Wind Speed Prediction with Wavelet Time Series Based on Lorenz Disturbance

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***Abstract*—Due to the sustainable and pollution-free characteristics, wind energy has been one of the fastest growing renewable energy sources. However, the intermittent and random fluctuation of wind speed presents many challenges for reliable wind power integration and normal operation of wind farm. Accurate wind speed prediction is the key to ensure the safe operation of power system and to develop wind energy resources. Therefore, this paper has presented a wavelet time series wind speed prediction model based on Lorenz disturbance. Therefore, in this paper, combined with the atmospheric dynamical system, a wavelet-time series improved wind speed prediction model based on Lorenz disturbance is proposed and the wind turbines of different climate types in Spain and China are used to simulate the disturbances of Lorenz equations with different initial values. The prediction results show that the improved model can effectively correct the preliminary prediction of wind speed, improving the prediction. In a word, the research work in this paper will be helpful to arrange the electric power dispatching plan and ensure the normal operation of the wind farm.**

***Index Terms*—ARMA model, Lorenz system, renewable energy, wavelet decomposition, wind speed prediction.**

I. INTRODUCTION

The increase of energy demand and the negative impact of fossil fuel consumption on global climate have set off a worldwide boom in renewable energy. The rapid development of renewable energy is coping well with the energy shortage and environment deterioration, so the demand for coal, oil, gas and other traditional fossil fuels will be less and less, thus forming a virtuous cycle of energy and environment.

According to the 2016 medium-term renewable energy market report released by International Energy Agency (IEA) , in 2015, renewable energy had become the world's largest source of new installed capacity, exceeding coal, and it can be expected that renewable energy installed capacity will continue to grow in the next five years. As an effective way to utilize wind energy resources, wind power generation has become the research object of each country. According to the 2015 annual report of IEA wind energy, in 2015, the global wind power installed capacity increased by 63GW, the total reached 433GW, meeting 4% of the world's electricity needs. However, wind power is still facing some challenges, including the instability of its output and its bad impact on power system operation. Reliable wind power forecasting is helpful for the power dispatching department to adjust the overall scheduling plan, configure the reasonable output of wind turbine, and save the conventional power generation. At the same time, the accuracy of wind power prediction is also the key factor to reduce the cost of power generation and maintain the competitiveness in the electricity market [1]. Therefore, the research on wind power development is focused on the improvement of wind speed and power prediction methods.

At present, short-term wind speed forecasting methods include Kalman filtering [2], neural network [3-5], grey prediction [6], time series [7, 8] support vector machine [9, 10] and so on. The above methods have their own advantages and some limitations. For example, neural network requires a large number of sample data for training and the selection of adjacent neighborhood points is difficult; Grey system theory is unsuitable for the prediction for non-stationary wind speed data. Supported Vector Machine (SVM) algorithm [11] is difficult to train with a large sample. Among these algorithms, the time series model [12] can be used to build precise prediction models with limited sample sequences and thus widely used, among which Autoregressive Integrated Moving Average (ARIMA) is the most typical model, transforming non-stationary time series into stationary time series, in which, taking the lagged value of the dependent variable, the present value and the lagged value of the random error term as independent variables, regression analysis is carried out.

The actual wind energy in the atmospheric system presents a typical non-linear characteristic, the randomness and volatility of wind speed poses a huge challenge to forecasting [13, 14]. As a deterministic system, the atmospheric dynamical system can be described by a set of Lorenz equations and the slight differences in the initial condition of the Lorenz equation will make the Lorenz equation to show different morphologies in the subsequent motions. Therefore, in the process of wind speed prediction, the atmospheric disturbance effect in the atmospheric dynamical system should be fully considered and the Lorenz system should be introduced as compensation for atmospheric disturbance, so that the wind speed prediction sequence can be more in line with the actual change rules of wind speed.

Considering the non-stationary wind speed sequences, the wavelet-time series model based on Lorenz system is established in this paper. Firstly, the non-stationary wind speed sequence is decomposed with wavelet decomposition and the trend sequence is predicted linearly, thus the original wind sequence are decomposed into single, smooth

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sequences and the time series modeling for these stationary sequences will have great improvement for the prediction effect than the time series on non-stationary sequence. At the same time, the Lorenz equation is used as the atmospheric disturbance model to explore the influence of the Lorenz equation with different initial conditions on the wind speed prediction disturbance to improve the prediction level of wind speed.

The structure of this paper is as follows: the Lorenz system and its movement pattern are introduced in the section II; The section III describes the modeling process of wavelet time series model; On the basis of the wavelet time series model, the wind speed forecasting model based on Lorenz disturbance is established in the section IV; The section V is the comparison of the prediction results and error analysis; The section VI summarizes the full text and makes the next research plan.

