns, the mean relative error (RE) was reduced from 0.3226 to 0.1958. However, the model's performance degraded under extreme conditions, indicating the need for more complex distributions or additional meteorological inputs in future work.

Yin et al. [24] built on these empirical strategies and proposed a climate-model-driven LSTM network to forecast monthly wind-power generation. Focusing on a Chinese wind farm operational since 2013, their framework first downscales Community Earth System Model (CESM) outputs such as geopotential height and sea-level pressure to site-specific meteorological predictors. These inputs feed into an LSTM network, whose architecture, including the number of memory cells per layer, hidden layers, the dropout rate, learning rate, input sequence length, batch size, and training epochs, is optimized through cross-validation. This enables the model to learn nonlinear relationships and retain long-term dependencies. The authors trained the network on theoretical power generation data from 2013 to 2018, using 2019 observations for validation. Evaluation metrics, including the deviation error, mean absolute error, bias proportion, and variance proportion, confirmed that the LSTM model closely matched actual generation, illustrating its high accuracy and reliability. Through the integration of climate forecasts, the model was able to capture inter-

annual variability and seasonal persistence, which are crucial for improving operational planning at quarterly and annual scales.

In contrast, Yu et al. [42] introduced a localized Gaussian process regression (GPR) approach enhanced by a Gaussian mixture copula model (GMCM) to capture non-Gaussian and nonstationary features in long-term wind-speed data across diverse U.S. climates. Their study considered sites in Denver (Colorado), Salt Lake City (Utah), Tucson (Arizona), and other locations chosen for their distinct wind regimes. First, the GMCM classifies the wind-speed time series into multiple components, each reflecting different non-Gaussian behaviors, defined by copula family selection and mixture weights, extracting component parameters such as means, variances, and tail dependencies. Then, Bayesian inference combines these components within a localized GPR framework, with a kernel function governed by length-scale and signal variance parameters, and noise variance is estimated via maximum likelihood, allowing the model to adapt to stochastic uncertainty and seasonal variation. The study showed that this hybrid GMCM-GPR approach, compared to conventional methods, offers superior accuracy in forecasting wind speed over extended horizons. This improvement directly benefits wind-power scheduling and turbine control strategies in variable environments.

Table 3 summarizes these four studies, comparing data periods, key inputs, modeling techniques, forecast lead times, and principal performance metrics. The table highlights how simple regression, distribution fitting, climate model integration, and copula-based decomposition each address different aspects of monthly wind forecasting, offering distinct trade-offs between data requirements and forecast skill.

Table 3. Comparative overview of monthly statistical methods.

Aspect	Statistical and Empirical Methods	Pattern Recognition Methods	LSTM Networks (Machine Learning)	Gaussian Mixture Copula Model
Authors	García-Bustamante et al. [40]	Lin et al. [41]	Yin et al. [24]	Yu et al. [42]
Application	Estimating monthly wind energy	Predicting monthly electricity generation	Forecasting monthly wind power	Long-term wind-speed forecasting
Location	Northeast Spain	Northern Hebei Province	Wind farm in China	Denver, CO; Salt Lake City, UT; Tucson, AZ
Methodology	Empirical wind-speed–power relationship	CDF and multi-scale patterns	LSTM with climate model	GMCM with Gaussian process regression (GPR)
Data Used	Wind-speed and-power data (1999–2003)	Historical wind-power data	Theoretical data (2013–2018), test data (2019)	Wind-speed data from various locations
Predictors	Wind-speed distribution, linear regression	Wind resource categories, periodic patterns	Meteorological elements, capacity planning	Non-Gaussian components of wind speed
Analysis	Power–curve interpolation, linear regression	Beta distribution, periodic pattern analysis	Nonlinear mapping with LSTM	Bayesian inference for stochastic components
Models	Frequency distribution, interpolation, regression	Beta distribution model	LSTM with CESM climate model	GMCM for classification, GPR for prediction
Findings	Reliable monthly wind energy estimates	Improved accuracy with periodic patterns	High accuracy with CESM and LSTM integration	Accurate long-term predictions across climates
Validation	Five wind farms in Spain	Wind farms in Hebei Province	Wind farm in China	Wind farms in U.S.
Advantages	Works well with limited data	Captures medium- and short-term patterns	Effective for nonlinear relationships	Handles uncertainty and seasonality
Key Insight	Linear relationship between wind speed and power	Multiscale periodic patterns improve accuracy	Climate models and neural networks integration	GMCM and GPR provide robust long-term predictions

3.2.2. Seasonal

- Climate predictors: Sea Surface Temperature (SST) and 850 hPa Geopotential Height (GPH850)

- Tree-Based Machine-Learning Algorithms

Seasonal forecasting extends the prediction horizon to several months ahead, capturing larger-scale atmospheric patterns that influence wind and solar resources. Zeng et al. [43] developed statistical models using July through to September sea surface temperatures and an 850 hPa geopotential height to predict November through to January wind speeds and solar radiations at Baoshan Weather Observation Station in the Yangtze River estuary in China. They analyzed daily wind-speed data from 1959 to 2017 and solar radiation data from 1958 to 2016, calculating three-month moving averages to highlight seasonal trends as a statistical smoothing parameter. Correlation analysis identified regions where the sea surface temperature and geopotential height were strongly linked to energy variables. Three regression models were then constructed: one based solely on linear time-varying regression time-only (LTRT), another combining a single climate predictor with the time (linear time-varying regression univariate LTRU), and a multivariable model incorporating several climate indices alongside the time (linear time-varying regression multivariable LTRM). Model performance was evaluated via seasonal skill scores and error metrics, revealing the highest forecast skill in winter and lowest in summer, demonstrating that climate predictors improve the forecast skill when seasonality strongly governs variability.

