Wind and Solar Integrated Power Prediction Method Research Based on DT-CWT and LSTM

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Abstract. It is very important to improve the wind and solar integrated output power load forecasting technology with the rapid construction of wind and solar hybrid power supply system and the increasing network complexity of microgrid energy system. On the basis of traditional load power forecasting, this paper proposes a wind and solar integrated power prediction method based on dual tree complex wavelet and long short time memory network. In this method, the original power data of photovoltaic and wind power are denoised by DT-CWT. After data reconstruction and transformation, the processed data are trained by multi-port long and short time memory network prediction model, so as to achieve wind power optical integrated power prediction purpose. Finally, the field data of wind and solar hybrid power supply system is used to verify the model. The results show that the method can effectively reduce the impact of power noise during prediction, and improve the accuracy of power prediction of wind and solar hybrid power supply system.

1. Introduction

In recent years, with the rapid construction of wind power generation and photovoltaic power generation, the wind and solar power grid connected at the same time causes random, intermittent and sudden fluctuations, which brings great challenges to the stability of the power grid and the guarantee of power quality. It also brings great pressure to the power grid dispatching personnel and maintenance personnel to arrange the planned power outage and load adjustment. In order to solve the current large-scale distributed micro-grid energy access, China's scientific research team also launched in-depth discussion on these issues [1-3]. Reference [4] proposed a wind and solar hybrid power supply system power prediction model. This method has high prediction accuracy, and has great application guidance and engineering practical value for wind and solar hybrid power prediction, but there is a problem of power noise impact. In reference [5], a prediction model based on the combination of singular spectrum analysis and LSTM is proposed. The model has good prediction performance and can effectively predict short-term wind power. However, there is a problem that there are not multiple types of power variables, and there are certain limitations. Reference [6-8] discussed the output power prediction method of photovoltaic energy system, and proposed many intelligent algorithms combined with artificial neural network and grey theory. Due to the lack of consideration of multi-dimensional environmental factors, the accuracy in practical engineering application cannot be guaranteed. The wide application of wind and solar integrated system is of great significance to the power prediction of wind and solar hybrid power supply system.
In view of the above problems and the shortcomings of the current research, this paper proposes a prediction model based on the combination of DT-CWT and LSTM. The model decomposes the original data by DT-CWT to decompose the noise signal and noise reduction power signal. The noise reduction power signal is combined with the photovoltaic power influencing factors and wind power influencing factors of the integrated wind and solar hybrid power supply system as the LSTM model training finally, the photovoltaic and wind power prediction data of the microgrid energy system are obtained. Combined with the curve fitting of the least square method, the photovoltaic and wind power prediction curves are obtained.

2. Dual Tree Complex Wavelet and Long Short Time Memory Network

2.1. Dual Tree Complex Wavelet

In the process of wind power and photovoltaic power prediction, especially in wind power prediction, high noise and low dimensional historical data information of the electric field are mixed. Moreover, due to the influence of many factors, the measurement data are abnormal. These noises and abnormal data soybean milk affect the accuracy of power prediction [9]. The development of discrete wavelet transform (CWT) is limited by its lack of translation invariance, redundant data and high computational cost. DTCWT uses two parallel real wavelet transform trees to decompose and reconstruct the signal, which makes it have good near translation invariance and multi direction selectivity. Compared with CWT, DTCWT has limited data redundancy. The two-level decomposition and reconstruction process of DTCWT is shown in Figure 1. Tree1 is a real part tree and Tree2 is an imaginary part tree.

The function base of DTCWT is to satisfy the requirements of Hilbert transform by using the wavelet function pair \( \psi_h(t) \) and \( \psi_g(t) \). As the real and imaginary parts, the complex wavelet can be expressed as \( \psi(t) = \psi_h(t) + i \psi_g(t) \).

Since the DTCWT transform is composed of two parallel wavelet transforms, according to the wavelet theory, the wavelet coefficients and scale coefficients of the above tree1 and Tree2 wavelet transforms can be calculated by formula (1) ~ (4), where

\[
\begin{align*}
b_i^{tree1}(m) &= \int_{-\infty}^{\infty} y(t) \psi_h(2^i t - m) \, dt \\
d_i^{tree1}(n) &= \int_{-\infty}^{\infty} y(t) \psi_g(2^i t - n) \, dt \\
b_i^{tree2}(m) &= \int_{-\infty}^{\infty} y(t) \psi_h(2^i t - m) \, dt \\
d_i^{tree2}(m) &= \int_{-\infty}^{\infty} y(t) \psi_g(2^i t - m) \, dt
\end{align*}
\]
Therefore, the wavelet coefficients and scale coefficients of DTCWT can be obtained [7]:

\[ b^w_i (n) = b^w_{rev} (n) + i b^w_{rev2} (n) \]  