II. LORENZ SYSTEM

Before the chaos, scientists had assumed that there were only four types of solutions to differential equations: fixed points, limit cycles, two-dimensional tori and divergent orbits. In 1962, Saltzman presented a seven variable fluid convection equation (1) in the study of thermal convection. The model was confined to a parallel layer with a fixed height, and the two layers remained at the same constant temperature difference. In 1963, E.N.Lorenz, a meteorologist at the Massachusetts Institute of Technology, obtained an ordinary differential equation (2) of a three-dimensional nonlinear system in the study of the convective nature of weather by simplifying the convection equation of the fluid [15,16], the equation is regarded as the first dynamical system showing chaotic state in the simplest way, which provides a theoretical basis for the later scholars to study the nonlinear nature of atmospheric dynamical systems and the dynamics of wind energy.

$$\begin{cases} \dfrac{\partial}{\partial t}\nabla^2\psi + \dfrac{\partial(\psi,\nabla^2\psi)}{\partial(x,z)} - g\varsigma\dfrac{\partial\theta}{\partial x} - \upsilon\nabla^4\psi = 0 \\ \dfrac{\partial\theta}{\partial t} + \dfrac{\partial(\psi,\theta)}{\partial(x,z)} - \dfrac{\Delta T_0}{H}\dfrac{\partial\psi}{\partial x} - \kappa\nabla^2\theta = 0 \end{cases} \tag{1}$$

where, ψ denotes a two-dimensional stream function, θ denotes a temperature difference from an equilibrium state, constants $g,\varsigma,\upsilon,\kappa$ denote gravity acceleration, thermal expansion coefficient, viscosity coefficient, and thermal conductivity respectively.

$$\begin{cases} \dot{x} = \sigma(y-x) \\ \dot{y} = -xz + rx - y \\ \dot{z} = xy - bz \end{cases} \tag{2}$$

where, x,y,z denote state variables, respectively, the intensity of convective motion, convective fluid flow in the horizontal and vertical temperature difference of temperature on the degree of deviation when no convection. σ,r,b denote dimensionless positive real numbers, which represent Prandtl number, Rayleigh number, and the amount associated with the size of the climate region. For the classical Lorenz system parameters $\sigma=10, b=\dfrac{8}{3}, r=28$, given the initial value $h=(x,y,z)=(1.1,1,1)$, for almost all initial conditions of the state, its system will belongs to an invariant set, as shown in Figure 1, indicating that the system has entered a chaotic state. The discovery of Lorenz system breaks the insurmountable obstacle between determinism and stochastic theory, and is widely used in science, engineering and mathematics as an interesting nonlinear dynamic phenomenon.

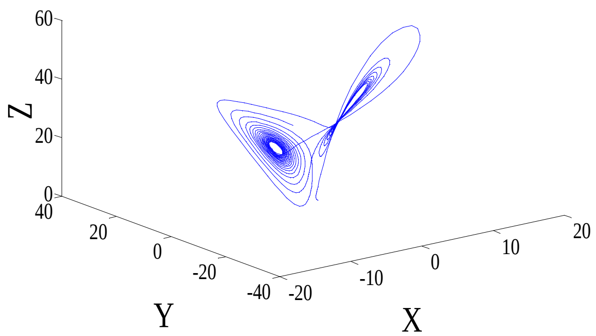
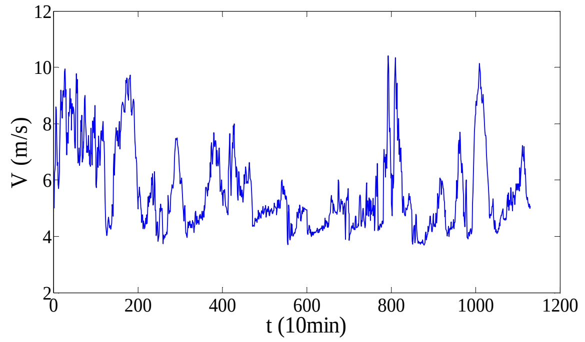


Figure 1. Lorenz attractor morphology with parameters $\sigma=10, b=\dfrac{8}{3}, r=28$

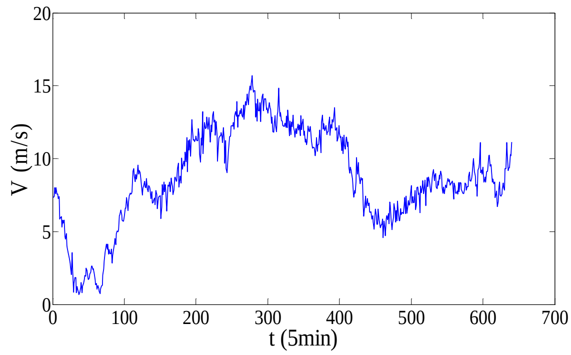
III. WIND SPEED PREDICTION WITH WAVELET TIME SERIES

