processes

Article

Optimal Scheduling Strategy of Wind Farm Active Power Based on Distributed Model Predictive Control

Jiangyan Zhao [1], Tianyi Zhang [2,*], Siwei Tang [1], Jinhua Zhang [2], Yuerong Zhu [2] and Jie Yan [3]

1 Power China Guiyang Engineering Corporation Limited, Guiyang 550081, China; zhaojiangyan@whu.edu.cn (J.Z.); tangsiwei66@gmail.com (S.T.)
2 School of Electrical Engineering, North China University of Water Resources and Electric Power, Zhengzhou 450045, China; zhangjh@ncwu.edu.cn (J.Z.); yuerongzi@126.com (Y.Z.)
3 College of New Energy, North China Electric Power University, Beijing 100096, China; yanjie_freda@163.com
* Correspondence: ztyzhang1128@163.com

Abstract: In recent years, the development and utilization of China's wind energy resources have been greatly developed, but the large-scale wind power grid connection has brought threats to the safe and stable operation of the power grid. In order to ensure the stability of the power grid, it is necessary to reduce wind power output fluctuation and improve the tracking accuracy of dispatch instructions. Therefore, based on the distributed model predictive control of wind farm active power distribution strategy, an ultra-short-term wind power hybrid deep learning predictive model is proposed. The prediction results of a wind farm in North China show that the hybrid neural network model can achieve high ultra-short-term wind power prediction accuracy and is suitable for active power control prediction models. A two-layer distributed model is proposed to predict the active power control architecture of wind farms by implementing the clustering process with the Crow Search Algorithm. The distributed model predictive control strategy is proposed in the upper layer, and the centralized model predictive control algorithm is adopted in the lower control structure and optimized. The results show that the dual-layer distributed model predictive control strategy can better track the active power distribution instructions, reduce output fluctuation and scheduling value changes, and enhance the robustness of active power regulation, which is suitable for active power online control in wind farms.

Keywords: GCN-LSTM; ultra-short-term wind power prediction; wind farms; distributed model predictive control; active power control

Citation: Zhao, J.; Zhang, T.; Tang, S.; Zhang, J.; Zhu, Y.; Yan, J. Optimal Scheduling Strategy of Wind Farm Active Power Based on Distributed Model Predictive Control. *Processes* **2023**, *11*, 3072. https://doi.org/10.3390/pr11113072

Academic Editors: Qi Liao, Hsin-Jang Shieh and Yamin Yan

Received: 23 September 2023
Revised: 20 October 2023
Accepted: 23 October 2023
Published: 26 October 2023

1. Introduction

Energy is the foundation of human survival and social development. Global climate change, environmental pollution, and rising energy costs are increasingly becoming urgent issues that need to be addressed by countries. The twentieth report also pointed out the need to actively and steadily promote carbon peaking and carbon neutrality, improve the control of total energy consumption and intensity, and promote the clean, low-carbon, and efficient utilization of energy [1]. The wind power installed capacity has been increasing year by year, and the scheduling and control strategies of wind power electricity systems are leading the development of energy into a new era. It is imperative to design effective and reliable strategies for controlling the active power of wind power.

The traditional active power control strategies of wind farms often adopt the feedback correction method and only use the power and load value to carry out active power control. The control strategies adopted, such as equal proportional distribution, variable proportional distribution, and sequential cutting machine, are based on a single and poor active power control precision and have lagged in time, lack flexibility, and effectiveness [2]. The output of the wind turbine always fluctuates randomly and the instructions issued by the dispatching department are constantly changing. Only a fixed single standard is used to classify the units, resulting in a decrease in the coordination degree between active power scheduling and system instructions. The specific classification index of the cluster has poor adaptability to the adjustment and change of the dispatching instructions, and cannot meet the needs of accurate control of active power, and the active power loss is greatly increased. Therefore, it is necessary to establish a more accurate wind power prediction model, and at the same time consider the coupling and constraints between different cluster individuals to implement distributed control. Such an active power control strategy is more targeted, conducive to improving control accuracy, smoothing wind power fluctuations, and making full use of wind power consumption space.

Artificial Neural Network (ANN) [3] and support vector machine are representative machine learning methods. Zhou et al. combined pole symmetric mode decomposition, extreme learning machine, and particle swarm optimization algorithm to build a short-term wind power prediction model. The average absolute percentage error in the experiment was less than 5%, and this method achieved a more accurate prediction effect [4]. Support vector machine is often combined with the meta-heuristic intelligent optimization algorithm. Lu et al. used the gray wolf optimization algorithm to optimize the kernel function parameters of the multi-output support vector machine model, and predicted the wind power of 15 wind farms, outperforming other benchmark models in terms of multiple error indicators such as improvement percentage [5]. Li et al. combined the improved Dragonfly algorithm with a support vector machine, and its model effectiveness was verified on the real data set of French wind farms, which is suitable for short-term wind power prediction [6]. In recent years, the traditional machine learning method has developed slowly in improving the accuracy of wind power prediction. The deep learning method based on large-scale and multidimensional data has been increasingly applied in the field of wind power prediction because of its powerful mapping ability. Deep learning methods widely used in wind power prediction include recurrent neural networks [7,8], convolutional neural networks, deep belief networks [9,10], and generative adversarial networks [11,12]. Among them, a convolutional neural network generally does not predict wind power alone but is often combined with a recurrent neural network or other intelligent optimization algorithms to build prediction models [13]. Duan et al. used a variational mode decomposition (VMD) technique to extract the local characteristics of the original wind power sequence, using long short term memory (LSTM) and a deep belief network built based on particle swarm optimization sequence prediction model, multiple child sequence prediction model by the nonlinear weighted combination, the short-term wind power prediction sequence [14] is obtained. From the above analysis, it can be seen that the current research on wind power prediction has certain shortcomings, such as failing to make full use of the spatial characteristics of wind turbines, and not considering the changes in the non-European spatial layout of wind turbines and environmental factors [15]. Therefore, finding a suitable method to simultaneously apply spatial state timing features and wind power series to wind power prediction, improving the utilization of spatially relevant information, mining spatial-temporal data associations, and referencing to numerical weather prediction (NWP) data are the keys to improving the accuracy of wind power prediction.

With the continuous development of wind power generation technology, the installed capacity of wind power continues to rise, which will put forward higher requirements on the active power distribution and output curve smoothing of wind farms. Literature [16] carries out active power control for a wind farm composed of double-fed induction generators. The central control layer sends power reference signals to each wind turbine separately, and the local wind turbine control layer ensures that the single machine tracks active power instructions. Literature [17] classifies wind turbines according to the statistics of the actual operating conditions of fans and ultra-short-term power prediction results and adjusts the output of fans according to the ranking table of active power regulation ability. The essence of the above method is the static optimal scheduling control of multiple moments, and only the current optimization of the control point is considered. Different from traditional open-loop scheduling control methods, model predictive control designs predictive models for concerned system variables and uses rolling optimization and closed-loop feedback correction to optimize control in the time domain, which is widely used in the field of new energy scheduling control [18]. The flexibility and fast dynamic performance of model predictive control (MPC) make it have obvious advantages in dealing with various practical complex problems, and formulate corresponding strategies to deal with various problems in the development process of wind power, so as to achieve multi-dimensional control goals. In order to reduce the fatigue load of wind turbines and take into account the high impedance ratio of the wind farm collector, Guo et al. proposed a distributed active power control strategy based on MPC to achieve optimal control of the pitch angle and generator torque of wind turbines and track the power reference value delivered by the system [19]. The main control objective of the literature [20] is that MPC controller can minimize the change of wind turbine axial force while solving the reference power. The effectiveness of the strategy is verified through a parallel large eddy simulation case study. Based on MPC, literature [21] designed prediction models in the time domain for optimization at different time scales, and set decision objectives according to different warning levels of new energy to ensure sufficient absorption space for wind power and improve the economy of system operation. Literature [22] proposes the application of finite control set model predictive control to power electronic devices of wind farms, aiming to improve the dynamic performance of static reactive compensators with the shortest execution time. This strategy has been verified in 10 MW wind farms.

In recent years, many scholars have carried out research on distributed model predictive control of wind farms. Literature [23] uses the distributed idea to coordinate the control actions among wind turbines affected by wake interaction and uses the iterative distributed control method to improve wind power utilization and reduce turbine load. Literature [24] established a piece-based static model based on input variables and state variables to represent the nonlinearity of wind turbines. After validity verification, it was applied to a distributed MPC prediction model to achieve optimal active power control objectives of scheduling instruction tracking and load minimization. From the above analysis, it can be seen that the current research on wind power prediction has certain shortcomings, such as failing to make full use of the spatial characteristics of wind turbines, and not considering the changes in the non-European spatial layout of wind turbines and environmental factors [15].

In previous studies, most researchers focused on the construction of state-space models, which largely relied on the linearization of nonlinear models and were not suitable for wind power changes with high noise and strong uncertainty. In addition, the above control methods do not directly consider the dynamic characteristics of wind power. Although the tracking accuracy of active power instructions has improved to a certain extent, the static control structure and method are not flexible and lag compared with the scheduling instructions of changes, and the power distribution lacks rationality and balance. When dispatching instructions are issued, the working state of the wind turbine should be considered first. The dynamic power characteristic parameters are used to cluster the fans and then carry out distributed active power control, which can adapt to different changes in dispatching instructions, improve the wind power absorption rate, and smooth the output curve.

2. Ultra-Short Term Wind Power Prediction Based on Graph Convolutional Networks-Long Short Term Memory (GCN-LSTM) Deep Neural Network

In order to improve the accuracy of ultra-short-term wind power forecasts, a neural network model has become a common method in recent years. Both short-term and long-term memory networks for time series prediction effect are good. The convolutional neural networks (CNN) are often combined with the LSTM model and are used to make up for the large amount of network computing and the defects of slow convergence speed. However, CNN can only process the data of the European space, which makes the topological information such as the location information of the wind farm not utilized. To make full use of the time-series data of wind farm and space information, improve the wind power prediction accuracy, fine regulation of wind turbines, first of all, use map CNN processing, coupling information fusion associated with topological structure of the fan, then multi-dimensional local spatial features of wind turbines are extracted, and deep-seated representations are sent into LSTM network for power prediction. An ultra-short-term wind power prediction method based on GCN-LSTM deep neural network is proposed. Finally, a domestic wind farm is taken as an example for simulation verification.