Moving from purely climate-informed regression to machine-learning applications, Ahmadi et al. [44] focused on six-month-ahead wind-power forecasting at Ghadamgah Wind Farm in Iran using tree-based learning algorithms. Their aim was to support grid operations facing high wind penetration by evaluating how different data processing choices affect forecast accuracy. Model 1 used statistical feature extraction of the mean and standard deviation of ten-minute wind-speed measurements at 40 m to examine the effect of data aggregation. Model 2 assessed the impact of sampling frequency by aggregating wind-speed data at 40 m into one-hour, twelve-hour, and twenty-four-hour intervals to assess the impact of sampling frequency. Model 3 investigated the measurement height by extrapolating wind speeds recorded at 30 m and 10 m to a reference height of 40 m using logarithmic wind profile relationships. Cross-validation prevented overfitting and independent testing on unseen data from different heights and locations, such as Khaf Wind Farm, which confirmed generalizability. Results showed that longer sampling intervals and height extrapolation can degrade accuracy, highlighting the importance of careful data processing in seasonal forecast models. While height extrapolation is a common approach, advances in observational networks now allow the direct use of multi-height measurements to improve model inputs. For instance, the FINO offshore research platforms measure wind speed at mast heights ranging from 30 m to 100 m, employing rigorous quality-control routines (ValidatF) to ensure data reliability [45,46]. The NOAA Integrated Surface Database compiles station measurements at various instrument heights with automated quality checks, providing a long-term record of sub-hourly wind observations [47]. The NREL Wind Integration National Dataset (WIND) Toolkit offers gridded wind profiles at different turbine hub heights (80 m, 100 m, and 120 m), which are validated against ground-based mast measurements [48]. Furthermore, the HadISD dataset applies stringent quality-control filters to sub-daily station logs, enhancing reliability for multiple height observations [49], and the newly released NOW-23 dataset delivers offshore wind-speed fields at 90 m and 120 m with improved spatial and temporal resolutions and validation against in situ platforms [50].

Table 4 presents a comparative overview of these seasonal statistical methods, showcasing differences in predictors, model structures, validation approaches, and forecast skills.

Table 4. Comparative overview of seasonal statistical methods.

Aspect	SST and GPH850 Climate Predictors	Tree-Based Learning Algorithms (ML)
Authors	Zeng et al. [43]	Ahmadi et al. [44]
Application	Predicting wind speed and solar radiation	Six-month-ahead wind-power forecasting
Location	Baoshan Weather Observation Station, Yangtze River estuary, China	Ghadamgah Wind Farm, Iran
Core Methodology	Statistical models using climate predictors (SST and GPH850)	Tree-based learning algorithms
Data Used	Wind speed (1959–2017) and solar radiation (1958–2016)	Wind-speed data at various heights and sampling intervals
Predictors	Sea Surface Temperature (SST) and Geopotential Height (GPH850)	Wind-speed measurements at 40 m, 30 m, and 10 m heights
Analysis Technique	Three-month moving averages, linear temporal regression models	Data aggregation, sampling time intervals, measurement heights
Models Developed	LTRT, LTRU, LTRM	Three models focusing on data aggregation, sampling intervals, and measurement heights
Key Findings	Highest predictive capability in winter, lowest in summer	Longer sampling intervals and extrapolated heights degrade accuracy
Cross-Validation	Leave-one-out-cross-validation	Employed to prevent overfitting
Real-World Validation	Compares the observed wind speed and solar radiation with the predicted values based on the selected models	Tested against unseen datasets from different heights and locations
Advantages	Identification of climate predictors for seasonal energy resource forecasting	Enhances reliability and efficiency of power grid operations with wind-power integration
Key Insight	Novel approach for anticipating seasonal availability of energy resources	Generalizable and reliable models for various conditions

3.2.3. Annual

- Grey Forecasting Model
- LSTM Neural Networks

Moving from seasonal to annual horizons requires methods that capture longer-term trends and reduce the influence of short-term fluctuations. Grey system models provide a framework for forecasting processes characterized by partial, noisy, or small-sample data [51,52]. These models begin with an accumulated generating operation (AGO), which smooths the original series into a monotonically increasing sequence before fitting a low-order differential or difference equation to the transformed data. In the GM(1,1) model, the AGO sequence is used to estimate the development coefficient and grey action quantity in a first-order continuous differential equation, whereas its discrete-time counterpart DGM(1,1) replaces this with a first-order difference equation to avoid differential approximations on strictly sampled records [53,54]. The multivariable GM(1,N) extends GM(1,1) by coupling one output series with N input series via multivariable differential equations, improving accuracy when relevant predictors exist but increasing parameter estimation complexity and risk of overfitting [55]. The Grey Verhulst model further adapts the framework by incorporating a saturation parameter to capture logistic (S-shaped) growth behavior, making it suitable for phenomena with upper limits [56]. After model fitting, an inverse AGO restores forecasts to the original scale. Chengwei et al. [57] illustrated the sensitivity of this approach to preprocessing choices by applying the GM(1,1) to forecast annual wind-power generation at the FUJIN wind farm in China. Because GM(1,1) assumes a monotonically increasing series, the authors introduced a preprocessing step that multiplies annual wind-power values by a geometric sequence to enforce monotonic growth. A five-order polynomial then converts wind-speed records into wind-power values, reflecting turbine performance. After applying AGO and fitting the model's differential equation, the study performed an inverse AGO to obtain forecasts in the original scale. Comparing predictions from the unprocessed and processed series showed that preprocessing reduced the normalized mean absolute error (NMAE) from 7.7994% to 7.0315%. The geometric-sequence ratio, set to 1.336 through trial and error, strongly influences accuracy, highlighting the need for careful parameter selection. Overall, this grey-model framework, with its tailored preprocessing,

provides an accurate approach for annual wind-power forecasting and offers operational managers a tool for long-term planning. Future research should focus on optimizing the geometric-sequence ratio to further improve precision.

An alternative to grey modeling is deep learning, particularly long-short-term LSTM networks, which can capture complex nonlinear relationships and long-term dependencies in wind data [58]. LSTM architectural networks rely on maintaining gated memory cells that learn what to retain or forget over time, thus regulating the information flow. Their performance hinges on hyperparameters, such as the hidden state size, number of layers, gate weight matrices, and learning rate. To balance forecast accuracy and model complexity, Pujari et al. [59] developed an LSTM network specifically optimized for two-year-ahead forecasting of wind characteristics at La Haute Borne wind farm in France. The study used the non-dominated sorting genetic algorithm NSGA II multi-objective optimization algorithm to tune the network size, regularization strength, and training epochs for two-year-ahead wind forecasting. This approach minimizes both prediction error and network size, yielding an LSTM architecture that achieves 97% accuracy while remaining parsimonious. The LSTM's gated structure, featuring input, output, and forgetting gates, allows it to learn both short-term variations and long-term seasonal cycles from historical wind-speed and -direction data. When applied to real wind farm observations, the optimized LSTM produced reliable long-term forecasts that can guide maintenance scheduling and energy trading decisions. Therefore, through integrating multi-objective optimization with deep learning, the study illustrated how advanced neural networks can address the variability inherent in wind data over extended horizons.