The randomness of wind speed is a typical nonlinear process and can be considered a nonlinear time series. The chronological order shows the order of data and the size of the data, which can show the dynamic process of wind speed and reflect the change of atmospheric motion. Wavelet analysis [17, 18] has a good time-frequency localization properties, through which the signal can be decomposed into the signal corresponding cycles, revealing the signal changes better. Therefore, the wind speed sequence, which is processed by wavelet, exhibits weak non-stationarity and can be more in line with the changing law of time series, reflecting the intrinsic nature of wind speed more accurately. Above all, this section combines the advantages of wavelet analysis and time series to establish a new wind speed prediction model.

In order to verify the adaptability of the research methods for different wind farms, we used the wind farm data of two different climatic types in Spain [19] and China to carry out modeling experiments. As shown in Figure 2, the wind speed distributions of the two wind farm in a given time period are respectively indicated. The measurement interval of Spanish wind speed data is 10min, and in China is 5min. It is obvious that the fluctuation of wind speed is stochastic and has a great fluctuation in a short period of time.



(a) Spanish wind farm (The t in all figure of the paper represents the number of data)

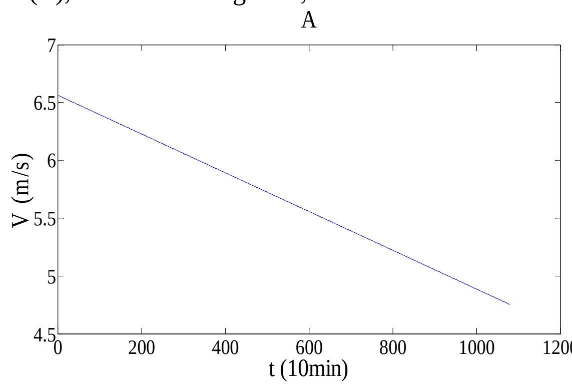


(b) China wind farm

Figure 2. Wind speed distribution

The wavelet-time series wind speed prediction models are established for the wind farms in Spain and China. The following is the detailed modeling process of the Spanish wind farm and the modeling process of the Chinese wind farm is similar.

(1) Decompose the training set of the original wind speed sequence into the trend item (A) and the item without trend(B), as shown in Figure 3;



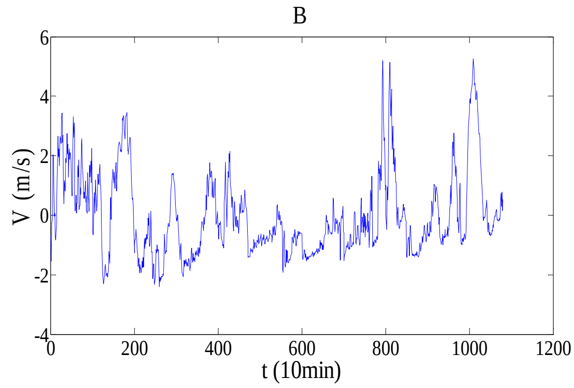


Figure 3. Trend series (A) and detrended series (B) of wind speed training set

(2) The Mallat algorithm is used for the wavelet transform of wind speed detrend sequences (B). Based on the multiresolution space decomposition of the function, the relation between wavelet transform and multiresolution decomposition is established and thus the fast wavelet transform is implemented by Mallat algorithm. Mallat fast wavelet decomposition [20] algorithm can be described as follows:

$$\begin{cases} c_{j,k} = \sum_{n \in Z} c_{j-1,k} h_{n-2k} \\ d_{j,k} = \sum_{n \in Z} d_{j-1,k} g_{n-2k} \end{cases} \tag{3}$$

$c_{j,k}$ denotes the low frequency information of original signal; $d_{j,k}$ denotes the high frequency; g_n denotes the impulse response of high pass filter associated with wavelet function; h_n denotes pulse response of low pass filter related to scaling function. When $j=1$ j=1, it represents the wind trend sequence (B), which can be used to obtain the low frequency and high frequency coefficients of the detrended series through several decompositions by g_n and h_n. Finally, the Mallat fast wavelet is used to reconstruct the operation and the formula is as follows:

$$c_{j-1,k} = \sum_n \left(h_{k-2n} c_{j,n} + g_{k-2n} d_{j,n} \right) \tag{4}$$

Since the wind speed detrended sequence (B) is a non-stationary random time series, the Daubechies wavelet is used to decompose it into 3 layers. The reconstructed signals are A3, D3, D2 and D1. A3 is low frequency information, D3, D2 and D1 is high frequency information. B=A3+D1+D2+D3, as shown in figure 4;

(3) Linear prediction of the trend item (A) is carried out and the ARMA model is used to predict the low frequency band signal (A3) and the high frequency band signals (D3, D2, D1) after the wavelet decomposition (the ARMA model of wavelet decomposition is uniformly denoted as W-ARMA);

(4) The prediction results of the high and low frequency bands are combined and then combined with the prediction results of the trend item to obtain the preliminary prediction value of the wind speed v_t.

