Combined Model for Short-term Wind Power Prediction Based on Deep Neural Network and Long Short-Term Memory

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Abstract: Wind power generation is affected by weather and historical wind power, which presents the characteristics of instability and high volatility. Most wind power prediction models ignore physics information. In this paper, a novel combined predicting model that simultaneously considers physics information and historical information is presented to address the drawbacks of existing models. First, the physical characteristics of wind speed, wind direction, and temperature are obtained by Deep Neural Network (DNN), and time-series characteristics from historical wind power are extracted by Long Short-Term Memory (LSTM). Then, the physical features and the time-series features are fully connected for feature fusion to obtain the final time-series physical features. Finally, the short-term wind power prediction is performed according to the obtained merged features. Experimental results demonstrate that the DNN-LSTM model proposed in this paper achieves high accuracy and stability, and provides technical support for wind power system dispatch.

Keywords: Short-term wind power prediction; DNN; LSTM; Feature fusion

1. Introduction
With the continuous reduction of non-renewable energy, renewable energy has gradually begun to replace oil and other resources, and becomes an important part of electricity. Wind energy not only has
the advantages of renewable energy but also is a green energy[1]. However, wind energy has the characteristics of non-linearity and instability, which cause a lot of wind curtailment and waste of resources. Sudden strong winds will also reduce the life of the wind turbine and increase the cost of wind power generation. Therefore, in order to reduce resource waste and power generation costs, improvement of wind power prediction accuracy has become a hot research topic.

The authors in [2] proposed intelligent algorithms to optimize artificial neural networks, which reduces the steps of parameter selection, but the prediction accuracy is not high. The authors in [3] combined artificial neural network and multi-layer perceptron to predict wind power, but it is prone to overfitting problems. LSTM attracts more and more researchers in the field of wind power predict. Most prediction models used signal decomposition technology combined with LSTM to predict the wind power at the next moment from the historical wind power, failure to consider the historical wind power record errors [4,5]. Other scholars used wind speed and wind direction as input vector to LSTM, but its prediction accuracy is lower than using historical power [6].

The above literatures show that DNN and LSTM are effective methods for wind power prediction, but they only consider historical time series or numerical weather predicts separately, and cannot mine features well. The DNN-LSTM model proposed in this paper fully considers these two types of features, DNN makes full use of the advantages of non-linear relationships and obtains the mapping relationship between numerical weather prediction and wind power. The special structure of LSTM enables it to obtain the relationship between time series, different input vectors make the whole model more reasonable and reliable.

2. Model framework

2.1. Data set description

The data set used in this article is the actual operating data provided by a wind farm in Inner Mongolia. The time resolution of the data is 1min, the sampling unit is small, and the fluctuation of the data is not obvious. For the missing information of the original data, the method of filling in adjacent values is used to complete. Since the collected information has different measurement scales, in order to avoid the resulting uncertainty of the solution, data standardization is used to reduce the impact of volatility and improve the prediction performance. For the original sequence data \( \{x_1, x_2, ..., x_n\} \), the normalized equation is

\[
p_i = \frac{x_i - \min_{1 \leq j \leq n} \{x_j\}}{\max_{1 \leq j \leq n} \{x_j\} - \min_{1 \leq j \leq n} \{x_j\}}
\]

The new data sequence \( p_1, p_2, ..., p_n \in [0,1] \) formed is dimensionless, and the scale standards can be unified in subsequent predictions to improve prediction accuracy.

2.2. DNN-LSTM model framework

There is a certain non-linear relationship between wind speed, wind direction, temperature and wind power, but the actual operating wind power is affected by other factors and, shows different wind power values from theoretical calculations. DNN has a good ability to map nonlinear relationships.
Fuzzy relationships can be obtained through deep learning without complex mathematical theory derivation, which reduces the workload. It's a good way to solve problems where the formula doesn't work. As a kind of recursive neural network, the LSTM can acquire the characteristics of time series data well, learn the input features with a long distance from the predicted value, and solve the problem that the neural network is prone to losing features. At the same time, the LSTM will not face gradient explosion and gradient disappearance phenomenon.

