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Ultra-short-term wind power forecasting techniques: comparative analysis and future trends

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In recent years, the integration of wind power into the grid has steadily increased, but the volatility and uncertainty of wind power pose significant challenges to grid planning, scheduling and operation. Ultra-short term wind power forecasting technology as the basis of daily scheduling decision can accurately predict the future hourly wind power output, and has important research significance for ensuring the safe and stable operation of power grid. Although research on ultra-short-term wind power forecasting technology has reached maturity, practical engineering applications still face several challenges. These challenges include the limited potential for improving the accuracy of numerical weather forecasts, the issue of missing historical data from new wind farms, and the need to achieve accurate power prediction under extreme weather scenarios. Therefore, this paper aims to critically review the current proposed ultra-short-term wind power forecasting methods. On this basis, analyze the combined power forecasting method under extreme weather scenarios, and illustrate its effectiveness through wind farm case studies. Finally, according to the development trend and demand of future power systems, future research directions are proposed.

KEYWORDS

ultra-short-term power prediction, numerical weather prediction, point prediction, probabilistic prediction, transitory weather

1 Introduction

The transition towards a new power system centered around renewable energy sources has necessitated the expansion of clean energy, particularly wind power, and the establishment of a low-carbon, secure, and efficient energy system to achieve China's "dual carbon" target (Ren et al., 2022). Nowadays, the wind power industry has witnessed rapid growth, and the wind power market continues to thrive (Hui et al., 2021). The intermittency and variability of wind energy, combined with the fluctuating nature of wind turbines, lead to fluctuations in wind power output (Li et al., 2023). Ultra-short-term wind power forecasting involves predicting power levels for the next 15 min to 4 h, aiding power dispatching departments in promptly adjusting their plans to accommodate changes in wind power output (WEN, 2007). Furthermore, these prediction results serve as the basis for optimizing peak regulation, frequency modulation, economic load dispatching, and spinning reserve regulation within the power system (Yang et al., 2022a; Xu et al., 2023). Consequently, researchers have devoted considerable attention to accurately predicting

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ultra-short-term wind power to enhance wind power integration capacity and improve the operational efficiency of the power system.

Early methods for ultra-short-term wind power prediction primarily relied on physical models and traditional time series analysis. However, physical models necessitate extensive initial information and involve complex calculations (Ma et al., 2020). Traditional time series methods are limited in their ability to consider various factors affecting wind power and exhibit poor performance when analyzing high-dimensional data (Hanifi et al., 2020). In recent years, with the advancement of big data and artificial intelligence technologies, data-driven approaches, particularly deep learning, have gained prominence in ultra-short-term wind power prediction due to their superior nonlinear fitting capabilities and high-dimensional data processing abilities. Nan Yang et al. conducted pioneering research on SCUC problem and proposed a data-driven SCUC expert system based on extended sequence-to-sequence (E-Seq2Seq). The system can accommodate dynamic multi-sequence mapping samples and comprehensively consider various input factors that affect SCUC decision-making. Compared with traditional methods, the system has stronger generality, higher solution accuracy and efficiency (Yang et al., 2022b). Nonetheless, statistical methods like deep learning exhibit a 'black box' property, lacking interpretability and physical meaning to support them (Hu et al., 2016). While some progress has been made in ultra-short-term wind power prediction, several challenges need to be addressed in light of the current status of wind power generation in China. Frequent occurrence of extreme weather events leading to abrupt and unpredictable changes in power output, negatively impacting prediction accuracy (Wang et al., 2019).

The research team involved in this study has previously conducted research on new energy power prediction and achieved significant results (Yu et al., 2021; Zhou et al., 2021; Yu et al., 2022a; Yu et al., 2022b; Yu et al., 2023). The paper is structured as follows. Section 2 emphasizes the difference between ultra-short term wind power forecast and short term wind power forecast, compares and analyzes the current forecasting methods, and analyzes the advantages and disadvantages of each method. Section 3 takes wind farms as an example to show the research results of ultra-short term wind power forecasting methods under extreme weather conditions. These cases show that accurate modeling during periods of extreme weather can significantly improve overall forecast accuracy; Section 4 presents some challenges in ultra-short term wind power forecasting, such as the accuracy of Numerical Weather prediction (NWP), small sample learning, time resolution of meteorological forecasting, and extreme weather scenario forecasting. It also provides insight into the prospects for future development.