2.1. Construction of Hybrid Deep Learning Prediction Model

At present, the deep learning prediction model of wind power mostly adopts a single time series analysis method, which only considers the power value and the change of NWP data in the time dimension. Whether it is the management of wind turbines or the prediction of wind power, it is often carried out in the basic unit of the station, rather than for a single wind turbine, and the biggest influencing factor of wind power—wind speed—always acts on all wind turbines in a space.

2.1.1. Graph Structure and Predictive Model Input Data

From the perspective of space, the geographical location, which is also one of the characteristics of wind turbines, represents the spatial correlation and dependence of each wind turbine [25], which plays a certain importance in wind power prediction. Based on this idea, the non-European spatial layout of the wind farm enables it to be constructed as a graph structure suitable for graph convolutional networks (GCN).

Using the wind turbine coordinates of the wind farm and the actual line connection, the diagram structure as shown in Figure 1 is generated. Each wind turbine is a node, and the connection line between two wind turbines is the edge. The characteristics of each wind turbine node include four dimensions, namely power, wind speed, wind direction, and temperature. The last three dimensions can be obtained from the NWP data of the wind farm. Thus, the structure, type, and scale of the graph are determined, and the basic input parameter matrix required by the GCN network is obtained.

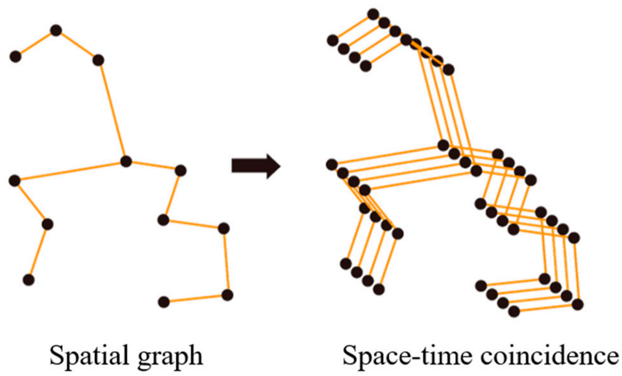


Figure 1. Generates a graph structure for predicting model inputs.

2.1.2. Construction of Wind Power Prediction Model in GCN-LSTM Network

NWP data and historical wind power data are used as the input of the GCN-LSTM prediction model, and the predicted wind power value is used as the output.

As the number of network layers increases, the receptive field becomes larger and larger, that is, the characteristics of the wind turbine node integrate the historical data of the local machine and more units. All the information in the graph is aggregated by graph convolution, and the first-order embedded representation of each wind turbine node is obtained after updating. The intuitive convolution diagram of the graph is shown in Figure 2. Multi-order neighbor information is obtained after multi-layer GCN. After obtaining the feature matrix H(i) of each node after multi-layer GCN, it is taken as the final node representation and fed into the downstream LSTM network. Finally, the parallel LSTM unit of GCN-LSTM obtains the time dependence from each node and obtains the prediction result sequence.

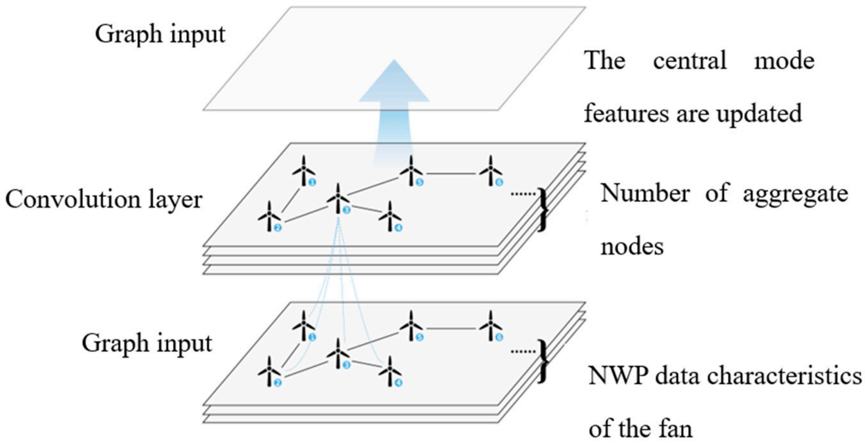


Figure 2. Schematic diagram of the convolution process.

At present, GCN is more suitable for shallow network structures. Due to the simple structure of a one-layer GCN network, the feature extraction power of the wind power data set is insufficient, while gradient disappearance and overfitting problems are easy to occur in a three-layer convolutional network structure, so two-layer GCN is used in the experiment.

GCN and LSTM are used to jointly build deep-learning models. The constructed prediction model consists of two layers of GCN, three layers of LSTM, one layer of Dropout, and one layer of fully connected layer. The ultra-short-term wind power prediction model based on GCN-LSTM is shown in Figure 3.

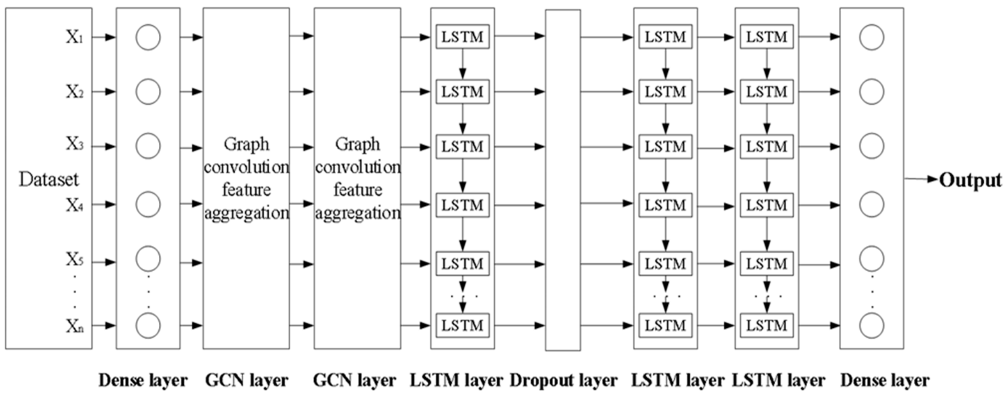


Figure 3. GCN-LSTM prediction model network structure.

The operation process of the GCN-LSTM deep learning ultra-short-term wind power prediction model is described as follows:

(1) The input layer data set uniformly passes the input data to the next layer of the neural network.
(2) Excavation and dimensionality reduction in deep features by two GCN layers.
(3) The first LSTM layer learns the autocorrelation between the NWP data and the deep information of the spatial dimension of the wind turbine and the wind power in time and passes it to the next layer.
(4) The operation performed by the Dropout layer is to randomly delete a portion of hidden neurons, preventing deep learning from overfitting.

(5) The second and third LSTM layers further conduct neural network self-learning on the information coming from the front to improve the accuracy of nonlinear fitting of the power prediction model.
(6) The network outputs wind power sequence through the final fully connected layer, rolling prediction for each cycle.

2.2. Analysis of Experiments and Examples

The data used to establish the study came from the measured data of a wind farm in North China in 2021, and the data used included four-time series of wind speed, wind direction, temperature, and wind power. The learning samples of the power prediction model may contain unreasonable data, and there are often missing data or data anomalies. The data anomaly of the learning sample weakens the correlation between the data and the wind power and affects the convergence speed and accuracy of the training algorithm. Therefore, in order to obtain accurate prediction results, it is necessary to preprocess the data.

2.2.1. Data Preprocessing and Experimental Design

The historical data of each sample of wind turbines include several dimensional characteristics of wind speed, wind direction, and temperature. The max-minimum normalization of the data of the characteristic dimension of each sample of wind turbines is carried out, respectively, as shown in Formula (1), and the original data is converted into a unified order of magnitude.

$$\tilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}},\ i = 1,\ 2,\ \ldots,\ \mathrm{n} \tag{1}$$

where: x_i is the original meteorological data of samples such as measured wind speed and temperature, $\tilde{x}_i$ is the normalized data, $x_{\max}$ and $x_{\min}$ represents the maximum and minimum values of the data set, respectively, and n is the number of samples.

In order to obtain the best LSTM parameter values, a model optimization algorithm is designed. The results show that the RMS error of the model is the smallest when the LSTM of three layers and the number of neurons in each layer are 32, 64, and 32, respectively. Therefore, the number of hidden layers of LSTM is finally selected as 3, and the number of neurons in each layer is 32, 64, 32. The GCN-LSTM prediction model can obtain the best prediction effect when the time sliding window size is 7 and the batch size is 16.

Finally, the experimental parameter settings of GCN-LSTM wind power prediction are obtained, which are described as follows. The weight matrix of GCN is randomly initialized in [0, 1], and the adjacency matrix size of GCN is 3×3, which is equivalent to the convolution kernel size of traditional convolutional neural networks. To achieve a single-step prediction of wind power, each read starts from the next row next to each other. The LSTM network time step is 7. The training parameter Settings of the LSTM network are shown in Table 1. lr is the learning rate, which controls the rate of weight updating; shuffle is true, and its representation randomly sorts the training data set before each training.

Table 1. LSTM network training parameter Settings.

Parameter Name	Parameter Value
Number of iterations	100
Batch_size	16
Learning rate	0.001
Dropout Layer weight	0.1
Activation function	sigmoid

Root mean square error (RMSE) and mean absolute error (RMSE) are selected as statistical indicators of wind power prediction error. MAE, mean absolute percentage error

(MAPE) [26,27]. The specific expressions of RMSE, MAE, and MAPE are as follows: (2) to (4):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x'(i) - x(i)\right)^2} \tag{2}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|x'(i) - x(i)\right| \tag{3}$$

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x'(i) - x(i)}{x(i)}\right| \times 100\% \tag{4}$$

where: $x(i)$ is the actual value, $x'(i)$ is the predicted value, and N is the number.

2.2.2. Analysis of Example Results

After the pre-processing of abnormal and missing data, the wind power sequence of 12 wind turbines in the wind farm is shown in Figure 4.