Table 5 provides a comparative overview of these annual forecasting approaches, highlighting differences in preprocessing requirements, model structures, forecasting horizons, and performance metrics.

Table 5. Comparative overview of annual statistical methods.

Aspect	Grey Model GM(1,1)	LSTM (Long-Short-Term Memory)
Authors	Chengwei et al. [57]	Pujari et al. [59]
Application	Forecasting annual wind-power generation at FUJIN wind farm	Forecasting wind characteristics for a wind farm in France
Core Methodology	Grey model GM(1,1) with preprocessing technique	LSTM networks enhanced by multi-objective optimization
Preprocessing Technique	Multiplies original data series with a geometric series	NSGA II for multi-objective optimization
Data Transformation	AGO to reduce noise and randomness	raw wind data conversion for training the LSTM networks
Prediction Accuracy	NMAE of 7.0315%, 0.7679% improvement over unprocessed series	97% accuracy
Data Processing	Uses five-order polynomial for wind-speed-to-power conversion	A multi-objective optimization algorithm (NSGA II) for determining the optimal network architecture and hyperparameters.
Model Evaluation	Compares prediction accuracy with and without preprocessing	LSTM models optimized for accuracy and parsimony
Practical Application	Enhances prediction accuracy for operational management	Applied to real wind farm data (La Haute Borne, France)
Future Research	Optimize selection of geometric series ratio	stochastic control of wind farms and robust wind farm layout optimization
Advantages	Improved prediction accuracy, handles non-monotonically increasing data	Effective for complex nonlinearities and long-term dependencies
Key Insight	Provides valuable insights for operational management and planning	Optimizes wind-power generation and manages variability

3.3. Hybrid Methods

3.3.1. Monthly

- Combining Artificial Neural Networks (ANN) with Particle Swarm Optimization (PSO)

- Horizontal–Vertical Integration (HVI) prediction method
- Adaptive Neuro-Fuzzy Inference System (ANFIS) and Generalized Regression Neural Networks (GRNN)
- ANN with grid search for optimization
- Combining machine learning and statistical methods
- Using Random Forest (RF), Extreme Gradient Boosting (XGB), Empirical Mode Decomposition (EMD), Extreme-Learning Machine (ELM), and Fractional Seasonal Grey Model (FSGM)

Hybrid approaches for monthly forecasting build on purely statistical methods by combining multiple techniques to capture complex features of wind data. A common goal is to improve accuracy by integrating machine learning with optimization, decomposition, or distribution-based components. The studies below illustrate how such hybrid frameworks evolve from optimizing network architectures to incorporating distribution information and ensemble learning.

Bou-Rabee et al. [20] pioneered the use of PSO to tune an ANN for one-month-ahead wind-speed predictions at coastal locations in Kuwait. In their framework, PSO parameters, including a swarm size of 30 particles, an inertia weight of 0.7, and cognitive/social coefficients of 1.5, were co-optimized with the ANN hidden-layer size (tested from 5 to 15 neurons) to minimize the RMSE and MAPE. Wind-speed forecasts were converted into wind-power density estimates via the standard cubic power curve. Across three sites, the PSO-tuned ANN achieved an MAPE of between three and six percent across all sites, indicating high precision. Also, through the comparison of support vector machines and standalone neural networks, this work demonstrated that optimizing neural network structure leads to more accurate power density predictions. These forecasts can guide grid integrations and reduce reliance on thermal generation, especially in coastal regions.

Building on the idea of hybrid neural-network architectures, Liu et al. [60] introduced a framework called HVI prediction to model monthly wind-speed distributions rather than single-point estimates. Their method combines convolutional neural networks and long-short-term memory layers (CNN-LSTM) parameterized by 3×3 convolutional filters (32 channels) and 50 LSTM units. It is a modified differential evolution algorithm that optimizes the network's learning rate of 0.001–0.01, the population size (20), the differential weight ($F = 0.5$), and the crossover rate ($CR = 0.9$). Data sampling and mapping techniques enable nonparametric estimations of wind distributions using information from the first three months to predict the distribution for the following month. Testing on nine wind stations (in unspecified locations) showed the method's robustness across different climates. Additionally, by integrating horizontal predictions (recent months) with vertical predictions (same month in previous years), this approach captures both seasonal patterns and short-term variations. In doing so, it extends Bou-Rabee et al.'s focus on point forecasts to distribution forecasting, offering richer information for risk management and decision-making.

Maroufpoor et al. [61] broadened the scope of hybrid methods by comparing six heuristic artificial intelligence (AI) techniques. These methods included multilayer perceptron (two hidden layers of 10 and 15 neurons), ANFIS with subtractive clustering (radius = 0.5) and fuzzy c-means (fuzzification = 2), GRNN with spread = 0.1, gene expression programming (population = 100, generations = 50), and MARS with interaction degree = 1. Data utilized for this study were obtained from two Iranian stations over 1996–2010 and included inputs of atmospheric pressure, temperature, relative humidity, and rainfall. Their results confirmed that heuristic artificial intelligence methods can generalize across locations with different climate characteristics. ANFIS performed best at one of the stations, while GRNN excelled at the other. Through the integration of several hybrid-like techniques in parallel, this study highlights the importance of method selection based on local conditions and

data availability. It also suggests that combining neural and fuzzy or regression techniques can yield reliable monthly wind-speed models, reinforcing the value of hybridization introduced by Bou-Rabee et al. and Liu et al.