2 Overview of ultra-short-term wind power forecasting technology

The wind power prediction technology system consists of numerical weather prediction, wind power prediction model, error correction, and application of prediction results (QIAO et al., 2017; Fu et al., 2023a), as illustrated in Figure 1. Initially, historical data from wind farms are collected using the Supervisory Control And Data Acquisition (SCADA) system, meteorological measurement stations, and NWP system for feature analysis. Subsequently, a prediction model is constructed based on the nonlinear relationship between wind power characteristics and wind power. The wind power prediction results are then evaluated, and an error correction model is introduced to optimize the prediction model by rectifying prediction errors. Ultimately, the wind power prediction results are applied to power grid dispatching, maintenance plan adjustments, auxiliary power market trading, and other relevant applications.

The ultra-short-term wind power prediction encompasses a rolling multi-step forecast of wind power output from wind farms over the next 15 min to 4 h. This model adopts a 15-min rolling prediction framework, comprising four steps within an hour. Using historical data at each time point, the model predicts the power value for the subsequent four steps, serving as the input for forecasting the power value in the following moment. This enables continuous rolling predictions.

In contrast to short-term wind power prediction, which only requires providing NWP data for the next 3 days, ultra-short-term prediction necessitates real-time updates of NWP data. Additionally, the physical method employed in ultra-short-term prediction involves modeling based on NWP information and geographical data such as landform, surface roughness, and turbulence intensity of the wind farm. It emphasizes the optimization of physical solution rules and the quality of NWP data. However, due to the complexity of the numerical simulation process and the extensive computational requirements, the physical method often results in lower prediction accuracy for ultra-short-term wind power forecasting (Chen et al., 2022). Consequently, physical methods are generally unsuitable for ultra-short-term prediction. In summary, this section provides a review of the application of data-driven methods (Yang et al., 2022c) in ultra-short-term wind power prediction, considering the current research focus in this field.

2.1 Point prediction method

The point prediction outcome refers to the specific value projected for a given future prediction time. Over the last decade, a significant proportion of domestic and international studies have focused on the point prediction research of ultra-short-term wind power, leading to a wealth of research outcomes. Currently, research on ultra-short-term wind power point prediction methods has achieved significant maturity (See Appendix Table A1 for details). However, point predictions only provide deterministic values and cannot quantitatively represent the uncertainty of wind power. Based on the point prediction model, data-driven techniques used in ultra-short-term wind power prediction can be categorized into statistical methods, artificial intelligence methods, and combined prediction methods.

On the other hand, the fluctuation process-based modeling method is a newly developed ultra-short-term prediction technology that has emerged with the advent of big data in recent years (Wang et al., 2016; Han and Alexander, 2022). This approach takes advantage of the inherent persistence patterns within wind power sequences at an ultra-short-term scale. By analyzing and extracting the evolutionary patterns of historically similar fluctuation states, it divides and combines the sequences to