(5) 

\[ b^s_i (n) = b^s_{rev} (n) + i b^s_{rev2} (n) \]  

(6) 

Finally, the wavelet coefficients and scale coefficients of DTCWT can be reconstructed by equations (7) and (8).

\[ b_i (t) = 2^{j/2} \left[ \sum_{n=-\infty}^{\infty} b^w_{rev} (n) \mathcal{P}^j_s (2^j t - n) + \sum_{k=-\infty}^{\infty} b^w_{rev2} (n) \mathcal{P}^j_s (2^j t - k) \right] \]  

(7) 

\[ d_i (t) = 2^{j/2} \left[ \sum_{n=-\infty}^{\infty} d^s_{rev} (n) \mathcal{P}^j_s (2^j t - n) + \sum_{k=-\infty}^{\infty} d^s_{rev2} (n) \mathcal{P}^j_s (2^j t - k) \right] \]  

(8) 

The reconstructed signal after DTCWT transformation can be expressed as formula (9).

\[ y(t) = b_i (t) + d_i (t) \]  

(9) 

2.2. Long and Short Term Memory Network

LSTM is a kind of recurrent neural network. Its internal structure mainly eliminates or increases the corresponding information through the gate, so as to get rid of the problem of insufficient gradient in the traditional recurrent neural network (RNN) training [10]. It establishes a storage unit inside, saves its sequence through memory event structure, and further extracts it from the training model. In the information storage, LSTM adds "forgetting gate" and "input gate". The "forgetting gate" is used to eliminate the invalid information components in the network, while the "input gate" adds corresponding effective new information. The combination of the two forms a network model with signal filtering and optimization [11-12]. The LSTM algorithm model is as follows:

\[ f_t = \sigma(W_f \{ h_{t-1}, x_t \} + b_f) \] 

\[ i_t = \sigma(W_i \{ h_{t-1}, x_t \} + b_i) \] 

\[ g_t = \tanh(W_g \{ h_{t-1}, x_t \} + b_g) \] 

\[ o_t = \sigma(W_o \{ h_{t-1}, x_t \} + b_o) \] 

\[ c_t = f_t * c_{t-1} + i_t * g_t \] 

\[ h_t = o_t * \tanh(c_t) \]  

(10) 

Among them, ft, it, gt, and ot are the output values of forgetting gate, input gate, update gate and output gate respectively. Wf, Wi, Wg and Wo are the link weights of each gate, and Bf, Bi, BG and Bo are the offset of each gate respectively. The input of the four gates includes the output value HT-1 of the LSTM at T-1 time and the input value XT at the present time. CT temporary information storage unit. \( \sigma \) is the sigmoid excitation function [13-14]. The structure of LSTM is shown in the figure below.

Figure 2. Configuration of the LSTM model.
3. Wind and Solar Integrated Power Prediction Model

3.1. Analysis of Influencing Factors of Wind and Solar Integrated Power Prediction

(a) Analysis of Influencing Factors of Wind Farm

According to the statistical investigation, the factors that affect the output power of wind turbines are mainly reflected in two aspects. One is environmental factors: wind speed, wind direction, ambient temperature, humidity and air pressure; the other is the influence factors of wind power installation location and equipment itself: generator type, installed capacity, equipment operation status, etc. In this paper, five key factors, namely wind speed $f_1$, ambient temperature $f_2$, humidity $f_3$, installed capacity $f_4$ and operating voltage $f_5$, are selected as the input set of subsequent power prediction model.

(b) Analysis of photovoltaic power factor

According to the reference [8], the main factors affecting the output power of photovoltaic power generation are: total radiation, direct radiation, scattered radiation, environmental temperature, module temperature, relative humidity, air pressure, wind speed, wind direction, cloud cover and other meteorological factors, as well as basic information such as longitude and latitude, altitude, angle of entry, capacity of photovoltaic power station, etc., but the key factor is total radiation $g_1$ Ambient temperature $g_2$, module temperature $g_3$, altitude $g_4$, incident angle $g_5$. In order not to affect the calculation speed of the model, this paper selects the key photovoltaic influencing factors: total radiation $g_1$, ambient temperature $g_2$, module temperature $g_3$, altitude $g_4$, incident angle $g_5$ as the input of the subsequent LSTM model.