Expanding on geographical and atmospheric inputs, Ulkat and Günay [62] proposed an ANN for the Aegean Region of Turkey (2000–2013), where historical wind data were sparse. Their model used the latitude, longitude, elevation, ambient temperature, pressure, relative humidity, and month of the year to predict the mean monthly wind speed. A leave-one-station-out validation showed mean absolute errors below 1.5 m per second at 48 of 55 stations. A subsequent grid search identified an optimal wind farm site with an average annual wind speed of 10.6 m per second and potential output of 1.79 megawatts. This work demonstrates how combining geographical variables with neural networks extends distribution and optimization-based hybrids into places lacking high-resolution wind data. It complements Liu et al.'s distributional focus by introducing spatially explicit inputs, thereby improving model applicability and site selection.

Majid [63] advanced hybrid modeling by integrating distribution fitting with error correction. In a coastal region of the northeastern United Arab Emirates, one year of wind-speed measurements was used to fit five candidate probability distributions (Weibull, exponential, Rayleigh, gamma, and lognormal). The lognormal distribution provided the best fit. A procedural algorithm then extracted monthly forecast errors computed by comparing predictions to observed values and used these errors to refine subsequent forecasts. This error-extraction mechanism addressed limitations in purely distribution-based models by dynamically adjusting predictions based on recent discrepancies. Validation against a Markov series analysis showed strong alignment, confirming that combining distribution fitting with temporal error feedback yields more accurate and adaptable monthly forecasts. Majid's approach therefore builds on Liu et al.'s distributional framework by adding an explicit error-correction layer.

Finally, Gao [64] demonstrated a comprehensive ensemble approach that incorporates signal decomposition, machine learning, and fractional grey modeling. Using Chinese wind-power generation data from 2010 to 2020, Gao first applied empirical mode decomposition to separate high-frequency and low-frequency components. Extreme gradient boosting then predicted high-frequency components, while extreme-learning machines modeled low-frequency trends. A fractional seasonal grey model addressed exponential growth in the data. Random forest combined predictions from these component models to produce a final wind-power forecast that captured both seasonal fluctuations and long-term growth. Complexity analyses using Lempel–Ziv and average mutual information metrics further refined the model inputs compared to Holt–Winters, SARIMA, support vector machines, and a standalone LSTM. This integrated framework achieved a lower mean absolute error, root-mean-square error, and mean absolute percentage error. Gao's work thus unifies previous hybrid ideas, the optimization of neural networks, distribution modeling, geographic inputs, and decomposition, into a single ensemble that outperforms each individual component.

Together, these studies illustrate the evolution of monthly hybrid methods: from tuning neural network topologies and forecasting point estimates to modeling distributions, incorporating spatial data, applying error correction, and finally integrating multiple decomposed components into an ensemble. Each approach builds on its predecessors, addressing specific limitations and progressively capturing more facets of wind data variability. Table 6 summarizes these hybrid methods, comparing their data sources, model components, forecasting horizons, evaluation metrics, and key innovations.

Table 6. Comparative overview of monthly hybrid methods.

Aspect	ANN with PSO Integration	HVI Prediction Framework	ANFIS and GRNN	ANNs with Grid Search	ML and Statistical Methods Integration	RF with XGB, EMD, ELM, and FSGM
Authors	Bou-Rabee et al. [20]	Liu et al. [60]	Maroufpoor et al. [61]	Ulkat and Günay [62]	Majid [63]	Gao [64]
Application	Forecasting wind-speed and wind-power density (WPD)	Forecasting monthly wind-speed distribution	Modeling monthly wind speeds	Predicting monthly wind speeds	Forecasting monthly wind energy	Predicting monthly wind-power generation
Location	Coastal sites in Kuwait	Nine wind stations (locations not specified)	Jolfa and Tabriz, East Azarbaijan Province, Iran	Aegean Region, Turkey	Coastal region in northeastern UAE	China
Core Methodology	ANN optimized with PSO	Hybrid CNN-LSTM with improved differential evolution algorithm	ANFIS with grid partition (GP) and subtractive clustering, GRNN	ANN with geographical and atmospheric data, grid search	Curve fitting with probability distribution functions, ML	RF integrated with XGB, EMD, ELM, and FSGM
Data Used	Wind speed, direction, frequency distribution	Wind-speed data from first three months for subsequent month	Meteorological input information	Geographical and atmospheric variables, monthly data	Wind-speed measurements, probability distribution parameters	Wind-power generation data from 2010 to 2020
Predictors	Wind speed, direction, frequency distribution	Data from first three months to predict next month	Atmospheric pressure, temperature, relative humidity, rainfall	Latitude, longitude, elevation, ambient temperature, atmospheric pressure, relative humidity, month of the year	Wind-speed measurements, Gaussian probability function	EMD for signal decomposition, XGB for high-frequency, ELM for low-frequency
Analysis Technique	ANN structure optimization with PSO	Data sampling and mapping, cyclic learning rate optimization	Heuristic methods, ANFIS-GP, ANFIS-SC, GRNN	ANN training, grid search for optimal location	Probability distribution function fitting, error extraction	Signal decomposition, hybrid model integration
Models Developed	ANN-PSO	CNN-LSTM	ANFIS-GP, ANFIS-SC, GRNN	ANN with grid search algorithm	ML-trained distribution, Markov series analysis	EMD-XGB-ELM, FSGM integrated with RF
Key Findings	High accuracy with MAPE between 3 and 6%, average wind speed increase at 70 m	Effective for various conditions, novel data sampling method	ANFIS-GP and GRNN showed highest predictive performance	High prediction accuracy, optimal location for wind energy	Reliable forecasting model, sensitivity to distribution parameters	Superior accuracy compared to conventional models
Cross-Validation	Standard statistical indices	Improved differential evolution optimization algorithm	Demonstrated generalization capability	Excluding data from each station for validation	Error estimation compared with Markov series analysis	Comprehensive modeling strategy with statistical and ML methods

Table 6. Cont.