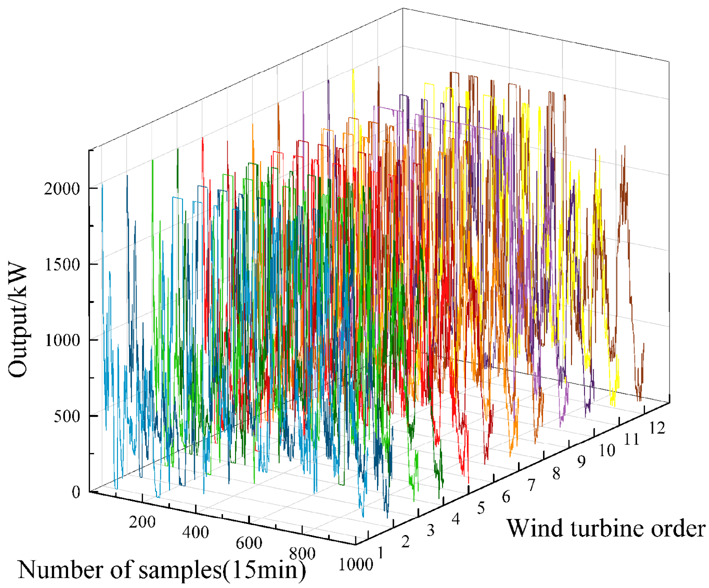
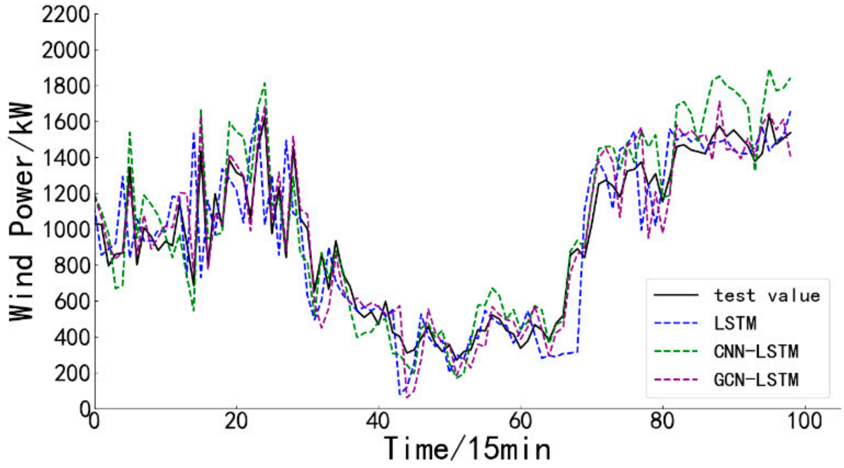


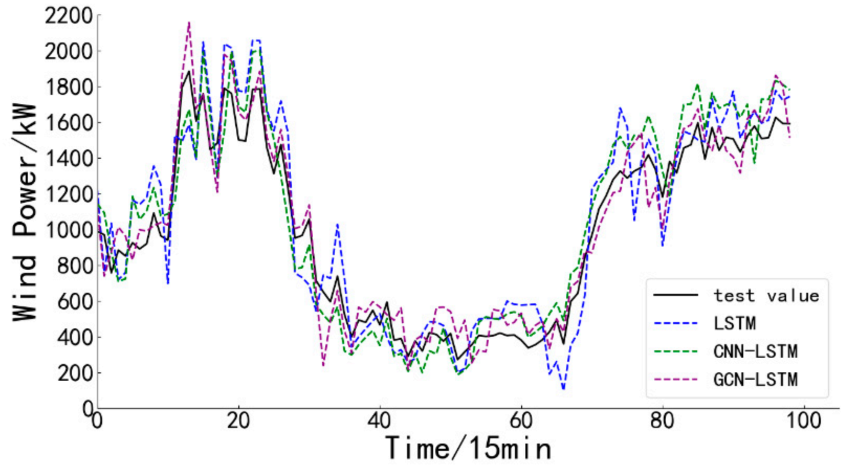
Figure 4. Ultra-short-term wind power forecast data set of wind turbines.

LSTM model, CNN-LSTM model, and GCN-LSTM model are used to compare and analyze the actual power curves and predicted power values of different wind turbines, as shown in Figure 5a,c. These show that the power predicted by the LSTM model with small fluctuations in a short time always tends to change linearly with time. It is because the ReLU function adopted by the LSTM layer is a piecewise linear function, and the filling of missing test data is also linear, resulting in an approximately horizontal line. However, the phenomenon that the forecast trend of LSTM is completely opposite to the actual value at some points is because LSTM focuses on the analysis of historical wind power, and can not make good use of the relationship between data when the power fluctuation is small.

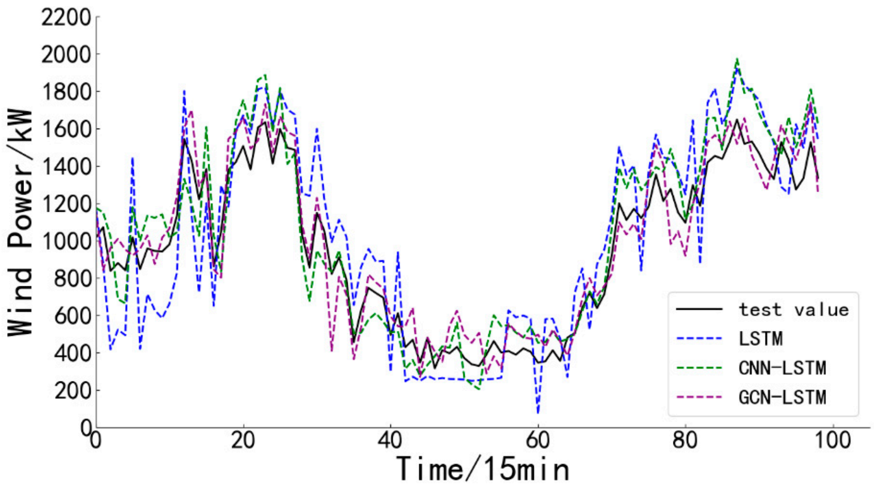
The average prediction error and prediction time of different models are shown in Table 2. The prediction errors of the GCN-LSTM network for different wind turbine sizes are shown in Table 3, and the evaluation indexes of prediction errors for different wind turbine sizes are shown in Figure 6. The RMSE value of the GCN-LSTM network model is the smallest. Compared with GCN-LSTM, the CNN-LSTM model is slightly slower, because the training process of CNN takes a long time. After the sample is fused and dimensionality reduction through the GCN network, the total prediction time is shortened by the LSTM layer.



(**a**) 9#Wind turbine

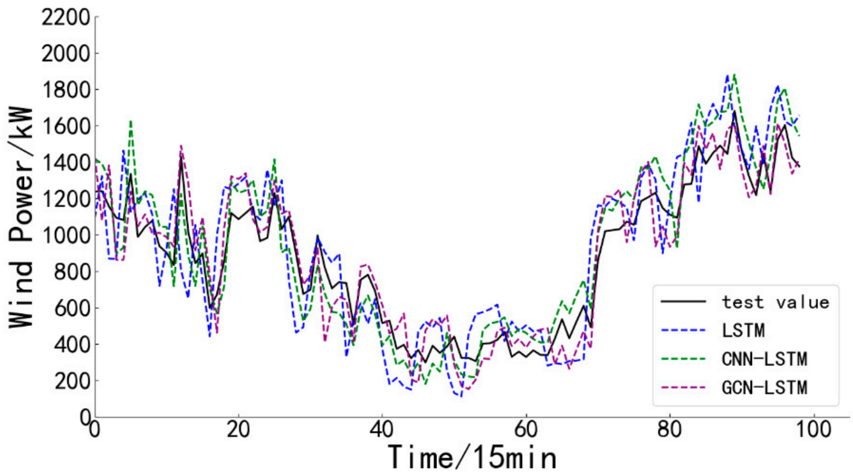


(**b**) 10#Wind turbine



(**c**) 11#Wind turbine

Figure 5. *Cont.*



(**d**) 12#Wind turbine

Figure 5. Wind power prediction curves of different models.

Table 2. Average prediction error and prediction time of different models.

Prediction Model	RMSE	MAE	MAPE (%)	Forecast Time/s
LSTM	240.75	199.98	27.12	61.2
CNN-LSTM	158.13	142.62	18.17	72.8
GCN-LSTM	137.88	115.66	16.05	68.5

Table 3. GCN-LSTM network prediction errors for different wind turbine sizes.

Wind Turbine Size	RMSE	MAE	MAPE (%)
Wind turbine group 1	133.16	106.80	15.67
Wind turbine group 2	138.24	110.36	14.68
Wind turbine group 3	138.85	122.44	17.83
Wind turbine group 4	141.62	125.40	16.87
Wind power plant	137.88	115.66	16.05

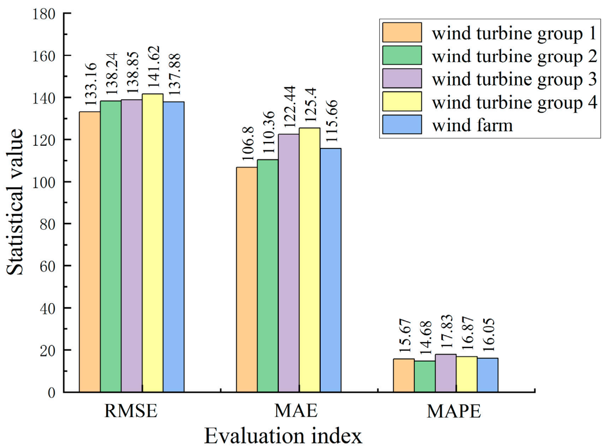


Figure 6. Prediction error evaluation index values of different wind turbine sizes.

As can be seen from Table 3, the three error evaluation indexes of wind farms are smaller than those corresponding to most wind turbine clusters, which indicates that the larger the wind turbine scale, the smaller the fluctuation of wind power value, and the smaller the prediction error of wind power by the proposed GCN-LSTM model. The GCN-LSTM deep learning model has achieved a more ideal effect for the power prediction of multiple wind turbines. The proposed model is not only suitable for the ultra-short-term wind power prediction of a single wind turbine but also suitable for the ultra-short-term wind power prediction of wind turbine groups and the whole field.