Considering the advantages of DNN and LSTM, the model framework is shown in Fig.1. The data collected by the wind farm is divided into physical information and time series information after data preprocessing. The physical information includes wind speed, wind direction, and temperature. Obtaining physical information through the DNN network to assign weights to different physical feature, inputting timing information into the LSTM network, and obtain timing feature through the LSTM network, then the above characteristics are merged through the fully connected layer to obtain more reasonable and reliable physical-timing characteristics. The prediction result of the output wind power through the output layer.

![Fig.1 DNN-LSTM model framework](image)

The overall network involves many parameters. After repeated experiments, the Adam function is selected as the network iterative optimizer. Due to the large number of input vectors, physical features are selected through two layers of DNN. The number of neuron nodes in the first layer of DNN is 128, because the power in life is positive, the neuron activation function chooses Relu, the number of neurons in the second layer of DNN is 3, the LSTM layer has 10 cells, activation function is Relu, the feature dimension of the input data is 120 and the feature dimension of the output data is 1. Training and testing under these parameters not only run faster, but also has the highest prediction accuracy under all experimental parameters.

3. Experiments and results

3.1. Evaluation indicators

This article uses mean absolute error (MAE) and mean square error (MSE) to evaluate the performance of various methods[7]. MAE can well reflect the actual situation of the predicted value error. The smaller the MAE, the more robust the prediction model against abnormal data. MSE can
evaluate the degree of data change. The smaller the value of MSE, the better the accuracy of the prediction model to describe the experimental data.

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |p_i - \bar{p}_i| \\
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (p_i - \bar{p}_i)^2
\]

\(p_i\) is the real power, \(\bar{p}_i\) is the predicted power, \(n\) is the total number of predictions.

3.2. Result analysis

This article uses 4800 samples in the data set as the training set and 1200 samples as the test set. Compare the commonly used algorithms in wind power: Back Propagation Neuron Network (BP)\[8\], DNN\[9\], LSTM\[10\], Gated Recurrent Unit (GRU)\[11\]. In order to verify the effectiveness of DNN combined with recurrent neural network in predicting wind power, experiments on combined prediction models of DNN and GRU were carried out at the same time. The MAE and MSE of the model used are shown in Tab.1.

| Methods  | MAE    | MSE    |
|----------|--------|--------|
| BP       | 0.05875| 0.00561|
| DNN      | 0.05567| 0.00505|
| LSTM     | 0.05249| 0.00538|
| GRU      | 0.05345| 0.00559|
| DNN-GRU  | 0.03908| 0.00254|
| DNN-LSTM | **0.03872** | **0.00253** |

Tab.1 Evaluation index results

It can be seen from the above table, compared with a single network, DNN-LSTM and DNN-GRU show better performance, indicating that the combined network has a better prediction effect. Compared with the classic wind power prediction methods, the DNN-LSTM model proposed in this paper has better prediction accuracy and better robustness.

![Fig.2 Comparison of prediction results](image-url)
Fig. 2 shows the prediction results of each algorithm, where the abscissa is the time and the ordinate is the power value. Compared with deep neural networks, the predictive ability of the BP model is worse. It can be clearly seen that the predictive results of DNN-LSTM model proposed in this article are closer to actual results, especially in places with large fluctuations, verifying the effectiveness of the method proposed in this article.

4. Conclusion
Improving the accuracy of short-term wind power prediction plays an important role in power dispatch, to consider both physical information and timing information when predicting, this paper proposes a model for short-term wind power prediction based on DNN-LSTM. The use of DNN to measure the importance of different physical information, and assign different weights to the input variables of the prediction model, thereby effectively extracting physical features and reducing model complexity. LSTM can model the time series of historical wind power data, and then extract the time series features. The extracted features are fully connected and fused, taking full account of the importance of physical features and temporal features. The model proposed in this paper can effectively use multivariate input information, and has higher prediction accuracy and generalization ability than traditional deep learning methods.

The prediction method for a single wind farm has limitations. So the subsequent experiments can increase the data and combine with wind farm location information, which will help to further improve the prediction accuracy and promote the advancement of practical applications.

Acknowledgements
This work was supported by the Science Project of Hainan University (KYQD(ZR)20021, KYQD(ZR)20022), Natural Science Foundation Project of CQCSTC (No. cstc2018jcyj AX0398).

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