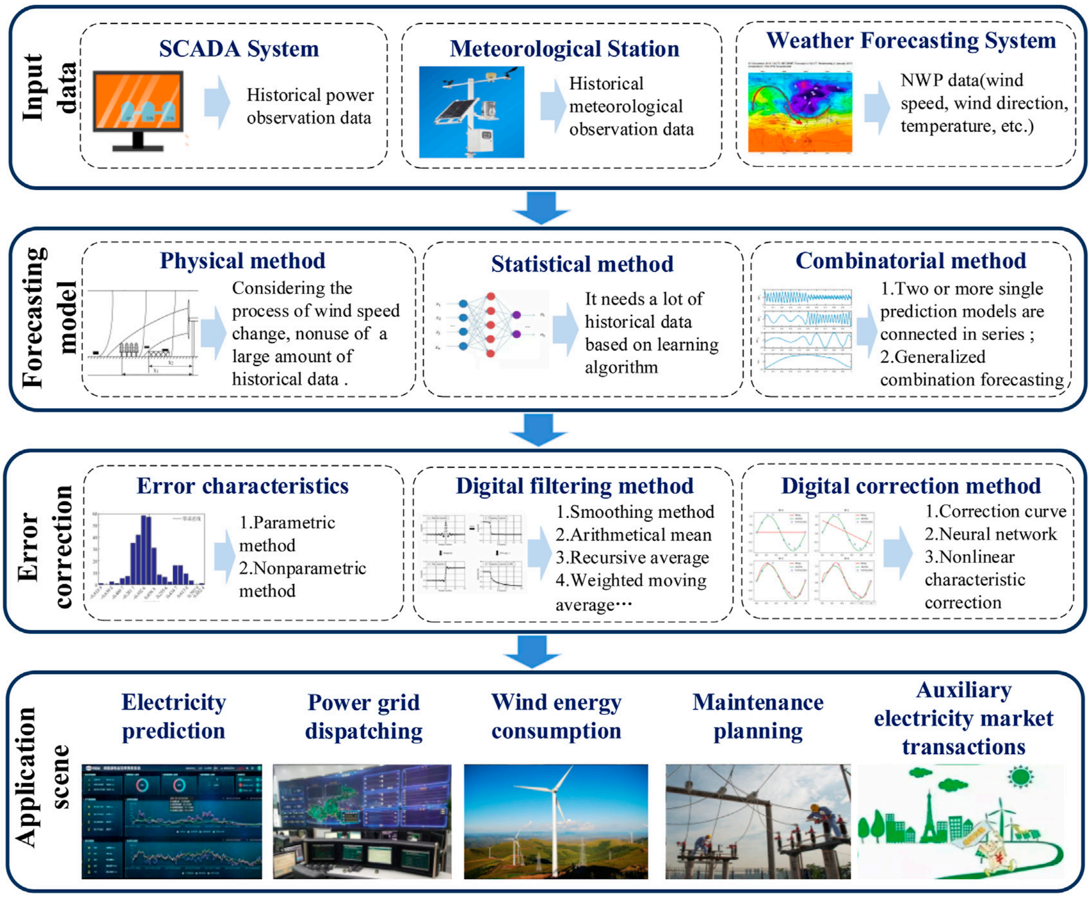

FIGURE 1
Wind power forecasting technology system.

judiciously determine the future processing state (Ding et al., 2019; Sun et al., 2022a; Zhu et al., 2023). The methodology entails several technical steps, such as extracting the principal fluctuation component of the power sequence, identifying local extreme points, generating composite fluctuation sequences, mining historical class fluctuation processes, and fusing future fluctuation trends (Zhang et al., 2019a). The technique is intricate, computationally demanding, and relies upon an ample availability of historical power data.

Through an examination of wind power fluctuation characteristics (Lin et al., 2012; Yang and Qi, 2015; Yang and Dong, 2016; Zhou et al., 2017), it has been substantiated that wind wave characteristics significantly impact prediction accuracy. Additionally, our research group has conducted extensive investigations into the division and fluctuation characteristics of wind power fluctuation processes, affirming that incorporating these inherent characteristics is an effective means of enhancing wind power prediction accuracy.

2.2 Probabilistic prediction

The volatility of wind resources and the increasing proportion of wind power lead to a significant rise in the uncertainty of wind power prediction. Point prediction merely predicts the expected value and cannot accurately depict the uncertainty of wind power output. Moreover, wind power exhibits violent fluctuations when weather patterns change abruptly. Thus, relying solely on point prediction cannot effectively assess potential risks or provide a safe power fluctuation range for power grid planning, operation, security, and stability analysis as a dispatching reference (Yu et al., 2023).

To address this issue, ultra-short-term probabilistic prediction emerges as a new prediction form, providing more comprehensive information and quantitatively reflecting the uncertainty of wind power. This has the added benefit of reducing spinning reserve capacity and cutting power grid operation costs (Yang et al., 2022d). Probabilistic forecasting can be classified based on the form of the prediction results, which includes interval prediction, quantile prediction, and probability density prediction (YanTangDai et al., 2021). Additionally, it can be divided into parametric and non-parametric methods depending on whether the probability distribution function needs to be assumed in advance (See Appendix Table A2 for details).