3. Cluster Strategy for Wind Turbines Based on Improved K-Means Clustering Algorithm

When optimizing active power control of wind farms, a centralized strategy or single-machine fine modeling strategy can be selected. However, the active power generation capacity of each fan is different, and the centralized strategy often reduces the reliability of the control, and cannot ensure that the control signal is calculated within a fixed time interval. However, the single-machine refined strategy requires solving multiple parameters in the wind farm during the simulation process, which leads to the increase in data storage and the excessive calculation burden of the controller, which greatly improves the simulation performance. On the other hand, wind turbines frequently track scheduling instructions and significantly change output, which is not conducive to reducing the climb rate and mechanical losses of fans. In order to take into account the fine control of the active power of the wind farm, optimize the computational efficiency of the control model, smooth the output of the wind farm, and solve the problem that the K-means clustering results are sensitive to the initial centroid, a K-means clustering method based on Crow Search Algorithm is proposed in the optimal scheduling of the active power of the wind farm by adopting the distributed control strategy of machine cluster division. It mainly studies the fan clustering method that is friendly to wind farm scheduling, designs four clustering indexes that can characterize the active power characteristics of fans from multiple angles, optimizes the optimal initial clustering center through the Crow Search Algorithm, and finally groups fans based on the K-means clustering method.

3.1. K-Means Clustering Algorithm Principle

K-means cluster analysis is a cluster analysis algorithm for iteratively solving sample objects, which is widely used in many fields. The important steps of complete cluster analysis include choosing the distance function, running the clustering algorithm, and evaluating clustering validity. The K-means clustering algorithm divides the feature matrix X of a group of N samples into K clusters without intersection and considers that the data in a cluster belong to the same class. Clustering is the result of clustering. The mean of all the data in a cluster is often called the Centroids of the cluster. In a two-dimensional plane, the horizontal coordinate of the center of mass of a data sample is the mean of the horizontal coordinate of the data cluster, and the vertical coordinate of the center of mass is the mean of the vertical coordinate of the data cluster. The same can be generalized to higher dimensions. The implementation of the clustering algorithm is described below. First, input N P-dimensional sample vectors, specify the maximum number of iterations as tmax and the number of clusters as K, and then randomly select K samples as the initial centroid. For each of the remaining sample points, the Euclidean distance or some other distance function from K centroids is traversed and assigned to the cluster with the smallest centroid distance. Based on the total sample data assigned to each previous centroid, the mean of all objects in each cluster is recalculated to obtain the new centroid. Repeat the steps to calculate the distance and determine the cluster where the center of mass is located. The difference between the old centroid and the new centroid is calculated. When the difference is less than the threshold value, the centroid does not move significantly, the samples in the cluster do not change, or the maximum number of iterations is reached, and the clustering results are divided.

3.2. Wind Turbine Cluster Index Design

Based on the wind speed and power characteristics of wind turbines, the smooth coefficient, active power trend index, generation potential coefficient, and anomaly coefficient are proposed as clustering indexes of wind turbines.

In order to quantify and distinguish the difference of active power output in the volatility of the time dimension, the index smoothness coefficient reflects the smoothness of the power curve of each wind turbine [28], and the fluctuation degree of active power of the wind turbine becomes one of the clustering considerations.

The adjacent active power points are fitted linearly by the least square method. The slope of the obtained line represents the trend of active power change of the unit, and the fitting slope is defined as the active power trend index.

In order to make full use of the available power of the wind farm and ensure the safety of the transmission channel, the proper dispatching command is sent to the less-than-full load unit, and the generation potential of the wind turbine is quantified and characterized.

Using the anomaly data identification method in literature [29], scattered points with substandard tightness are identified as anomalies. In this paper, the anomaly coefficient is used to characterize the numerical characteristics of abnormal data points.

3.3. Improved K-Means Clustering Algorithm for Wind Turbine Clustering

To solve the problem that the classical K-means clustering algorithm cannot achieve the global optimal clustering result because of its strong dependence on the initial clustering center, the Crow Search Algorithm is used to improve the clustering accuracy and clustering stability, so that several wind turbines with multidimensional similarity are clustered into a cluster to achieve the best clustering effect.

The change of the measured wind speed and power of the wind turbine and the predicted value of the active power limit the search space of the crow within a certain range, so the feasibility of the new position should be judged after each update of the position. As the result of CSA optimization is the clustering center of the K-means algorithm, the final value should be within the upper and lower limits of the characteristic indicators calculated by each wind turbine. The mathematical model to check the feasibility of crow position is expressed as the following Formula (5):

$$\boldsymbol{X}^{i,iter+1} = \begin{cases} \boldsymbol{X}^{i,iter+1}, \ \min([r_s \ r_a \ r_p \ r_{P-V}]) \le \boldsymbol{X}^{i,iter+1} \le \max([r_s \ r_a \ r_p \ r_{P-V}]) \\ \boldsymbol{X}^{i,iter}, \ \text{o.w.} \end{cases} \tag{5}$$

where: For the D-dimensional search space, the position vector of the ith crow at the iter iteration is $\boldsymbol{X}^{i,iter} = [x_1^{i,iter}, \ x_2^{i,iter}, \ \ldots, \ x_{\mathrm{d}}^{i,iter}]$, where, $iter = 1, \ 2, \ \ldots, \ \text{iter\_max}$, $i, \ j = 1, \ 2, \ \ldots, \ \mathrm{N_c}$.

4. Active Power Control Strategy of Wind Farm Based on Distributed MPC

While the global wind power installed capacity continues to increase, the amount of abandoned wind is still high, and the active power regulation ability of wind farms still needs to be improved. The traditional centralized control method has high requirements on the central controller and poor parallel computing ability. In order to optimize the utilization of wind energy resources and fine-tune the on-site wind turbines, it is necessary to study how to actively control the active power output of the wind farm effectively, and how to coordinate the changes of wind power and superior scheduling instructions, so that the issued scheduling instructions can maintain the local optimal within each control time and adapt to the uncertain environment. Therefore, a two-layer active power control method for wind farms is proposed, which is divided into different scales in time and space to control the active power of wind farms.

4.1. Hierarchical Active Power Scheduling Strategy for Wind Farms

The static scheme adopted by the traditional active dispatching control has high efficiency but a relatively simple structure, which does not consider the objective factors such as the difference in wind conditions and power generation status of each fan, ignores the uncertainty of wind power generation, and has a low degree of intelligence. In order to achieve the safe and stable operation of the system we must improve the active power control accuracy of wind farms, improve the tracking accuracy of wind farm active power dispatching instructions, carry out active adjustments according to the deep power characteristics of wind turbines, smooth wind power output curve and make full use of wind power consumption space, etc., create an operation control scheme from the perspective of multi-time scale active control management strategy of wind farm, and formulate a double-layer distributed active power dispatching.

4.1.1. Multi-Time Scale Active Power Control Management Strategy

In order to smooth the wind power output curve and improve the wind power consumption rate, active power control strategies are developed for different time scales. Based on the idea of "multi-level coordination and step-by-step refinement", a multi-time scale active power control management strategy is constructed based on the time scale of intra-day rolling scheduling and real-time online rolling scheduling plans, as shown in Figure 7. Based on the measured active power output value, the deviation of the daily plan is corrected in real-time to reduce the unbalance of power caused by uncertainty. With the shortening of the time scale, the precision of the active power control plan increases, and the active power tracking becomes more accurate.

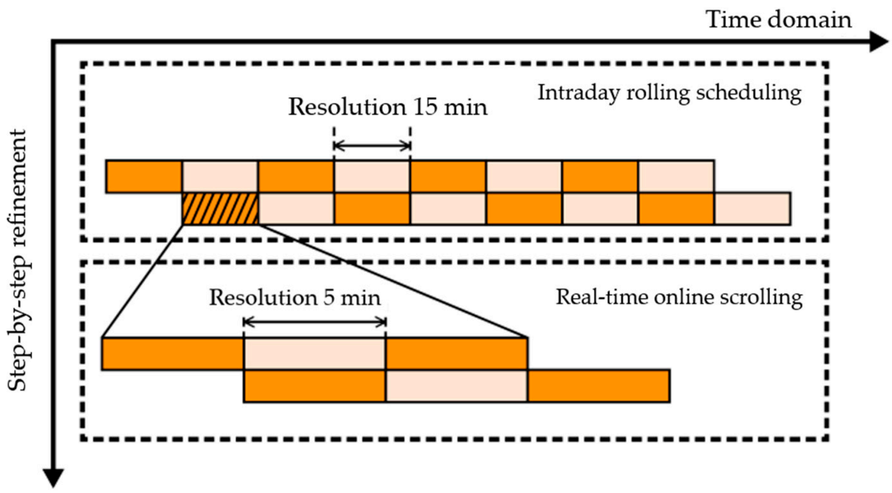


Figure 7. Schematic diagram of multi-time scale active power control management for wind farms.

4.1.2. Hierarchical Control Framework for Active Power of Wind Farm

The hierarchical control strategy for the active power of wind farms based on distributed MPC can be expressed in the following Figure 8. In this paper, GCN-LSTM deep neural network model is used to forecast ultra-short-term wind power. Four clustering criteria are formulated by combining the measured power values, predicted power values, and dynamic temporal correlation of power over a period of time. The improved K-means clustering algorithm proposed based on CSA aggregates wind turbines into several clusters, and makes effectiveness evaluation according to evaluation indicators.

4.2. Design and Solution of Dual-Layer Distributed Active Power Prediction Controller for Wind Farms

The key to a two-layer distributed active predictive control strategy for wind farms lies in the realization of distributed model predictive control.

The wind farm is divided into multiple wind turbine clusters by using the improved K-means clustering algorithm. The DMPC controller corresponding to each cluster calculates the optimal active power command sequence according to the measured value of the past state, the predicted value of the future state, and information shared by the neighbor subsystem. The first of these values is sent to the MPC controller in the lower wind turbine balancing layer. The DMPC of each subsystem shares information through the communication network. In addition, the DMPC controller needs to take into account the synergies and constraints between the various clusters. The DMPC controller is optimized to realize the optimal control and stable operation of wind power active power. The design and solving methods of each layer model predictive controller are introduced below.