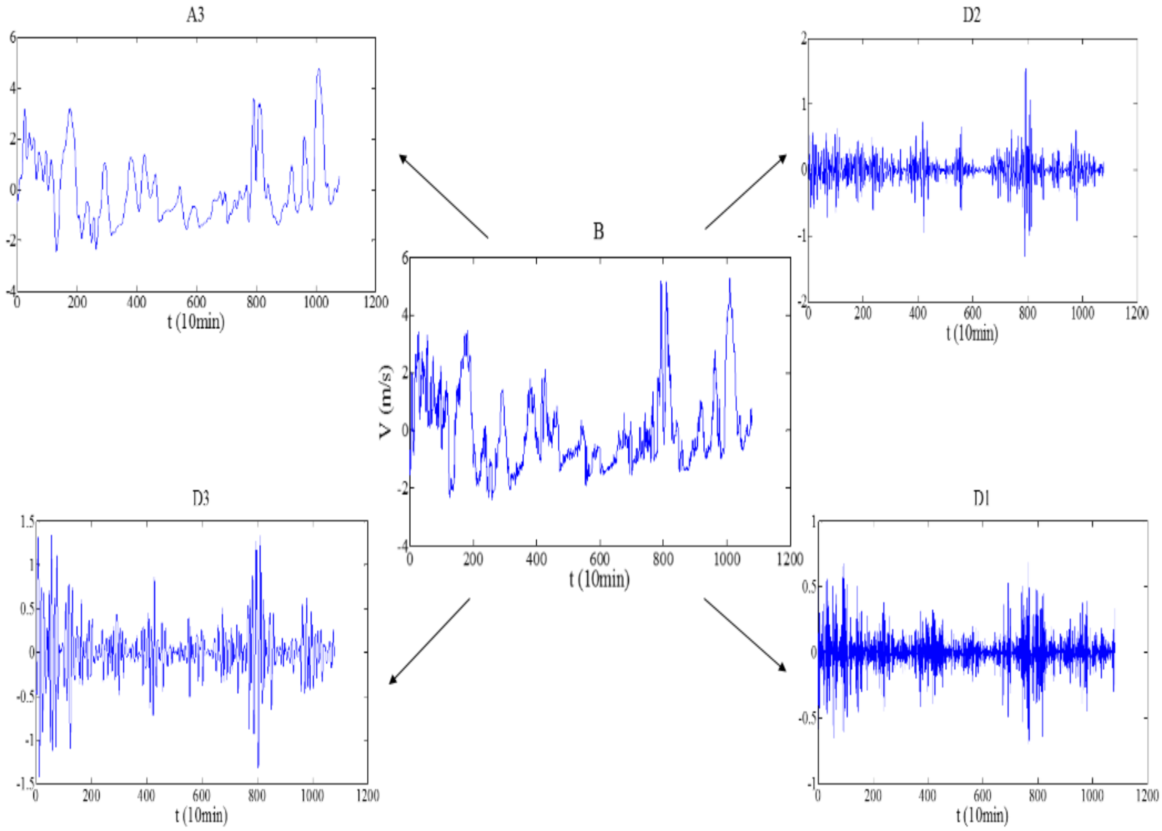


Figure 4. Wavelet decomposition of wind speed detrended series

IV. Wind Speed Prediction with Wavelet Time Series Based on Lorenz Disturbance

It can be clearly seen from Figure 2 that for the same parameters, the small differences in the initial conditions make the Lorenz attractor exhibit different morphologies. The small interference of the atmospheric system may have an unavoidable effect on the wind power prediction. In this section, we use the Lorenz disturbance to improve the W-ARMA prediction model of the two wind farms, that is, by optimizing the wind speed prediction by the disturbance sequence, better predictive results will be obtained. At the same time, Back Propagation (BP) neural network prediction model [21] is used as the contrast model.

The modeling step of the W-ARMA wind speed prediction model based on Lorenz is as follows:

First, solve the Lorenz equation. In this section, the parameters of Lorenz equation of the section II are set as follows: $\sigma = 10, b = \frac{8}{3}, r = 28$. The initial conditions are $h = (0.01,1,1)$ and $h = (0.001,1,1)$ respectively. At present, the Lorenz equation is in an unstable state and exhibits chaotic states of randomness. The fourth-order Runge-Kutta method is used to solve the Lorenz equation, and the time series of the two sets of disturbance variables x, y, z are obtained as shown in figure 5. It can be seen that the subtle changes in the initial conditions during the evolution of time will make the orbit of the system state in the form of exponential separation [22].