Aspect	ANN with PSO Integration	HVI Prediction Framework	ANFIS and GRNN	ANNs with Grid Search	ML and Statistical Methods Integration	RF with XGB, EMD, ELM, and FSGM
Real-World Validation	Datasets from three coastal locations	Data from nine wind stations	Tested at Jolfa and Tabriz stations	660 data points from 55 stations	Error extraction method compared with Markov series analysis	Applied to wind-power generation data in China
Advantages	Optimizes ANN structure, high prediction accuracy	Innovative sampling and optimization, applicable to various conditions	High predictive performance of ANFIS-GP and GRNN	Robust framework for regions with insufficient data	Enhanced accuracy, insights into wind energy sensitivity	Accurate predictions, handles complex dynamics
Key Insight	Highly accurate prediction model for WPD	Improves prediction accuracy by considering wind-speed distribution	Potential for climate change-related wind-speed prediction	Identifies optimal locations for wind energy conversion	Sophisticated means to predict wind energy production	Captures high-frequency variations and exponential growth patterns

3.3.2. Seasonal

- Combining an HP Filter, Grey Model (GM(1,1)), and Hodrick–Prescott (HP) Filter

Seasonal hybrid methods extend monthly approaches by explicitly separating long-term trends from recurring seasonal patterns. One example is the HPF-GM(1,1) model developed by Qian and Wang [65]. This model first applies the Hodrick–Prescott filter to historical wind-power data from 2013 to 2019 in China, isolating the seasonal component. Next, it employs the GM(1,1) grey model on the deseasonalized series to capture the underlying exponential growth trend. Conventional grey models such as GM(1,1), DGGM(1,1), and SGM(1,1) struggle with seasonal variability or demand large datasets, conditions often unmet by wind-power records. By contrast, HPF-GM(1,1) handles small sample sizes while accurately characterizing both trend and seasonality. The key forecasting parameters in this framework include the HP filter smoothing parameter λ (which controls the trend–cycle trade-off), the development coefficient a , and grey action quantity b estimated in the GM(1,1) differential equation. It also included the accumulated generating operation (AGO) and its inverse, as well as performance metrics MAPE and RMSE.

During validation, HPF-GM(1,1) consistently outperformed the three conventional grey models in terms of the mean absolute percentage error and root-mean-square error, demonstrating its ability to reproduce historical seasonal fluctuations. When forecasting the wind-power output for 2020 and 2021, the model projected a continued upward trajectory punctuated by predictable seasonal peaks and troughs. These forecasts helped identify periods of high and low generation, guiding operational planning. Based on their findings, Qian and Wang recommended policy measures for the Chinese wind industry. These measures include coordinating generation modes to balance seasonal oversupply and undersupply, investing in grid infrastructures capable of long-distance transmission, evaluating the potential of offshore wind farms to smooth seasonal variability, and promoting a mix of large-scale and distributed developments to enhance flexibility.

Table 7 summarizes key details of the HPF-GM(1,1) model, including data sources, methodological steps, evaluation metrics, and policy insights.

Table 7. Overview of seasonal hybrid methods.

Aspect	HPF-GM(1,1) Integration
Authors	Qian and Wang [65]
Application	Forecasting seasonal wind-power generation in China
Core Methodology	Integration of Hodrick–Prescott (HP) filter and grey model GM(1,1)
Data Used	Seasonal wind-power generation data from China (2013–2019)
Predictors	Seasonal fluctuations and exponential growth trends
Analysis Technique	HP filter to characterize seasonality, GM(1,1) for growth trends
Comparison Models	GM(1,1), DGGM(1,1), SGM(1,1)
Key Findings	Superior performance in capturing seasonal fluctuations
Forecasting Period	Predictions for 2020 and 2021
Forecasting Results	Continued upward trend with seasonal variations
Policy Recommendations	- Develop coordinated power generation modes - Improve power grid construction for long-distance transmission - Evaluate offshore wind power - Combine large-scale and distributed development
Advantages	Accurate seasonal fluctuation capture, effective with small sample sizes
Key Insight	Combines strengths of HP filter and GM(1,1) for better accuracy

3.3.3. Annual

- Combining machine learning with statistical methods
- Integrating LSTM networks with regional analysis
- ARIMA model with backpropagation neural networks
- Improved Ensemble Empirical Mode Decomposition (EEMD) with Gated Recurrent Unit (GRU) neural networks and ARIMA

- Using Copula functions with LSTM networks

Annual hybrid methods integrate diverse modeling techniques to address the challenges of forecasting wind power and related energy variables over horizons of one year or more. These approaches combine statistical analysis, machine learning, signal decomposition, and auxiliary information such as regional characteristics or meteorological dependencies to capture both long-term trends and sub-annual variations. The following studies illustrate how hybrid frameworks have evolved to improve accuracy and applicability in annual and multiyear forecasting contexts.

Azad et al. [66] developed a data fusion algorithm that merges multiple neural networks with statistical preprocessing to predict hourly wind speeds for the following year at two Malaysian meteorological stations, Kuala Terengganu and Mersing. The key forecasting parameters in this framework included the decomposition components (trend, seasonal, and cyclical), neural network hyperparameters (number of modules and hidden layers, and neurons), genetic algorithm settings (population size, crossover rate, and mutation rate), and the mean absolute error (MAE) evaluation metric. First, historical wind-speed data were analyzed to extract subpatterns such as seasonal cycles and short-term fluctuations using statistical time-series techniques. These subpatterns were then input into separate neural network modules, each tailored to learn location-specific characteristics. Combining the outputs through fusion layers enabled the model to achieve a mean absolute error of approximately 0.8 m/s, outperforming standalone neural networks and traditional regression models. The study's data preparation involved segmenting monthly average wind-speed data into trend, seasonal, and cyclical components, which helped the neural networks focus on nonlinear relationships without being distracted by noise. Optimization techniques, such as genetic algorithms, were applied to tune the network architecture and training parameters, ensuring robustness despite limited data. Overall, the study demonstrated that integrating statistical decomposition with neural-network learning can yield accurate year-ahead wind-speed forecasts, even in regions with complex patterns.

Building on the idea of incorporating auxiliary information, Wang et al. [67] introduced an annual forecasting model for wind power in northwestern China that leverages regional similarity factors within an LSTM network. The study area encompasses five provinces, Qinghai, Xinjiang, Gansu, Ningxia, and Shanxi, each with distinct terrain and wind-resource characteristics. Researchers first divided the region into subareas based on geographic and climatic features, such as elevation and prevailing wind regimes. A regional similarity factor was then computed by comparing statistical descriptors (for example, mean wind speed and variance) across subareas. These factors were appended to LSTM inputs, allowing the network to learn both temporal dependencies and spatial correlations. Compared to individual station forecasts, the regional LSTM reduced the average forecasting error by 20.8% in a case study conducted in northern Xinjiang. The main parameters here include the regional similarity descriptors (mean and variance), LSTM hyperparameters (number of layers, units per layer, and learning rate), and the spatial segmentation criteria. This improvement underscores the value of integrating location-based information into long-term models, enabling more accurate projections by capturing inter-area relationships.