The parametric method involves transforming probabilistic prediction into a parameter estimation problem. It assumes that wind power or its prediction error follows a known distribution in advance, such as the Gaussian distribution function,

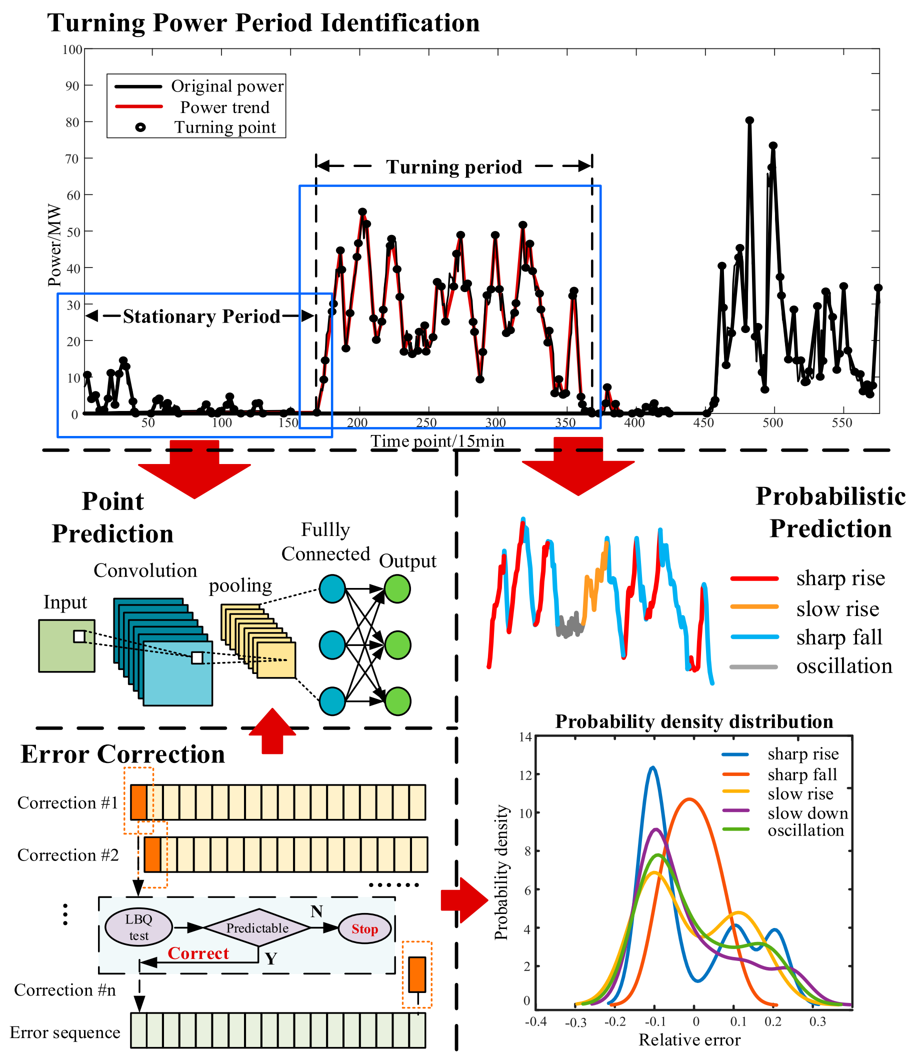

FIGURE 2
Framework of sub-forecast method for ultra-short-term wind power under transition weather environment.

exponential distribution function (Zhu et al., 2019), beta distribution function (Yuan et al., 2019), or a combination of these probabilistic distributions. The Maximum Likelihood Estimation (MLE) and Delta method are then employed to estimate the parameters of the distribution function. However, due to the subjective inclusion of prior knowledge in parametric methods, it is often challenging to fit the model to the real distribution (Ding et al., 2013). Consequently, the assumption concerning the shape of the distribution is a key focus of current research, with the Gaussian and Beta distributions being two commonly used choices.

The non-parametric method does not make assumptions about the distribution of wind power or prediction error in advance. Instead, it fits the distribution based on the characteristics and properties of the data itself. Common data analysis methods include the empirical cumulative distribution method (Pinson and Kariniotakis, 2010), Quantile Regression (QR) method (He et al., 2021), Kernel Density Estimation (KDE) (Xu et al., 2021), and Lower Upper Bound Estimation (LUBE) (Li et al., 2020).