The second is the formation of Lorenz comprehensive disturbance flow (LCDF). The solution space of Lorenz equation is a three-dimensional vector, while wind velocity is a one-dimensional real number. In order to eliminate the influence of different dimensions, we introduce Manhattan distance as the mapping function to reduce the dimension of disturbance variables. A three-dimensional disturbance variable can be mapped by Manhattan distance as a distance function, called LCDF [21, 23]. Before calculating the LCDF, we first need to standardize the data to eliminate the influence of the order of magnitude, the formula is:

$$\hat{x}_t = \frac{x_t - \overline{x}}{S_x}, \hat{y}_t = \frac{y_t - \overline{y}}{S_y}, \hat{z}_t = \frac{z_t - \overline{z}}{S_z} \tag{5}$$

where, $x_t, y_t, z_t, t = 1, 2, ..., n$ represents the numerical solution of Lorenz equation, $\overline{x}, \overline{y}, \overline{z}$ and S_x, S_y, S_z , respectively denote mean and standard deviation of $\{x_t\}, \{y_t\}, \{z_t\}$. In order to facilitate the unity of writing symbols, the normalized data $(\hat{x}_t, \hat{y}_t, \hat{z}_t)$ will be still denoted (x_t, y_t, z_t).

The Manhattan distance is defined as:

$$d_M(h_t, h_0) = |x_t - x_0| + |y_t - y_0| + |z_t - z_0| \tag{6}$$

where, $h_t(x_t, y_t, z_t)$ represents the movement state at a certain moment in the Lorenz system, and $h_0(x_0, y_0, z_0)$ is the equilibrium state.

By the formula (2) - (4), the three-dimensional solutions of the Lorenz equation can be normalized and the Manhattan distance relative to the initial state can be obtained, that is, Lorenz integrated disturbance flow. The disturbance is shown in Figure 6.

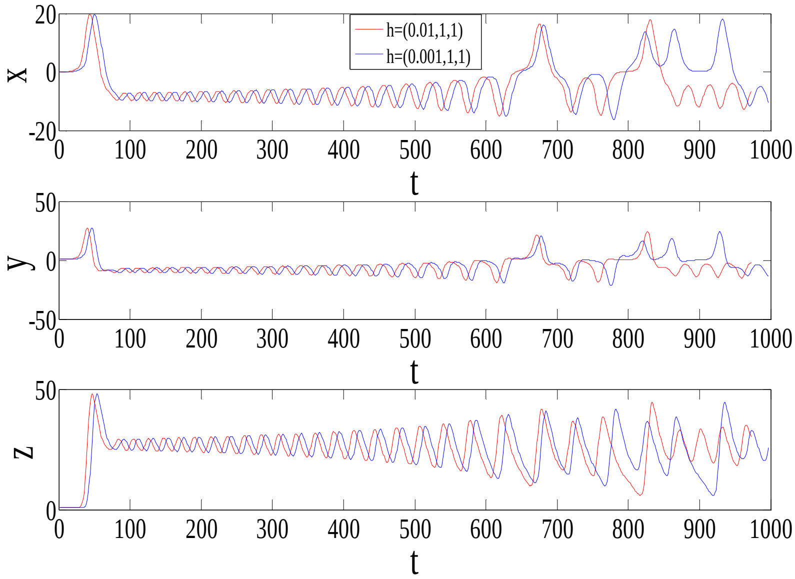


Figure 5. The solution curves of the disturbance variables x, y, z of the Lorenz equation

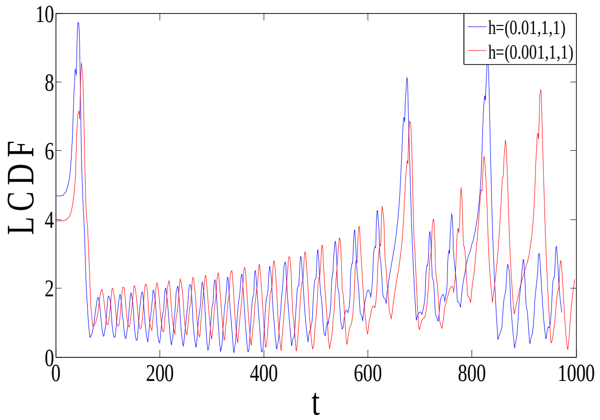


Figure 6. The distribution of LCDF in Manhattan distance form

The third step: the correction effect of Lorenz Comprehensive Disturbance Flow on v_t is discussed. In this paper, the disturbance model corresponding to W-ARMA model is named LD-W-ARMA model, and its disturbance correction formula is defined as