Recognizing that socioeconomic and infrastructure factors can also influence energy forecasts, Jingying et al. [68] adapted hybrid modeling to electric load predictions by incorporating macroeconomic indicators. Although their primary focus was on electricity load rather than wind generation, the methodology paralleled wind forecasting in its emphasis on trends and seasonality decomposition. The model began with functional nonparametric techniques to identify periodic monthly load patterns, capturing recurring cycles such as seasonal demand spikes. Next, an ARIMA component isolated long-term trends, and a backpropagation (BP) neural network refined predictions by learning residual nonlinearities. The key parameters in

this study were the ARIMA order (p,d,q) , BP network architecture (layers, neurons, activation functions), and selected macroeconomic predictors. Through the incorporation of macroeconomic and social development indicators such as gross domestic product growth, population changes, and industrial activity levels, the hybrid model adapted forecasts to local conditions. This combination improved the load prediction accuracy, which, in turn, suggests that analogous approaches could enhance wind-power forecasts when region-specific economic or infrastructure variables are available.

Cao et al. [29], on the other hand, addressed the inherent multiscale variability in wind-power time series by developing a combined EEMD-GRU-ARIMA framework for annual and monthly distribution forecasts at wind farms in Liaoning Province, China. The main forecasting parameters included the EEMD ensemble count and noise amplitude, GRU hyperparameters (hidden size, learning rate, and number of layers), ARIMA orders (p,d,q) , and the frequency-band definitions. First, the ensemble empirical mode decomposition (EEMD) algorithm decomposed the observed monthly wind-power series into intrinsic mode functions, representing high-frequency (HF), medium-frequency (MF), and low-frequency (LF) components. The HF and MF components, which contained abrupt fluctuations and random variations, were predicted using GRU neural networks, leveraging their ability to model nonlinear and time-dependent patterns. LF components, characterized by clear periodicity and autocorrelation, were forecasted with an ARIMA model. Irregular ultra-high-frequency (UHF) noise was omitted due to its unpredictability. Finally, the predicted components were recombined to form the annual forecast. This decomposition-driven approach reduced forecasting errors by 20.8 p compared to single-station models, highlighting how targeting each frequency band with specialized methods can capture both long-term growth and seasonal fluctuations more effectively.

Finally, Han et al. [69] extended hybrid annual forecasting for the joint prediction of wind and photovoltaic (PV) power generation in China and the United States. Their method first employed copula functions to extract key meteorological factors—such as temperature, humidity, and wind speed—that exhibited nonlinear dependencies with wind and PV outputs. The key parameters included the choice of copula and its dependence parameter, the set of meteorological inputs, LSTM hyperparameters (layers, units, and cell size), and the training window length. Copulas captured complex joint distributions without assuming normality, allowing for accurate identification of input variables. Next, separate LSTM networks were trained for wind and PV generation using these copula-derived predictors and historical power output data from 2012 to 2016. Finally, a combined LSTM model forecasted aggregate renewable generation and tested it on 2017 data. Across multiple stations, this hybrid approach reduced the mean absolute percentage error and root-mean-square percentage error relative to persistence and support vector machine benchmarks. The study integrated statistical dependence modeling with deep learning to show that hybrid frameworks could handle limited data samples and capture interdependencies among different renewable sources. Their approach delivers reliable mid-to-long-term forecasts that inform grid planning, trading strategies, and reserve allocation.

Together, these annual hybrid studies illustrate a progression from single-site neural fusion (Azad et al. [66]) to regionally informed deep learning (Wang et al. [67]), the incorporation of socioeconomic indicators (Jingying et al. [68]), frequency-based decomposition (Cao et al. [29]), and joint renewable forecasting (Han et al. [69]). Each approach addresses specific limitations of purely statistical or machine-learning methods such as small sample sizes, a lack of spatial context, or multi-modal dependencies by combining complementary techniques.

Table 8 compares key aspects of these models, including data sources, hybrid components, forecasting horizons, evaluation metrics, and notable findings.

Table 8. Comparative overview of annual hybrid methods.

Aspect	ML and Statistical Methods Integration	Integration of LSTM and Regional Similarity Analysis	ARIMA Model and BP Neural Network Integration	EEMD, GRU, and ARIMA Integration	Copula Functions and LSTM Networks
Authors	Azad et al. [66]	Wang et al. [67]	Jingying et al. [68]	Cao et al. [29]	Han et al. [69]
Application	Predicting hourly wind-speed data for the subsequent year	Medium- and long-term forecasts of wind power	Annual and monthly long-term power load forecasting	Medium- and long-term electricity forecasting for wind farms	Mid-to-long-term wind and photovoltaic (PV) power generation
Location	Kuala Terengganu and Mersing, Malaysia	Northwestern China (Qinghai, Xinjiang, Gansu, Ningxia, Shanxi)	Regional power loads (locations not specified)	Wind farms in Liaoning Province, China	Wind farms and PV power stations in China and the US
Core Methodology	Data fusion algorithm with neural networks	LSTM with regional similarity analysis	ARIMA model with BP neural network	Improved EEMD with GRU neural networks and ARIMA	Copula functions with LSTM networks
Data Used	Hourly wind-speed measurements	Regional wind-power data	Regional economic and social development indicators	Wind-power data decomposed into multiple subsequences	Historical power generation data and meteorological factors
Predictors	Wind-speed characteristics from past years	Regional characteristics and similarities	Macro indicators (economic and social development)	Decomposed data components (high, medium, low frequency)	Key meteorological factors and historical power generation
Analysis Technique	Data preparation and hybrid optimization	Regional similarity factor, area division	Functional nonparametric method	Time-series decomposition, targeted forecasting strategies	Copula functions for dependency patterns, LSTM for prediction
Models Developed	Neural networks with location-specific adjustments	Regional similarity factor integrated with LSTM	Trend and periodicity analysis	EEMD for decomposition, GRU for randomness, ARIMA for periodic trends	Joint wind and PV power generation models using LSTM
Key Findings	Low MAE (approx. 0.8 m/s), high accuracy	Significant error reduction (20.80%) with regional similarities	Integration of macro indicators improves forecasting accuracy	Significant improvement in prediction accuracy, effective regional segmentation	Superior performance compared to persistence and SVM models
Cross-Validation	Multiple neural networks to capture general trend	Case study in northern Xinjiang	Functional nonparametric method	Decomposition into subsequences, targeted AI methods for each component	Benchmarking against persistence and SVM models
Real-World Validation	Effective data fusion algorithm for accurate prediction	Verified through regional similarity and area division methods	Applicable across regions with economic and social indicators	Applied to wind farms in Liaoning Province, China	Tested on datasets from 2012 to 2017
Advantages	Accurate long-term prediction, hybrid optimization approach	Incorporates regional characteristics for higher accuracy	Considers economic and social development indicators	Addresses limited historical data, handles complex multiscale characteristics	Accurate long-term forecasts, handles nonlinear and dependent patterns
Key Insight	Effective for closely following actual wind-speed series	Enhances precision by considering regional similarities	Augments load forecasting by integrating macro indicators	Accurate prediction framework for complex influencing factors	Enhances strategic planning and operational decisions in renewable energy