3 Research on extreme value prediction considering extreme weather scenarios

Despite the progress made in ultra-short-term wind power prediction, current single-value prediction methods lack extreme weather prediction models, resulting in poor prediction accuracy and stability. Extreme weather events that significantly impact wind turbines can be classified into two main categories. Firstly, severe convective weather conditions like typhoons lead to significant and rapid changes in wind speed, causing extreme power fluctuations within a short period. Offshore wind power generation, in particular, is highly susceptible to typhoons. As offshore wind power continues to expand, the research on power prediction for offshore wind generation becomes a crucial future development focus. Secondly, extremely cold weather, including cold waves and freezes, has seen three times faster growth in total installed wind power capacity in cold climates across North America, Europe, and Asia compared to the global average annual growth rate of offshore wind capacity. Extremely low ambient temperatures trigger the shutdown of wind turbines due to low-temperature protection mechanisms, resulting in a sudden and substantial power deficit. Furthermore, despite the overall accuracy level of existing research on ultra-short-term wind power prediction meeting the required standards, there are significant local errors, increasing the risks of wind abandonment and peak load loss. Therefore, studying extreme value prediction under extreme weather scenarios holds great significance.

The research team involved in this work has a solid research foundation regarding ultra-short-term wind power forecasting technology in extreme scenarios. They propose an ultra-short-term segmented prediction method for offshore wind power based on the adaptive division of extreme weather periods, the technical flow chart is shown in Figure 2. To validate the algorithm's effectiveness and superiority under extreme weather scenarios, wind farm data from Texas, United States was taken as the sample for verification. The selected validation dataset covers 4 days (from September 12 to 15, 2019), including extreme weather events. Specific improvement methods include a hybrid model based on the Convolutional Neural Network (CNN) and the Long and Short Time Memory (LSTM) network in the stationary period, combined with an Improved Attention Mechanism (IAM) for point prediction. Meanwhile, during periods of power timing mutation, the probabilistic prediction method based on variable bandwidth kernel density estimation is adopted.

Among them, the evaluation indexes of point prediction performance include Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The calculation formulas are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{1}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{2}$$

Where, $\hat{y}_i$ is the actual power at time i, y_i is the predicted power at time i.

And the evaluation indexes of probability prediction performance include the prediction interval coverage index, reliability index, and comprehensive performance index to measure the overall performance of the forecast. The calculation formulas are as follows:

$$R_{PICP} = \frac{1}{W}\sum_{w=1}^{W}k_{wa} \tag{3}$$

$$R_{PINAW} = \frac{1}{T}\sum_{t=1}^{T}\delta_w(x_t) \tag{4}$$

$$\delta_w(x_t) = U(x_t) - L(x_t) \tag{5}$$

$$R_a = R_{PICP} - a = \frac{1}{W}k_{wa} - a \tag{6}$$

Where: W is the number of points to be predicted, k_{wa} is the Boolean value, and T is the prediction time interval, $U(\cdot)$ and $L(\cdot)$ are respectively the upper and lower limits of power prediction, a is the degree of confidence.

The Prediction Interval Coverage Percentage (PICP) reflects the probability of the actual value falling within the upper and lower bounds of the prediction interval. A PICP less than a renders the prediction invalid, while a higher PICP indicates a greater probability of the actual power falling within the prediction limits, thereby enhancing the prediction efficacy. The Reliability index Ra measures the deviation between the interval coverage rate and the preset confidence level. A positive Ra implies a favorable deviation with higher reliability than the given confidence level. The Prediction Interval Average Width (PINAW) evaluates the clarity of the prediction model. When the predicted results have the same PICP, a smaller PINAW corresponds to better prediction accuracy. Both the accuracy of point prediction and probability prediction results for full-time periods and subsection prediction were quantitatively analyzed and presented in Figure 3 and Table 1, respectively.

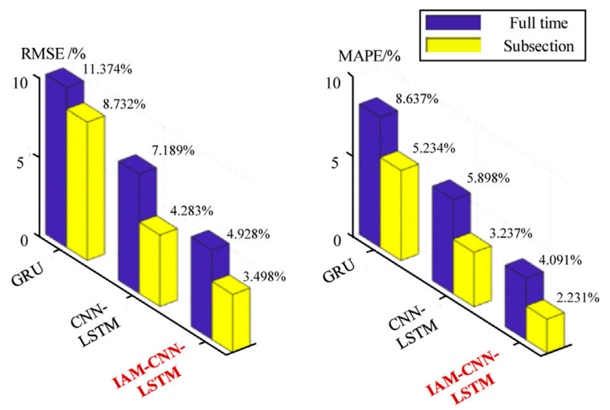

FIGURE 3
Comparison of single value prediction results in segmental prediction.