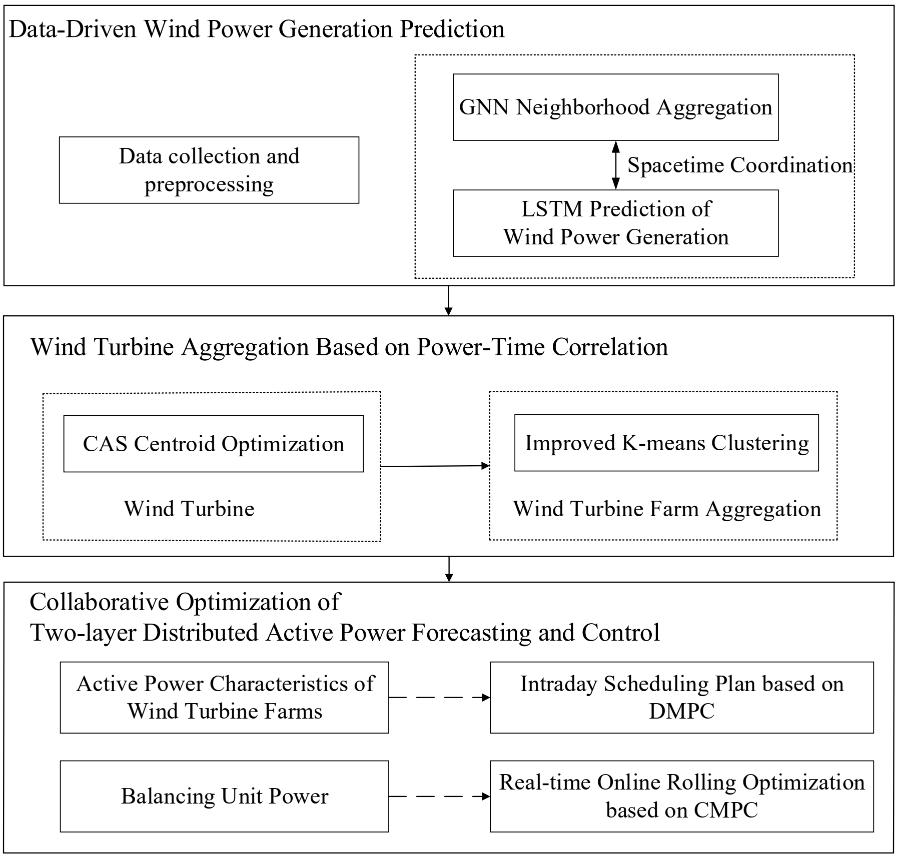


Figure 8. Optimal control strategy for active power of wind farm based on distributed model predictive control.

4.2.1. Design of Upper Layer DMPC Controller Based on Scheduling Coordination Dynamic Index Optimization Method

In this paper, the scheduling coordination dynamic index active power optimization strategy is applied to the distributed active power predictive control layer, and the relationship between the clustered index and the upper control is established. The ultra-short-term wind power prediction model of GCN-LSTM based on a deep neural network is adopted in the upper layer DMPC of a two-layer distributed active power control architecture. The optimization time domain of the intraday rolling scheduling plan is 2 h, the sampling point resolution and the prediction time step are both 15 min, and the output power prediction model can be expressed as the following Formula (6):

$$\begin{aligned} &\boldsymbol{P}_i^{for} = [P_i^{for}(t+\Delta \mathrm{t}_1),\ P_i^{for}(t+2\Delta \mathrm{t}_1),\ \ldots,\ P_i^{for}(t+\mathrm{T}_1\cdot\Delta \mathrm{t}_1)] \\ &i = 1,\ 2,\ \ldots,\ \mathrm{Cl} \end{aligned} \tag{6}$$

where: $\boldsymbol{P}_i^{for}$ is the predicted output power sequence of the i cluster, Cl is the cluster number of wind turbines, and the prediction time domain $\mathrm{T}_1 = 8$.

In order to ensure the maximum number of wind turbines in the wind farm, the optimal scheduling of the cluster coordination layer takes maximizing wind power output as the control goal and requires the active power regulation to be as small as possible. The objective function is expressed as follows (7):

$$\min J_{WTC} = \sum_{k=1}^{\mathrm{T}_1}\sum_{i=1}^{\mathrm{Cl}}\left(\left[P_i^{dis}(t+k\Delta \mathrm{t}_1) - P_i^{for}(t+k\Delta \mathrm{t}_1)\right]^2 + \left[P_i^{dis}(t+k\Delta \mathrm{t}_1) - P_i^{real}(t)\right]^2\right) \tag{7}$$

The constraint conditions mainly include absolute power limit and incremental limit [30], which should meet the following Equations (8) to (11):

(1) Scheduling plan tracking constraints, as follows (8):

$$\sum_{i=1}^{\mathrm{Cl}} P_i^{dis}(t+\Delta \mathrm{t}_1) = P_{sys}^{dis} \tag{8}$$

(2) The sum of the active power output of the wind farm is less than or equal to the total installed capacity of the wind farm, as follows (9):

$$\sum_{i=1}^{\mathrm{Cl}} P_i^{dis}(t+\Delta \mathrm{t}_1) \le P_{WF}^{N} \tag{9}$$

(3) The sum of active power output of each cluster is less than the installed capacity of the cluster, as follows (10):

$$0 \le P_i^{dis}(t+\Delta \mathrm{t}_1) \le P_{WTCi}^{N},\ i = 1,\ 2,\ \ldots,\ \mathrm{Cl} \tag{10}$$

(4) The change rate of active power output of the fleet is within a reasonable range, as shown in Equation (11):

$$\left| \frac{P_i^{dis}(t+\Delta \mathrm{t}_1) - P_i^{real}(t)}{P_i^{real}(t)} \right| \le C_{WF},\ i = 1,\ 2,\ \ldots,\ \mathrm{Cl} \tag{11}$$

where: $P_i^{dis}(t+\Delta \mathrm{t}_1)$ is the scheduling value of the i cluster after 15 min; $P_i^{real}(t)$ is the measured power value of the i cluster measurement system at time t; P_{sys}^{dis} is the wind farm intra-day rolling plan scheduling instruction issued by the scheduling department; P_{WF}^{N} is the total installed capacity of the wind farm; P_{WTCi}^{N} is the installed capacity of cluster i; C_{WF} is the limit of active power climb rate of the wind farm. The intra-day rolling plan resolution is Δt_1 = 15 min, T_1 is the optimization period, and the cluster coordination layer optimizes the planned value for the next 2 h each time, then the optimized time domain T_1 = 8. The control time domain of the upper DMPC is T_{c1} = 4, and the control instructions of 4 time points are obtained after each solution of the penalty function, and only the first active command is sent to each wind turbine group.

In the feedback correction link of the upper layer of distributed active power scheduling, the deviation between the actual output power of the wind power cluster and the control instruction is compared, and the current actual active power value of the wind power cluster is taken as the initial value of a new round of rolling optimization scheduling. The ultra-short-term wind power prediction error is corrected, so that the output active power value of the wind power cluster at the next moment is more realistic, and a closed-loop control is formed. The feedback correction is calculated as follows (12):

$$P_{i,0}(t+\Delta \mathrm{t}_1) = P_i^{real}(t+\Delta \mathrm{t}_1) \tag{12}$$

where: $P_{i,0}(t+\Delta \mathrm{t}_1)$ is the initial active power optimization value of wind turbine group i at time $t+\Delta \mathrm{t}_1$, and $P_i^{real}(t+\Delta \mathrm{t}_1)$ is the measured active power output value of wind turbine group i at time $t+\Delta \mathrm{t}_1$.

4.2.2. Lower Layer CMPC Controller Design

The prediction model of the wind turbine in the lower centralized MPC adopts the linearized state space model established in the literature [31], and the matrix form is expressed as the following Equation (13):

$$\begin{cases} \dot{\tilde{\boldsymbol{x}}} = \boldsymbol{A}\tilde{\boldsymbol{x}} + \boldsymbol{B}\tilde{\boldsymbol{u}} + \boldsymbol{E}\tilde{\boldsymbol{v}} \\ \tilde{\boldsymbol{y}} = \boldsymbol{C}\tilde{\boldsymbol{x}} + \boldsymbol{D}\tilde{\boldsymbol{u}} \end{cases} \tag{13}$$

where: $\boldsymbol{x} = [\omega_m\ \omega_r\ \theta]^{\mathrm{T}}$ is the state variable, and $\tilde{\boldsymbol{x}}$ is the offset between the state variable and the nominal system state; $\boldsymbol{y} = [\omega_m\ P_g]^{\mathrm{T}}$ is the output variable, $\tilde{\boldsymbol{y}}$ is the offset between the output and the steady-state value; $\boldsymbol{u} = [\beta\ T_m]^{\mathrm{T}}$ is the control variable, $\tilde{\boldsymbol{u}}$ is the offset between the input and the operating point. $\boldsymbol{v}$ is the wind speed, $\tilde{\boldsymbol{v}}$ is the offset value between the wind speed and the steady state value, and is the uncertainty.