$$f_{LD}\left(v_1,v_2,\ldots,v_k\right)=v\left(v_1,v_2,\ldots,v_k\right)+LD\left(l_1,l_2,\ldots,l_k\right) \quad (7)$$

where, $f_{LD}\left(v_1,v_2,\ldots,v_k\right)$ denotes the corrected wind speed prediction value; $v\left(v_1,v_2,\ldots,v_k\right)$ denotes the preliminary wind velocity prediction value; $LD\left(l_1,l_2,\ldots,l_k\right)$ denotes the applied Lorenz disturbance amount, defined as

$$LD\left(l_1,l_2,\ldots,l_k\right)=a\times L\left(l_1,l_2,\ldots,l_k\right) \quad (8)$$

where, a denotes the disturbance coefficient, which signifies the positive and negative enhancement of the disturbance sequence respectively. $L\left(l_1,l_2,\ldots,l_k\right)$ denotes a continuous sequence of the LCDF disturbance sequence, indicating the disturbance intensity, and k denotes the number of prediction samples. In the process of establishing the wind speed prediction model, the optimal perturbation coefficients and perturbation intensities can be obtained with the objective of minimizing the mean absolute error between the actual wind speed and the predicted value.

Combined with the above wavelet time series wind speed prediction model and the improved wind speed prediction model based on Lorenz system, the detailed modeling flow chart is shown in Figure 7.

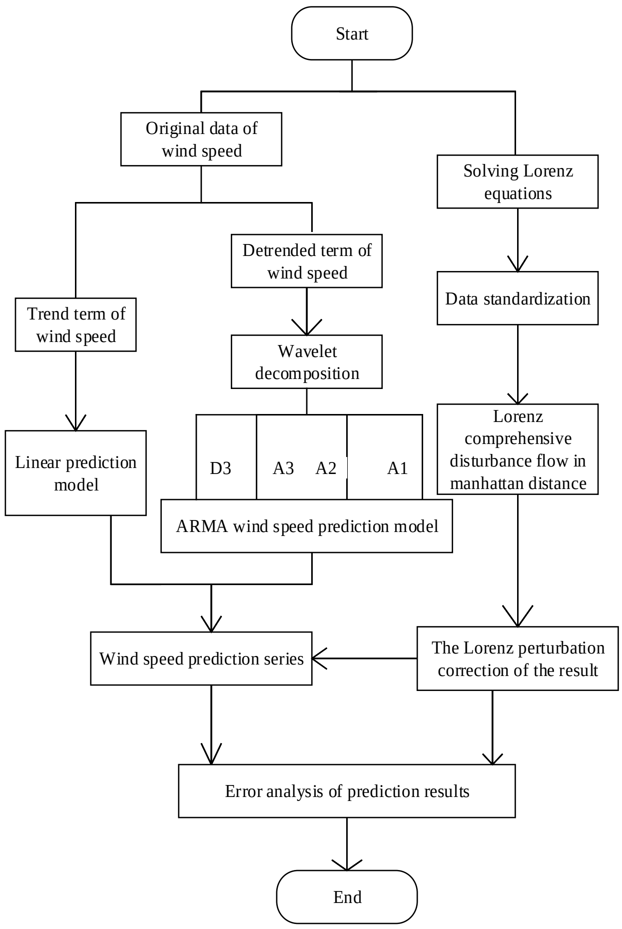
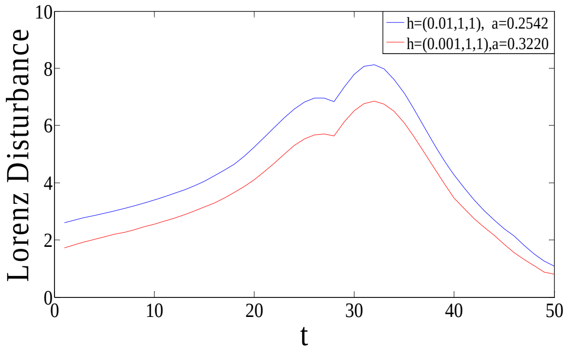


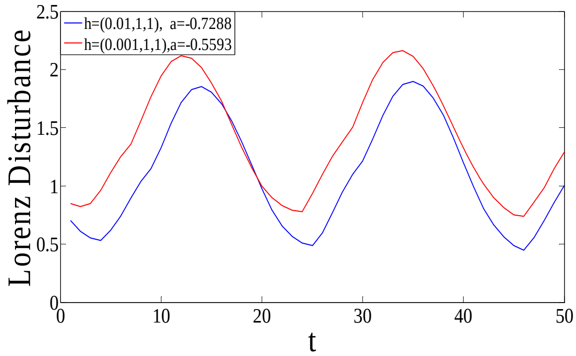
Figure 7. Modeling flow chart of LD-W-ARMA wind speed prediction model