Figure 4 displays the combined prediction results wherein the actual power timing curve lies within the estimated confidence interval. The point prediction period exhibits a high degree of fitting between the predicted and actual power curves. During the probabilistic prediction period, the lower confidence interval surrounds the higher confidence interval, effectively avoiding quantile crossovers. This demonstrates the proposed method's strong overall performance, especially its adaptability for predicting offshore wind power in extreme weather conditions. However, it is essential to focus on real-time detection and identification of turning weather periods.

4 Conclusion and future trends

Due to the large proportion of wind power in the power system, the inherent randomness, intermittency and uncertainty of wind power pose major challenges to grid connection, power system scheduling and consumption. In this paper, the literature of ultra short term wind power forecasting is reviewed, and the advantages and disadvantages and applicability of point forecasting and probability forecasting are compared and analyzed. In addition, taking a wind farm as an example, a case study of ultra-short term wind power accurate forecasting method under extreme scenarios is carried out to prove the

TABLE 1 Comparison of probability prediction results in segmented prediction.

Forecasting strategy	Degree of confidence	90%	70%	50%
Full-time period forecasting	PICP	91.00	71.89	51.16
	PINAW	27.15	21.85	16.24
	Ra	1.84	1.89	1.16
Subsection forecasting	PICP	91.73	71.61	51.24
	PINAW	27.67	23.51	17.81
	Ra	1.73	1.61	1.24

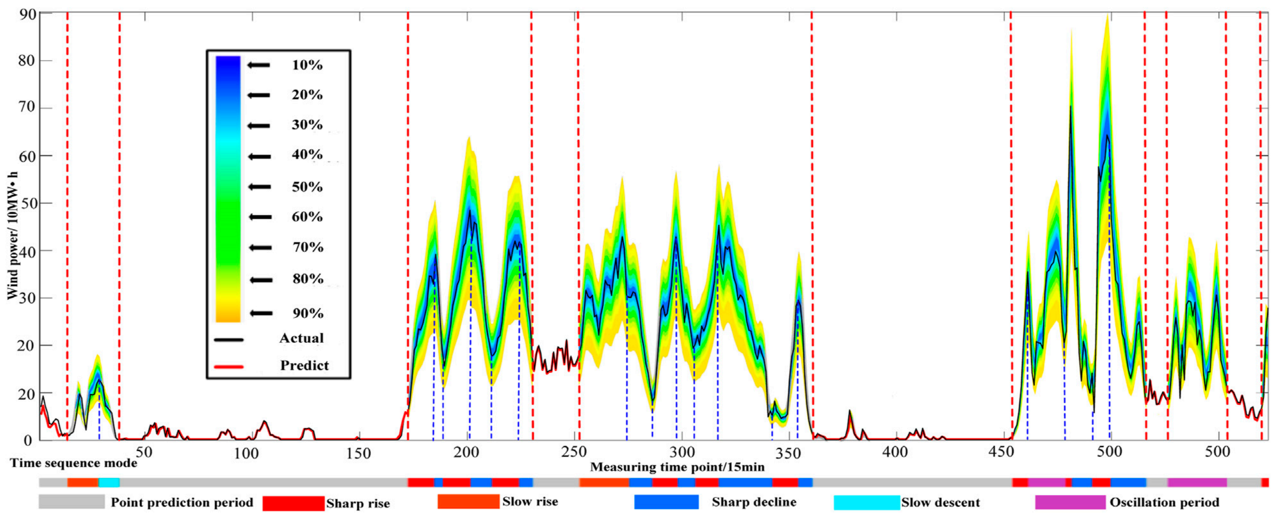

FIGURE 4
Combined forecast results under transitional weather scenarios.

feasibility of the proposed combined forecasting method. In the future, combining numerical weather forecasts with real-time meteorological data warnings should be considered to establish an advanced prediction model for such transitional periods. This will further enhance the accuracy and timeliness of ultra-short-term wind power prediction in extreme weather scenarios.