As the actual engineering stroke mechanism is limited by mechanical strength and safety, the constraint conditions mainly include the upper and lower threshold constraints of the control variables, which should meet the following Equations (14) to (19):

(1) The sum of the active power change of the wind turbine is equal to the active power reference change value of the cluster, as follows (14):

$$\begin{array}{l} \sum\limits_{j=1}^{\mathrm{m}_i} \left[P_{g,j}(t+\Delta \mathrm{t}_2) - P_{g,j}^{real}(t) \right] = P_i(t+\Delta \mathrm{t}_1) - P_i^{real}(t + s\cdot \Delta \mathrm{t}_2) \\ s = 0,\ 1,\ 2 \end{array} \tag{14}$$

(2) Generator angular velocity threshold constraints, as shown in Equation (15):

$$\omega_{m\ \min} \le \omega_{m,j}(t+\Delta \mathrm{t}_2) \le \omega_{m\ \mathrm{rated}},\ j = 1,\ 2,\ \ldots,\ \mathrm{m}_i \tag{15}$$

(3) Generator torque threshold constraint and change rate constraint, as follows (16):

$$\begin{cases} T_{m\ \min} \le T_{m,j}(t+\Delta \mathrm{t}_2) \le T_{m\ \max} \\ -\Delta T_{m\ \max} \le T_{m,j}(t+\Delta \mathrm{t}_2) - T_{m,j}^{real}(t) \le \Delta T_{m\ \max} \end{cases},\ j = 1,\ 2,\ \ldots,\ \mathrm{m}_i \tag{16}$$

(4) Wind turbine blade pitch Angle physical structure constraints and change rate security constraints, as shown in Equation (17):

$$\begin{cases} \beta_{\min} \le \beta_j(t+\Delta \mathrm{t}_2) \le \beta_{\max} \\ -\Delta\beta_{\max} \le \beta_j(t+\Delta \mathrm{t}_2) - \beta_j^{real}(t) \le \Delta\beta_{\max} \end{cases},\ j = 1,\ 2,\ \ldots,\ \mathrm{m}_i \tag{17}$$

(5) The output power of the unit is within a reasonable range, as follows (18):

$$0 \le P_{g,j}(t+\Delta \mathrm{t}_2) \le P_{g\ \mathrm{rated}},\ j = 1,\ 2,\ \ldots,\ \mathrm{m}_i \tag{18}$$

(6) The wind turbine climb rate is within the permitted range, as follows (19):

$$\left| \frac{P_{g,j}(t+\Delta \mathrm{t}_2) - P_{g,j}^{real}(t)}{P_{g,j}^{real}(t)} \right| \le C_{WTN},\ j = 1,\ 2,\ \ldots,\ \mathrm{m}_i \tag{19}$$

where: m_i is the number of wind turbines contained in the i-th cluster; $P_{g,j}(t+\Delta \mathrm{t}_2)$ and $P_{g,j}(t)$ are, respectively, the dispatching value of the j wind turbine after 5 min and the measured power at time t; $\omega_{m,j}(t+\Delta \mathrm{t}_2)$ and $\omega_{m,j}^{real}(t)$ are the generator speed after 5 min of the j wind turbine and the measured speed at time t, respectively. $\omega_{r,j}^{real}(t+\Delta \mathrm{t}_2)$ and $\omega_{r,j}^{real}(t)$ are, respectively, the wind turbine angular velocity after 5 min of the j wind turbine and the measured wind turbine angular velocity at time t. $\omega_{m\min}$ and $\omega_{m\ \mathrm{rated}}$ are the minimum and rated speed of the generator; $\omega_{r\min}$ and $\omega_{r\ \mathrm{rated}}$ are the minimum speed and rated speed of the turbine; $P_{g\ \mathrm{rated}}$ is rated active power of wind motor; C_{WTN} is the limit of single-machine climb rate. T2 represents the optimization period. The wind turbine balance layer optimizes the active power reference value of the future 15 min each time, and the intra-day rolling plan resolution Δt2 = 15 min, then the time domain T2 = 3 is optimized. The control time domain of the lower CMPC is Tc2 = 3, and the reference value of single output at 3 time points is obtained after each solution of the penalty function, and only the first item is sent to each wind turbine. At this point, the two-layer model predicts that the lower layer of active power control completes an online rolling optimization.

In the feedback correction section of the lower layer of distributed active power control, the error weighting method is used to correct the output value of the forecast model at other times in the future. Due to model mismatch, external interference, and uncertainty factors, the actual output value at time $t+\Delta t_2$ is different from the predicted output at time t to time $t+\Delta t_2$, so for unit j, the prediction error at time $t+\Delta t_2$ is as follows (20):

$$\Delta y_j(t+\Delta t_2) = y_j(t+\Delta t_2|\, t) + y_j^{real}(t+\Delta t_2) \tag{20}$$

where: $\Delta y_j(t+\Delta t_2)$ is the output variable error of unit j at the $t+\Delta t_2$ moment;$y_j(t+\Delta t_2|t)$ is the time-to-time $t+\Delta t_2$ forecast output of unit j at time t; $y_j^{real}(t+\Delta t_2)$ is the measured output value of unit j at the $t+\Delta t_2$ moment.

After the error is weighted, the output value of the predicted output sequence of unit j at other times except time $t+\Delta t_2$ is corrected, as shown in Equation (21):

$$\hat{\boldsymbol{Y}}_j = \boldsymbol{Y}_j + \boldsymbol{h}\cdot \Delta y_j(t+\Delta t_2) \tag{21}$$

where: $\boldsymbol{Y}_j = [y(t+\Delta t_2|\, t),\ y(t+2\Delta t_2|\, t),\ y(t+3\Delta t_2|\, t)]$ is the predicted output of T_2 moments in the future of the system under the action of control variables $u(t+\Delta t_2|\, t)$ at time t; $\hat{\boldsymbol{Y}}_j = [\hat{y}(t+\Delta t_2|\, t),\ \hat{y}(t+2\Delta t_2|\, t),\ \hat{y}(t+3\Delta t_2|\, t)]$ is the predicted output value taking into account the error correction at time $\mathrm{t}+\Delta t_2$; $\boldsymbol{h} = [h_1,\ h_2,\ \ldots,\ h_{T_2}]$ is the error correction vector, and $h_1 = 1$.

4.2.3. Optimal Solution of Active Power Predictive Control Problem

Combined with the proposed scheduling coordination dynamic index optimization strategy, the paper adopts the sequential method to solve the problem [32].

When MPC is applied to wind power control, the active power control problem of each time step is transformed into a quadratic optimization solution problem, with the purpose of finding a control strategy that can satisfy the constraint conditions while minimizing the penalty function [33]. Firstly, vectorization transformation is performed on the control objective function of the upper cluster, and the following Equation (22) is obtained:

$$\min J_{WTC}(t) = q\left[P_i^{dis}(t) - P_{WF}^{for}(t)\right]^2 + \left\|\boldsymbol{P}_i^{dis}(t+\Delta t_1) - \boldsymbol{P}_i^{real}(t)\right\|_{\boldsymbol{R}}^2 \tag{22}$$

where: $P_{WF}^{for}(t)$ is the ultra-short-term wind power predicted value of wind farm at time t; q is the error weight; control weight matrix $\boldsymbol{R} = block - diag[r_1,\ r_2,\ \ldots,\ r_8]$.

Applying the same method, the objective function of the i-th wind turbine group in the lower layer is expressed in vector form as Equation (23):

$$\begin{aligned}\min J_{WTi}(t) \;=\; & \left\|\boldsymbol{\omega}_{m,j}(t+\Delta t_2) - \boldsymbol{\omega}_{m,j}^{real}(t)\right\|_{\boldsymbol{G}}^2 + \left\|\boldsymbol{P}_{g,j}(t+\Delta t_2) - \boldsymbol{P}_{g,j}^{real}(t)\right\|_{\boldsymbol{L}}^2 \\ & + \left\|\boldsymbol{T}_{m,j}(t+\Delta t_2) - \boldsymbol{T}_{m,j}^{real}(t)\right\|_{\boldsymbol{W}}^2 + \left\|\boldsymbol{\beta}_j(t+\Delta t_2) - \boldsymbol{\beta}_j^{real}(t)\right\|_{\boldsymbol{Z}}^2\end{aligned} \tag{23}$$

where G, L, W, and Z are the penalty weighting matrices of generator rotor angular speed, output power, pitch angle, and motor torque, respectively, and they are all three-dimensional diagonal matrices. The elements in R, G, L, W, and Z are assigned according to the principle that the greater the time distance, the smaller the weight.

In order to save computing time and improve control efficiency, the penalty function is transformed into a quadratic programming problem (QP). The form of quadratic programming is as follows (24):

$$\min f(x) = \frac{1}{2}x^T \boldsymbol{H} x + g^T x \tag{24}$$

Based on the constraints of Equations (8) to (11) and (14) to (19), the quadratic programming is solved, and the dual-layer distributed model is obtained to predict the active power commands of each cluster of active power control daily rolling planning and each unit of online rolling scheduling. The rationality and precision of active power distribution of wind farms are improved, so as to achieve multi-objective active power coordination optimization.

5. Control Effect Comparison and Performance Analysis of Dual-Layer Distributed Active Power Predictive Control Strategy

(1) Control performance of the upper DMPC

As can be seen from Figure 9, the dispatch command of 11:45–12:30 is greater than the predicted wind power value. On the premise of ensuring the safety of the unit and the transmission channel, the actual output of the wind farm using the DMPC control strategy is closer to the active power dispatch command, while the control methods are relatively conservative for the wind farm dispatch. This indicates that DMPC's active power control strategy can improve the utilization rate of wind power and better coordinate the scheduling index.

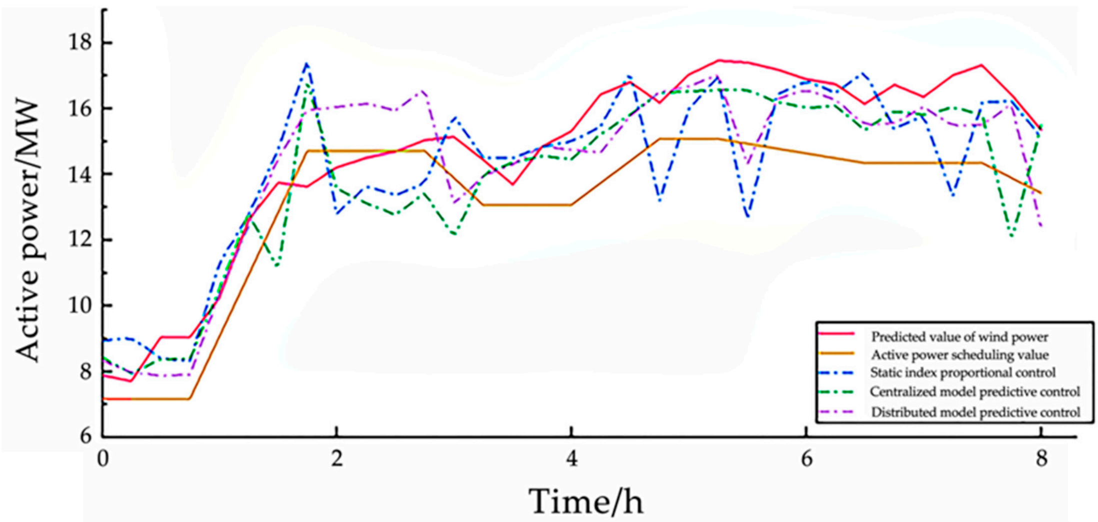


Figure 9. Active power control results of wind farms under different strategies.