V. LD-W-ARMA Model Results and Error Analysis

Based on the description of section III, IV and the modeling flow chart of Figure 7, wind speed forecasting models for two wind farm based on Lorenz perturbation are established respectively, and the parameters of each models are estimated by using MATLAB software [24]. The optimal perturbation coefficients and perturbation intensities (part of Figure 6) are obtained, as shown in figure 8. The trends of the two disturbance intensity curves of two farms are almost the same, but the numerical difference is large. The disturbance coefficient of the Spanish wind farm in Figure 8 (a) is positive, indicating that the preliminary prediction sequence of the wind speed is smaller than the actual wind speed sequence value, thus the positive disturbance sequence is needed to be modified. The disturbance coefficient of the Chinese wind farm in Figure 8 (b) is negative, indicating that the wind speed prediction sequence value is greater than the actual wind speed sequence, needing an imposing of a negative disturbance sequence correction. For the same wind farm, with different initial values of the Lorenz equation, the optimal Lorenz disturbance intensity and disturbance coefficient are different, but the sign of the disturbance coefficient are consistent, which depends on the preliminary prediction of wind speed.



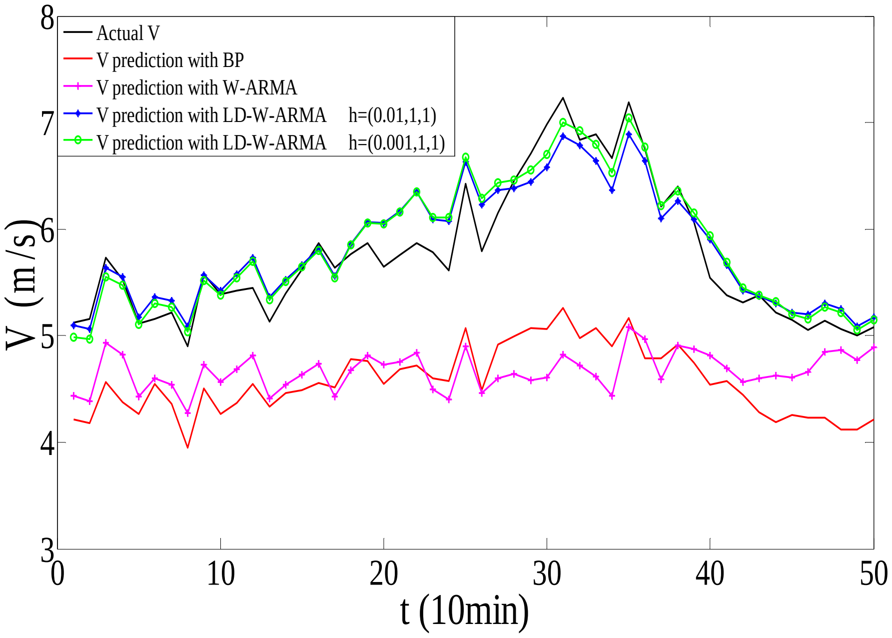
(a) Wind farm of Spain



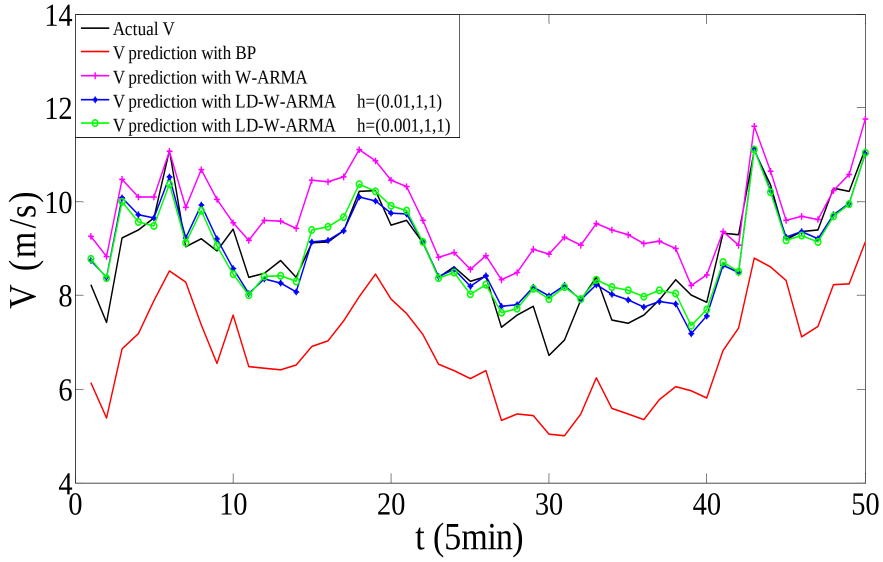
(b) Wind farm of China

Figure 8. The disturbance intensity and disturbance coefficient of LD-W-ARMA model. h represents the initial value, and a represents the disturbance coefficient.