4. Challenges and Future Directions

4.1. Challenges Across Studies

Accurately forecasting long-term wind power remains a complex task. The inherent variability and stochastic nature of wind speed introduce significant uncertainty, and single-method approaches often fail under changing conditions. Gao [64] and Gong et al. [70] emphasize that wind-power time-series data exhibit high complexity and randomness, causing instability in models that rely exclusively on one technique. Bett et al. [71] report that seasonal strategy simplifications can yield skillful winter forecasts in Europe but struggle during non-winter months. Lledó et al. [26] and Bell and Kirtman [72] note that forecast skill varies widely by season and region, particularly when geographical and atmospheric conditions differ from model assumptions. For example, Lockwood et al. [73] identify a negative correlation between summer forecasts and Rossby-wave influence in the UK, highlighting how large-scale atmospheric dynamics degrade seasonal predictions.

Data limitations exacerbate these issues. Ahmed et al. [74] describe how sparse measurement networks and limited historical records reduce model reliability across regions. Campos et al. [75] similarly highlight that coarse spatial resolutions in numerical models fail to capture critical local features, such as coastal currents or mountain-induced flows that influence wind patterns. Bell and Kirtman [72] and Bell and Kirtman [76] also show that ocean model grids often miss narrow currents like the Kuroshio, leading to systematic errors in offshore wind estimates. Lledó et al. [26] further observe mismatches between power-curve inputs and outputs from seasonal climate systems, resulting in biases when converting predicted wind speeds into energy.

Model complexity and integration present additional challenges. Maroufpoor et al. [61] and Malik and Savita [77] warn of overfitting and parameter sensitivity when artificial neural networks incorporate diverse meteorological and geographic inputs. Gong et al. [70] point out that combining multiple models such as ordered weighted averaging (OWA) and Markov chains requires careful calibration to avoid conflicts among differing mathematical assumptions. Borunda et al. [78] highlight that the cubic relationship between wind speed and power amplifies even small speed errors into large power deviations, making hybrid or ensemble approaches both necessary and difficult to tune. Soret et al. [79] stress that seasonal forecasts must align with energy sector decision processes, yet integration into operational workflows remains limited.

Extending forecasts over long horizons further magnifies these problems. Malhan and Mittal [80] show that their ensemble model lost stability beyond a one-year lead time, while Jung and Schindler [81] demonstrate that cluster-based classifications of wind regimes become unreliable as initial conditions and data resolution change. Jingying et al. [68] document that many long-term models lack regional adaptability, producing forecasts that cannot be applied universally. Finally, Cao et al. [29] emphasize that insufficient historical data and multiscale influencing factors such as turbine upgrades or land-use changes limit the accuracy of long-range wind-power predictions for individual wind farms.

Furthermore, many long-term forecasting frameworks omit key atmospheric drivers of wind speed, such as boundary-layer height variations, stability indices, temperature gradients, and large-scale circulation modes (e.g., North Atlantic Oscillation and El Niño–Southern Oscillation) all of which govern wind shear, turbulence, and regime shifts and whose exclusion can degrade model performance under changing conditions [72,81]. Equally important is the nonstationarity of wind-speed records: long-term climate trends and random fluctuations (for example, extreme events or abrupt regime shifts) mean that historical data may not represent future atmospheric behavior, leading to overconfident forecasts when regimes evolve [26,80]. Addressing these gaps will require integrating

relevant climate indices and adopting regime-aware or nonstationary modeling techniques to preserve forecast skill as the climate continues to change.

4.2. Future Directions Across Studies

Many studies have proposed several avenues to address challenges posed by long-term forecasting approaches, focusing on model enhancement, data expansion, regional adaptation, and operational integration.

Developing integrated frameworks that blend machine learning with advanced statistical methods can mitigate single-model instability. Gao [64] recommends coupling empirical mode decomposition with machine learning algorithms to isolate and model distinct frequency components. Gong et al. [70] advocate OWA-Markov hybrids that dynamically weight component forecasts based on recent performance. Bett et al. [71] and Bell and Kirtman [72] call for higher-resolution dynamical models, both atmospheric and oceanic, to capture finer-scale processes, while Soret et al. [79] suggest combining multi-model ensembles, including statistical, dynamical, and data-driven forecasts, to form consensus products that balance individual model biases. Ahmed et al. [74] and Han et al. [69] urge the adoption of advanced machine learning techniques such as convolutional neural networks or long-short-term memory networks that can learn spatiotemporal dependencies and optimize parameters to handle environmental stochasticity.

Many studies emphasize the importance of expanding high-quality datasets and fostering collaboration across institutions. Maroufpoor et al. [61] and Campos et al. [75] call for data sharing among academic, industry, and government agencies to build comprehensive wind-resource archives. Cao et al. [29] highlight the necessity of validating models with operational data from active wind farms and power systems. Malik and Savita [77] recommend incorporating additional meteorological and geographic variables such as digital elevation models or soil moisture indices to improve neural network performance. Broad collaborations can standardize evaluation protocols, promote reproducibility, and accelerate the translation of research into practice.