Figures 10–12 show that the dynamic index DMPC cluster active power control strategy based on scheduling instruction coordination ADAPTS to various scheduling instruction changes. Specifically, when the active power command rises, the power generation space of each cluster can be fully utilized. When the active power command drops, it can limit the change of the scheduling value of adjacent control steps within a certain range, and balance the output of each group. When the active command is stable, the DMPC reduces the fluctuation of the group of instructions and reduces the mechanical loss as much as possible.

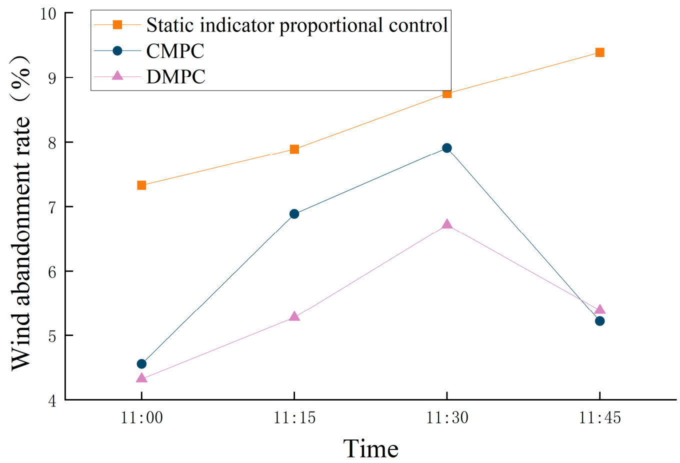


Figure 10. Cluster control results from different strategies during the rise period of wind farm dispatching instruction.

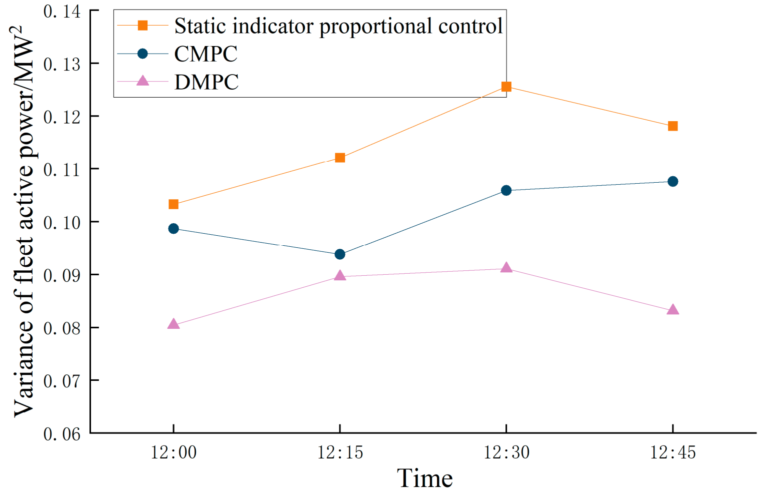


Figure 11. Cluster control results from different strategies during the stationary period of wind farm dispatching instruction.

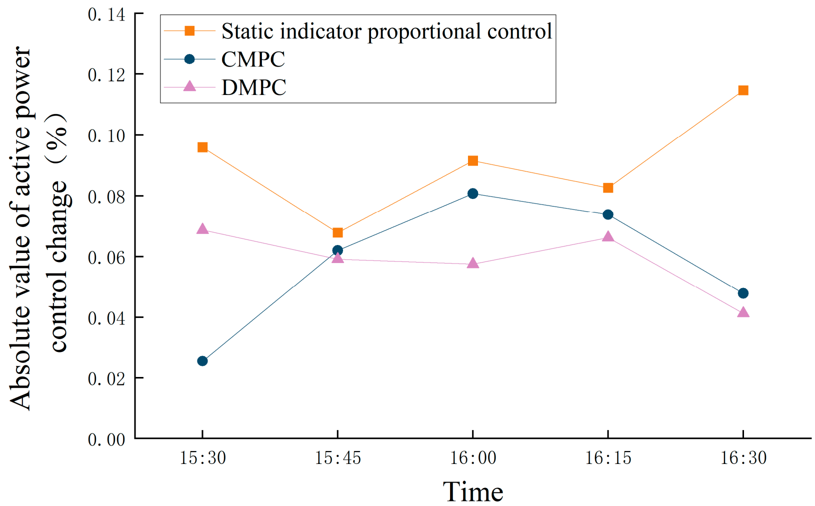


Figure 12. Cluster control results of wind farm dispatching instruction decline period with different strategies.

(2) Control performance of the lower CMPC

As can be seen from Figures 13 and 14, the output curve of the centralized model predictive control method is smoother. Since the scheduling instructions of proportional distribution largely depend on the predicted power value of the wind turbine, the power prediction sequence is highly volatile, and the feedback link of active power output is ignored in traditional proportional distribution. Therefore, the scheduling result of the low-level centralized MPC is superior to the proportional active scheduling strategy.

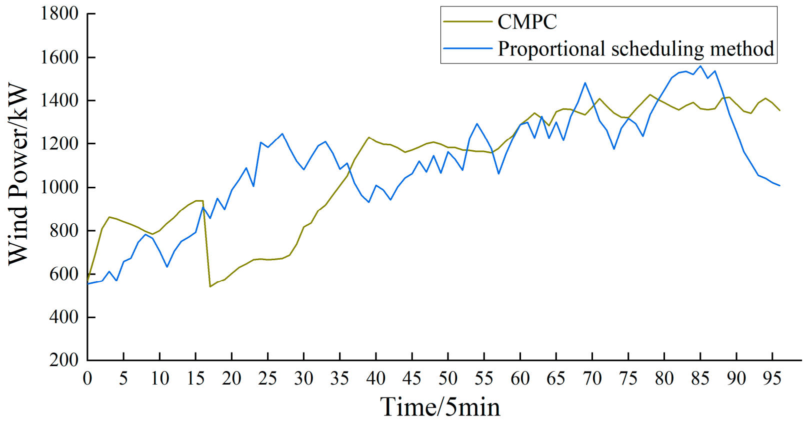


Figure 13. Active power control results of wind turbine 10# under different strategies.

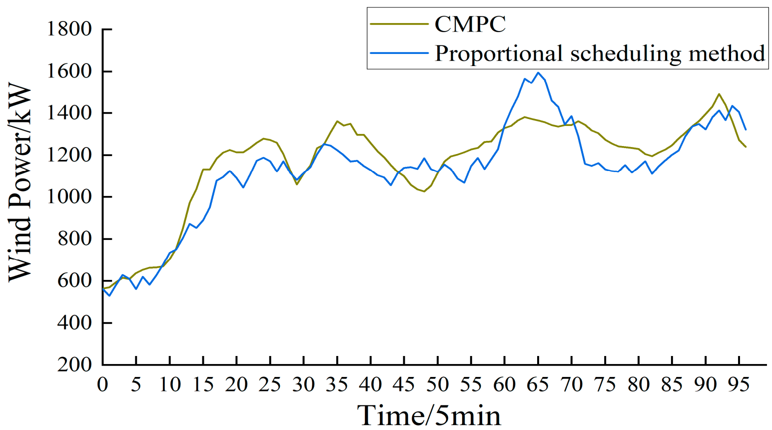


Figure 14. Active power control results of wind turbine 11# under different strategies.

For most of the time of fan 11#, the output value of active power control using the lower centralized MPC is higher than the active power output of proportional scheduling, and the average active power of the former is 8.61% higher than that of the latter. The average active power optimization of the centralized MPC for fan 10# is smaller than that of the proportional scheduling mode. The average active power optimization of the two strategies is 1099.11 kW and 1108.50 kW, respectively, mainly because the dispatching output of the centralized MPC for fan 10# is smaller than that of the proportional scheduling mode during the period of 11:25 to 12:55. The specific reasons are analyzed as follows. The wind farm received the dispatch instruction from TSO during this period and was in a stable state and transitioned to a declining state. At 11:25, the output of other units in the same group as fan 10# was at a higher level, resulting in a smaller dispatch instruction from the centralized MPC controller to fan 10#. After the subsequent optimization of the time domain of the fleet division and the update of the online rolling plan, the power of fan 10# changes steadily and gradually increases.

6. Conclusions

China's wind power technology is developing rapidly. In order to help the process of carbon neutralization and carbon peaking, we must improve the utilization rate of wind energy and the regulation performance of wind power control systems, and promote the development and consumption of clean energy. It is urgent to solve the problem that the randomness of wind energy brings as an impact to the power grid, and it is necessary to study the wind power prediction and optimization controls. The main research work of this paper is as follows:

(1) The proposed GCN-LSTM ultra-short-term wind power prediction model is used to construct a neural network input data set, aggregate neighbor node information at each sampling moment by using graph convolutional network, and input deep features into a long and short-term memory neural network for deterministic wind power prediction after feature fusion and dimensionality reduction. The time-sliding window size and batch size of the LSTM network can obtain the optimal combination settings through experiments. The model makes full use of the information fusion of neighboring nodes and reduces the amount of data input to the LSTM network, which improves prediction efficiency and accuracy.

(2) An improved K-means clustering method for wind turbines based on a Crow Search Algorithm is proposed. Based on the smooth degree, changing trend, shape characteristics, and abnormal data of fan power, four time-varying fan clustering indexes are designed to reflect wind power characteristics from multiple angles. The Crow Search Algorithm is used to optimize the initial centroid of K-means clustering. Experimental results show that the contour values of the proposed clustering method under different clustering indexes are superior to classical K-means clustering. The improved K-means algorithm based on CSA centroid optimization can achieve accurate and effective wind turbine clustering, providing solid conditions for active power refining control of wind farms.