According to the preliminary prediction value of wind speed and optimal Lorenz disturbance intensity and disturbance coefficient, the wind speed prediction curves of different wind farms and models can be obtained as shown in figure 9. We can see that wind speed prediction curve of BP neural network model and W-ARMA model of two wind farm can describe the trend of the original wind speed series, but the W-ARMA model is closer to the original wind speed data. It is clear that the pink prediction sequence obtained from the W-ARMA model of the Spanish wind farm is below the original wind speed data, requiring a positive disturbance sequence to be added to make it more consistent with the original wind speed sequence; the preliminary prediction of the wind speed obtained from the W-ARMA model of the Chinese wind farm is above the original wind speed sequence, requiring a negative disturbance sequence. This is consistent with the sign of the optimal disturbance coefficients we get. The LD-W-ARMA models after Lorenz equation disturbance correction with the initial values $(0.01,1,1)$ and $(0.001,1,1)$ are also closer to the actual wind speed sequence while maintaining the trend of



(a)Wind farm of Spain



(b)Wind farm of China

Figure 9. Wind speed prediction curve of LD-W-ARMA model

the original wind speed sequence. This fully shows that for different wind farms, the perturbation sequence obtained by Lorenz equations with different initial values modifies the initial prediction wind speed series to a certain extent, and the satisfactory prediction results are obtained.

In this paper, the LD-W-ARMA model is established using the data of two wind farms. The mean absolute error (MAE), root mean square error (RMSE) and absolute mean percentage error (MAPE) and the comprehensive evaluation is carried out, and the calculation is shown in formula (7). The prediction accuracy of each model are shown in Table I, we can see that the prediction accuracy of the BP neural network model is larger than that of the W-ARMA model. At the same time, the error indexes of both the two models are much larger than the prediction accuracy of the corresponding Lorenz disturbance model. This not only shows that the prediction effect of the ARMA model after wavelet processing is significant, but also shows the good improvement effect of the Lorenz equation on the preliminary prediction of wind speed. In the prediction model of the Spanish wind farm, the MAE of the LD-W-ARMA model with initial values of $(0.01,1,1)$ and $(0.001,1,1)$ decreased by 83.5% and 85.2% respectively, and the RMSE decreased by 83.0 % at least and the two indexes decreased by 58.5% and 53.2% respectively in China model. These intuitionistic data show that with the Lorenz equation as the disturbance model, the Lorenz disturbance significantly improves the prediction results of the wind speed and the prediction accuracy of the model. For different initial values, the disturbance effect of the Lorenz equation is different, but the preliminary prediction sequence of wind speed is modified to a certain extent and satisfactory prediction results can be obtained.

$$
\begin{aligned}
MAE &= \frac{1}{k}\sum_{t=1}^{k}\left|v(t)-f(t)\right| \\
RMSE &= \sqrt{\frac{1}{k}\sum_{t=1}^{k}\left(v(t)-f(t)\right)^2} \\
MAPE &= \frac{1}{k}\sum_{t=1}^{k}\left|\frac{v(t)-f(t)}{v(t)}\right|\times 100
\end{aligned}
\tag{9}
$$

where, $v(t)$ denotes the original values of wind speed; $f(t)$ denotes the prediction values of wind speed; k denotes the number of prediction samples.

TABLE I. ERROR ANALYSIS WIND SPEED PREDICTION MODELS

Model / Error	Wind farm in Spain				Wind farm in China			
	BP	W-ARMA	LD-W-ARMA (0.01,1,1)	LD-W-ARMA (0.001,1,1)	BP	W-ARMA	LD-W-ARMA (0.01,1,1)	LD-W-ARMA (0.001,1,1)
MAE(m/s)	1.1849	1.0888	0.1802	0.1614	2.0199	0.8400	0.3367	0.3479
RMSE(m/s)	1.2359	1.2417	0.2231	0.2093	2.0455	0.9983	0.4670	0.4640
MAPE(%)	20.23	18.10	3.10	2.81	23.15	10.11	4.03	4.14

VI. CONCLUSION

In this paper, the wavelet time series wind speed prediction model based on Lorenz perturbation is established, and the simulation experiment is carried out using the measured data of wind farm in two different regions of Spain and china. The experimental results show that for different wind farms, Lorenz equation effectively improves the prediction accuracy of wind speed; for the same wind farm, the Lorenz equation with different initial values has different effects on the wind speed prediction model, but prediction accuracies of all the original models were greatly improved.

In view of the significant improvement effect of Lorenz disturbance on the wind speed prediction model, we will continue to consider the influence of Lorenz equations with different Rayleigh numbers on the wind power prediction in the next research work to achieve a better prediction.

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