In addition, although China has made great progress in ultra-short term wind power forecasting, there are still challenges in dealing with the uncertainties of wind power, which are reflected in the following aspects: 1) The improvement of the accuracy of electric power forecasting is limited by the level of NWP, and the progress is slow (Liu H. et al., 2020; Niu and Ji, 2020); 2) It is an urgent task to solve the problem of missing sample data in data processing (Zhang et al., 2021; Fu et al., 2023b; Tong et al.; Wang et al., 2023); 3) Due to the limitations of the current time scale of numerical weather forecasting, it is necessary to study short-term and immediate forecasting with more practical applications (Kumar et al., 2022); 4) With the explosive growth of newly built new energy stations, it is particularly important to improve the online adaptive learning ability (Li et al., 2021) of the model due to the more complex operating conditions of the equipment in these scenarios and the more changeable meteorological conditions.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

GY: Writing–review and editing. LS: Writing–original draft. QD: Project administration, Writing–review and editing. GC: Project administration, Writing–review and editing. SW: Project administration, Writing–review and editing. DX: Software, Writing–review and editing. XC: Investigation, Writing–review and editing. WL: Formal Analysis, Writing–review and editing.

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Conflict of interest

Authors QD, GC, and SW were employed by Power Dispatching Control Center of State Grid Shaanxi Electric Power Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Comparison of the advantages and disadvantages of the point prediction method.

Category	Advantage	Limitations	Method	Literature
Physical method	It does not need a lot of historical data and is suitable for new power plants.	The calculation process is complex and the requirements of initial information quality are extremely high.	Takens' theorem	Ma et al. (2020)
Statistical method	The modeling is simple, and the accuracy is high when the data is complete.	A large amount of historical data is needed, and the consistency of historical data change rule is required.	ARIMA-Kalman	Liu et al. (2012)
			An improved grey model based on background value optimization	Zhang et al. (2019b)
			ARIMA-GARCH	Ding et al. (2017), Singh and Mohapatra (2019)
			RWT-ARIMA	
Artificial intelligence method	Deep mining is the hiding law of nonlinear wind power data, simple modeling, and fast calculation speed.	Lack of physical support, the modeling process has a ' black box' property and has high requirements on the quantity and quality of input data.	GA-SVM	Liu et al. (2015)
			KNN	Yesilbudak et al. (2017)
			LSTM	Banik et al. (2020)
			GRU	(Yu et al., 2022b)、 (Yu et al., 2023)
			An improved AM combined with the CRS algorithm	(Yu et al., 2022b)、 (Sun et al., 2022b; Su et al., 2022; Aslam et al., 2023)
			Dual-attention Mechanism	
			Similar Day Attention Mechanism	
			BiLSTM	(Yu et al., 2022a)、 (Liu et al., 2020b)
Combination forecast method	Integrate the advantages of each prediction model, avoid the shortcomings of a single prediction method, and improve the prediction accuracy.	It is easy to cause error accumulation, and there is no theoretical basis for the selection of methods and the distribution of weights.	EEMD-LASSO-QRNN	Lin and Liu (2011), He and Wang (2021)
			EMD-SVM	
			WD-LSTM	Liu et al. (2020c)
			CNN-LSTM	Lu et al. (2022)
			Combinatorial forecasting methods for different time section differentiation.	Wang et al. (2017)

TABLE A2 Comparison of probabilistic forecasting methods.

Category		Advantage	Limitations	Method	Literature
Parametric method	Gaussian distribution	Data processing and the model's evaluation become simpler and easier	There can be cases where assuming or estimating the output distribution shape is neither reasonable nor possible	KDE-Gaussian	Niu et al. (2022)
				Truncated Gaussian	Pinson et al. (2006))
	Exponential distribution			Piecewise exponential error distribution model	Zhu et al. (2019)
	Beta distribution			PSO-Beta	Yuan et al. (2019)
Nonparametric method	Empirical cumulative distribution	No parameter estimation required	The calculation is complex and requires a large amount of historical data	Adaptive resampling	PINSON and KARINIOTAKIS (2010)
	QR	Flexibility; Probability distribution functions and prediction intervals are easily obtained	Computationally intensive	CSI-SVQR	He et al. (2021)
				ELM-QR	Wan et al. (2016)
				Heteroscedastic spline regression and robust spline regression model	Wang et al. (2018)
	LUBE	Simplify the calculation process and reduce the calculation cost	The model parameters need to be obtained by combining the optimization algorithm	CSS-LUBE	Wu et al. (2018)
				A new deep LUBE based on root mean square back propagation algorithm	Li et al. (2020)
	KDE	Easy to implement, good flexibility	A large amount of historical data is needed for fitting, which is vulnerable to bad data interference	Variable bandwidth KDE	(Yu et al., 2022b; Yu et al., 2023)
				Bootstrap-Kernel density method	Xu et al. (2021)