(3) The proposed dual-layer distributed wind farm active power model predictive control strategy. The simulation results of a wind farm with 12 fans show that the upper-layer control strategy can make full use of the power generation space of each cluster during up-up power scheduling, effectively reducing the fluctuation degree of optimization instructions during balanced power scheduling, and reducing the change of cluster scheduling values during power reduction scheduling. The lower layer control strategy effectively smooths the wind power output curve, improves the tracking accuracy of active power to instructions, improves the optimization efficiency, enhances the robustness and scalability of active power control, and improves the overall active power control performance compared with other control algorithms.

In this paper, research work has been carried out on ultra-short-term prediction of wind power and optimal control of active power of wind farms, and some progress has been made. There are still some problems and shortcomings in this paper, which can be further improved and discussed in future work:

(1) Considering the efficiency of unit grouping, this paper designs an improved K-means clustering algorithm and a variety of clustering indicators. For randomly fluctuating wind turbine power sequences, clustering methods that are more suitable for the overall time series data, such as feature space transformation clustering method or multi-resolution analytical clustering method, can be designed to obtain higher quality cluster analysis results and further improve the refined regulation and control ability of active power of wind farms.

(2) The distributed model prediction control of dynamic indicators carries out a unit clustering in each control step, the group results change dynamically according to the active characteristics, and the group regulated by each distributed controller is not fixed, so the communication structure requires each distributed controller to be connected to all fans, which increases the scheduling cost at a certain level. At

the same time, on this basis, a more rigorous comparative analysis is required to determine the location of the distributed controller.

Author Contributions: Conceptualization, J.Z. (Jiangyan Zhao) and J.Z. (Jinhua Zhang); writing—original draft preparation, T.Z. and Y.Z.; writing—revision, T.Z.; supervision, S.T.; project administration, J.Z. (Jinhua Zhang) and J.Y.; All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported in part by the National Key Research and Development Program Project (Grant number: 2019YFE0104800).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Xinhua News Agency. Holding High the Great Banner of Socialism with Chinese Characteristics and Striving together to Build a Modern Socialist Country in an All-round Way—Report at the 20th National Congress of the Communist Party of China [EB/OL], 2022-10-25. Available online: http://www.gov.cn/xinwen/2022-10/25/content_5721685.htm (accessed on 15 September 2023).
2. Zhong, W.; Li, Z.; Xiao, Y.; Jia, J.; Xu, S.; Liu, Y.; Cui, Y. Active Hierarchical Progressive Control Strategy of Highly Penetrated Networked Wind Power Cluster. *Power Syst. Technol.* **2018**, *42*, 1868–1874. [CrossRef]
3. Medina, S.V.; Ajenjo, U.P. Performance Improvement of Artificial Neural Network Model in Short-term Forecasting of Wind Farm Power Output. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 484–490. [CrossRef]
4. Zhou, J.; Yu, X.; Jin, B. Short-Term Wind Power Forecasting: A New Hybrid Model Combined Extreme Point Symmetric Mode Decomposition, Extreme Learning Machine and Particle Swarm Optimization. *Sustainability* **2018**, *10*, 3202. [CrossRef]
5. Lu, P.; Ye, L.; Zhong, W.; Qu, Y.; Zhai, B.; Tang, Y.; Zhao, Y. A novel spatio-temporal wind power forecasting framework based on multi-output support vector machine and optimization strategy. *J. Clean. Prod.* **2020**, *254*, 119993. [CrossRef]
6. Li, L.L.; Zhao, X.; Tseng, M.L.; Tan, R.R. Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm. *J. Clean. Prod.* **2020**, *242*, 118447. [CrossRef]
7. Shao, H.; Deng, X.; Jiang, Y. A novel deep learning approach for short-term wind power forecasting based on infinite feature selection and recurrent neural network. *J. Renew. Sustain. Energy* **2018**, *10*, 043303. [CrossRef]
8. Huang, B.; Liang, Y.; Qiu, X. Wind power forecasting using attention-based recurrent neural networks: A comparative study. *IEEE Access* **2021**, *9*, 40432–40444. [CrossRef]
9. Wang, K.; Qi, X.; Liu, H.; Song, J. Deep belief network based k-means cluster approach for short-term wind power forecasting. *Energy* **2018**, *165*, 840–852. [CrossRef]
10. Wang, S.; Sun, Y.; Zhai, S.; Hou, D.; Wang, P.; Wu, X. Ultra-short-term wind power forecasting based on deep belief network. In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019; pp. 7479–7483.
11. Zhou, B.; Duan, H.; Wu, Q.; Wang, H.; Or, S.W.; Chan, K.W.; Meng, Y. Short-term prediction of wind power and its ramp events based on semi-supervised generative adversarial network. *Int. J. Electr. Power Energy Syst.* **2021**, *125*, 106411. [CrossRef]
12. Liu, Y.; Yang, M.; Yu, Y. Transformational weatherahead wind power prediction based on multi-scenario sensitive weather factor optimization and small sample learning and expansion. *High Volt. Technol.* **2023**, *49*, 2972–2982.
13. Jalali, S.M.J.; Ahmadian, S.; Khodayar, M.; Khosravi, A.; Shafie-khah, M.; Nahavandi, S.; Catalao, J.P. An advanced short-term wind power forecasting framework based on the optimized deep neural network models. *Int. J. Electr. Power Energy Syst.* **2022**, *141*, 108143. [CrossRef]
14. Duan, J.; Wang, P.; Ma, W.; Fang, S.; Hou, Z. A novel hybrid model based on nonlinear weighted combination for short-term wind power forecasting. *Int. J. Electr. Power Energy Syst.* **2022**, *134*, 107452. [CrossRef]
15. Ye, L.; Zhang, C.; Tang, Y.; Sun, B.H.; Zhong, W.Z.; Lan, H.B.; Liu, H.; Li, P.; Huang, Y.H. Active Power Stratification Predictive Control Approach for Wind Power Cluster with Multiple Temporal and Spatial Scales Coordination. *Zhongguo Dianji Gongcheng Xuebao/Proc. Chin. Soc. Electr. Eng.* **2018**, *38*, 3767–3780. [CrossRef]
16. Chen, Z.; Liu, J.; Lin, Z.; Duan, Z. Closed-loop active power control of wind farm based on frequency domain analysis. *Electr. Power Syst. Res.* **2019**, *170*, 13–24. [CrossRef]
17. Deng, H.; Tang, L.; Wu, X. Real-time active power control strategy of wind farm based on fan regulation capability ranking. *Power Grid Technol.* **2018**, *42*, 2577–2584.
18. Müller, M.A.; Allgöwer, F. Economic and Distributed Model Predictive Control: Recent Developments in Optimization-Based Control. *SICE J. Control Meas. Syst. Integr. (SICE JCMSI)* **2017**, *10*, 39–52.
19. Guo, Y.; Gao, H.; Wu, Q.; Østergaard, J.; Yu, D.; Shahidehpour, M. Distributed coordinated active and reactive power control of wind farms based on model predictive control. *Int. J. Electr. Power Energy Syst.* **2019**, *104*, 78–88. [CrossRef]
20. Hansen, A.D.; Sørensen, P.; Iov, F.; Blaabjerg, F. Centralized power control of wind farm with doubly fed induction generators. *Renew. Energy* **2006**, *31*, 935–951. [CrossRef]

21. Boersma, S.; Rostampour, V.; Doekemeijer, B.; Van Geest, W.; van Wingerden, J.W. A constrained model predictive wind farm controller providing active power control: An LES study. *J. Phys. Conf. Ser.* **2018**, *1037*, 032023. [CrossRef]
22. Nasiri M, R.; Farhangi, S.; Rodriguez, J. Model predictive control of a multilevel CHB STATCOM in wind farm application using diophantine equations. *IEEE Trans. Ind. Electron.* **2018**, *66*, 1213–1223. [CrossRef]
23. Ren, J.; Xue, C.; Ma, X. Flexible scheduling model predictive control with new energy resource classification. *Smart Power* **2020**, *48*, 30–36+88.
24. Bay, C.J.; Annoni, J.; Taylor, T.; Pao, L.; Johnson, K. Active power control for wind farms using distributed model predictive control and nearest neighbor communication. In Proceedings of the 2018 Annual American Control Conference (ACC), Milwaukee, WI, USA, 27–29 June 2018; Volume 2018, pp. 682–687.
25. Treiber, N.A.; Heinermann, J.; Kramer, O. Wind Power Prediction with Machine Learning. In *Computational Sustainability*; Springer International Publishing: Berlin/Heidelberg, Germany, 2016; pp. 13–29.
26. Hu, Y.L.; Liang, C. A nonlinear hybrid wind speed forecasting model using LSTM network, hysteretic ELM and Differential Evolution algorithm. *Energy Convers. Manag.* **2018**, *173*, 123–142. [CrossRef]
27. Luo, D.; An, Y. GSSPA forecasting model for urban water supply in Zhengzhou under policy orientation. *J. North China Univ. Water Resour. Electr. Power (Nat. Sci. Ed.)* **2019**, *40*, 30–36.
28. Howlader, A.M.; Senjyu, T.; Saber, A.Y. An Integrated Power Smoothing Control for a Grid-Interactive Wind Farm Considering Wake Effects. *IEEE Syst. J.* **2015**, *9*, 954–965. [CrossRef]
29. Wang, Y.M.; Liu, H.; Song, P. Wind turbine abnormal operation data cleaning method based on multi-stage progressive recognition. *Renew. Energy* **2020**, *38*, 1470–1476.
30. Ye, L.; Zhang, C.; Xue, H.; Li, J.; Lu, P.; Zhao, Y. Study of assessment on capability of wind accommodation on regional power grids. *Renew. Energy* **2019**, *133*, 647–662. [CrossRef]
31. Zhang, J.; Liu, L.; Liu, Y.; Zhu, Y.; Yan, J. Research on robust model predictive control strategy of wind turbines to reduce wind power fluctuation. *Electr. Power Syst. Res.* **2022**, *213*, 108809. [CrossRef]
32. Trodden, P.; Richards, A. Cooperative distributed MPC of linear systems with coupled constraints. *Automatica* **2013**, *49*, 479–487. [CrossRef]
33. Lu, P.; Ye, L.; Pei, M. Active power model forecasting coordinated control strategy for wind power clusters. *Proc. CSEE* **2021**, *41*, 5887–5900.