3.2. Prediction Model Based on DT-CWT and LSTM

The wind and solar integrated prediction model based on DT-CWT and LSTM uses DT-CWT to decompose the output power signals of wind power and photovoltaic after noise reduction. Combined with various influencing factors of wind power and photovoltaic as multi port LSTM input, through the training of LSTM network, the prediction curve of integrated wind and solar output power is finally obtained. The prediction model based on DT-CWT and LSTM can not only improve the noise reduction performance, but also improve the prediction accuracy of wind and solar integrated output power, which can provide guidance and support for reasonable power dispatching, operation and maintenance. The algorithm flow of the integrated prediction model based on DT-CWT and LSTM is shown in Figure 3.

Implementation steps of wind and solar integrated prediction based on DT-CWT and LSTM:

1) The original data includes wind power $P_1$, photovoltaic output power $P_2$, wind power output factors (wind speed $f_1$, ambient temperature $f_2$, humidity $f_3$, equipment installed capacity $f_4$ and equipment operating voltage $f_5$), photovoltaic output power influencing factors (total radiation $G_1$, ambient temperature $G_2$, module temperature $G_3$, altitude $G_4$, incident angle $G_5$) The on-line monitoring system of the power station can obtain real-time data.

2) Data denoising and preprocessing. The data of wind power $P_1$ and photovoltaic output power $P_2$ are decomposed by DT-CWT algorithm. The decomposed wavelet transform coefficients are transformed by inverse DT-CWT to obtain two groups of wavelet components, which are wind power $P_{h1}$ and photovoltaic output power $P_{h2}$ after noise reduction.
(3) The wind power output power $P_{h1}$, photovoltaic output power $P_{h2}$, wind power output power influence factors (wind speed $f_1$, ambient temperature $f_2$, humidity $f_3$, equipment installed capacity $f_4$ and equipment operating voltage $f_5$), photovoltaic output power influencing factors (total radiation $g_1$, ambient temperature $g_2$, component temperature $g_3$, altitude $g_4$, incident angle $g_5$) after noise reduction $H_1$ and influencing factors form wind power input matrix $X_1$, photovoltaic output power $P_{h2}$ after noise reduction and influencing factors photovoltaic input matrix $X_2$, $X_1$ and $X_2$ matrix models are shown in formula (4). $X_1$ and $X_2$ are input into the long-term and short-term memory network to train the prediction model. Finally, the data of wind power prediction power $P_{y1}$ and photovoltaic power prediction power $P_{y2}$ are obtained.

$$X_1 = [P_{h1}, f_1, f_2, f_3, f_4, f_5]$$
$$X_1 = [P_{h2}, g_1, g_2, g_3, g_4, g_5]$$

(4) The prediction curve was fitted. In this paper, the least square method is used to fit the data of wind power predicted power $P_{y1}$ and photovoltaic power $P_{y2}$, and the prediction curves of wind power predicted power $P_{y1}$ and photovoltaic predicted power $P_{y2}$ are obtained. The least square fitting model is as follows:
\[ P_i (P_h) = \sum_{i=0}^{n} a_i P_h^i \]

\[ \eta = \min \sum_{i=0}^{n} \left[ P_h^i - y_i \right]^2 \]

(12)

4. Field Data Verification

In order to verify the validity and feasibility of the model, this paper selects the measured power data of a wind farm and photovoltaic power station in ShanXi province for verification. There are 133892 data, 80% of which are training data and 20% are prediction data. As shown in Fig. 4, the process of 800 iterative training for the above data is shown.

![Figure 4. Data iteration training process.](image)

The prediction results of wind power data are shown in Figure 5 (each point on the abscissa represents 5 minutes, and the ordinate is the output power)

![Figure 5. Prediction results of wind power data.](image)

The following figure shows the prediction results of photovoltaic data, as shown in Figure 6 (each point on the abscissa represents 5 minutes, and the ordinate represents the output power)
From Figures 4 to 6, it can be seen that the model has a good accuracy for the wind and solar integration prediction. Through the statistical analysis of the data, the average accuracy rate of wind power prediction is 94.7%; the average accuracy rate of photovoltaic prediction calculation is 96.5%. The effectiveness and feasibility of the model are verified by the actual data input.

5. Conclusion
Wind and solar integration has become a research hotspot in the next generation power grid. Power prediction is a key link in the application of wind and solar hybrid system, which plays an important role in the effective consumption of renewable energy and the flexible conversion of electric energy. In this paper, based on the existing power prediction methods, a wind and solar integrated power prediction method based on dual tree complex wavelet and long-term memory network is eliminated. This method can effectively reduce the impact of power noise during prediction, and improve the accuracy of power prediction of wind and solar hybrid power supply system.

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