Accounting for regional climate change scenarios is essential to capture evolving wind regimes. Jung and Schindler [81] propose embedding future emission pathway outputs from Coupled Model Intercomparison Projects into forecasting pipelines to anticipate shifts in dominant flow patterns. Borunda et al. [78] show that selecting appropriate probability distributions such as Weibull or lognormal for each region enhances model accuracy. Increasing spatial resolution in downscaled climate projections can reduce uncertainty and enable site-specific long-term forecasts. Likewise, Jingying et al. [68] demonstrate that incorporating local socioeconomic indicators (e.g., land-use changes or infrastructure development) can improve long-term-load forecasts, a strategy that may translate to wind resource models by including factors such as vegetation cover or turbine height upgrades.

To ensure forecasts inform real-world decisions, researchers urge co-designing tools with energy operators and regulators. Lledó et al. [26] propose customized forecasting services that output electrical reserve requirements or risk metrics instead of raw wind speeds. Soret et al. [79] emphasize embedding forecasts within grid management platforms to enhance dispatch decisions. Malhan and Mittal [80] recommend simplifying complex ensemble algorithms into user-friendly interfaces, facilitating adoption by smaller utilities. Han et al. [69] report that validating models using diverse operational datasets from onshore turbines to offshore wind farms ensures robustness across climatic zones. Collaborative pilot projects between forecasters, transmission operators, and market participants can refine these tools, aligning research outputs with practical needs such as maintenance scheduling, market bidding strategies, and long-term investment planning.

5. Conclusions

This review has systematically examined challenges, methodologies, and future directions in long-term wind forecasting. Forecast horizons ranging from one month to several decades each demand tailored approaches. For monthly forecasts, hybrid machine-learning frameworks such as PSO-tuned ANNs [20], HVI distribution models [58], and ensemble decompositions with EMD and ELM [62] are recommended for their ability to capture both point estimates and full wind-speed distributions. Seasonal forecasting benefits most from methods that explicitly separate trend and cycle; the HPF-GM(1,1) hybrid [65] consistently outperformed the conventional grey models in reproducing seasonal peaks and troughs under small-sample conditions. For annual horizons, multi-scale decomposition combined with specialized models such as EEMD-GRU-ARIMA [29] for frequency-band forecasting or regional-similarity LSTMs [67] offered robustness to both long-term growth and sub-annual variability, while grey preprocessing (e.g., GM(1,1) with geometric scaling) remained valuable when data were sparse [55,56]. For multiyear projections, integrating downscaled climate scenarios and nonstationary regime models (e.g., embedding CMIP outputs and large-scale indices like ENSO/NAO [72,81]) is essential to anticipate evolving wind regimes.

A key insight is that no single technique suffices across all horizons. Hybrid and ensemble frameworks, which integrate diverse data sources and modeling paradigms, consistently outperform standalone models. Yet, challenges remain; forecast skill varies by region and season, model complexity can lead to overfitting, data limitations constrain spatial accuracy, and long horizons magnify uncertainty. To address these, coordinated efforts should focus on expanding high-quality wind archives, standardizing core input parameters, and developing regime-aware, nonstationary modeling frameworks that incorporate boundary-layer stability, circulation indices, and random climate fluctuations.

While this review focuses on predictions, it is equally important to distinguish these methods from projections. Predictions use statistical and machine-learning frameworks tuned to historical observations. They reproduce variability and deliver near-term outlooks. Projections, by contrast, employ scenario-based ensembles of downscaled GCMs or regional climate models to diagnose nonstationary regimes and explore future wind-pattern shifts under different emissions pathways. As such, projection frameworks offer a basis for planning under future climate change.

Moving forward, aligning research innovations with practical grid and market requirements will be crucial. This entails co-designing forecasting tools with energy operators, embedding operational feedback loops, and tailoring methods to local conditions, whether optimizing neural architectures in data-rich settings, applying grey-filter hybrids under data paucity, or leveraging climate projections for multiyear planning. Additionally, recommending specific forecasting strategies for each situation can enable the wind energy sector to deploy more reliable tools and facilitate the sustainable integration of wind power into global energy systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AGO	Accumulated Generating Operation
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BP	Backpropagation
CDF	Cumulative Distribution Function
CESM	Community Earth System Model
CNN	Convolutional Neural Networks
CR	Crossover Rate
DGGM	Discrete Grey GM(1,1) Model
EMD	Ensemble Empirical Mode Decomposition
EMD	Empirical Mode Decomposition
ELM	Extreme-Learning Machine
FSGM	Fractional Seasonal Grey Model
GP	Grid Partition
GM	Grey Model
GMCM	Gaussian Mixture Copula Model
GPH850	850 hPa Geopotential Height
GRNN	Generalized Regression Neural Network
GRU	Gated Recurrent Unit
GPR	Gaussian Process Regression
HF	High Frequency
HP	Hodrick–Prescott
HPF	Hodrick–Prescott Filter
HVI	Horizontal–Vertical Integration
hPa	Hectopascal
LF	Low Frequency
LSTM	Long-Short-Term Memory
LTRM	Linear Time-varying Regression Multivariable
LTRT	Linear Time-varying Regression Time-only
LTRU	Linear Time-varying Regression Univariate
MARS	Multivariate Adaptive Regression Spline
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MF	Medium Frequency
ML	Machine Learning
NMAE	Normalized Mean Absolute Error
NSGA II	Non-dominated Sorting Genetic Algorithm II
NRMSE	Normalized Root-Mean Square Error
PC	Principal Component
PSO	Particle Swarm Optimization
RE	Relative Error
RF	Random Forest
RMSE	Root-Mean-Square Error
S2S	Subseasonal-to-Seasonal
SARIMA	Seasonal Autoregressive Integrated Moving Average
SST	Sea Surface Temperature
SGM	Seasonal Grey Model

UHF	Ultra-High-Frequency
WPD	Wind-Power Density
XGB	Extreme Gradient Boosting

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