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A Novel Hybrid Model for Wind Speed Prediction Based on VMD and Neural Network Considering Atmospheric Uncertainties

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ABSTRACT Considering the strong fluctuation and the nonlinearity of wind speed, and atmospheric uncertainties, wind speed prediction based on the hybrid model is presented, which is composed of the neural network, variational mode decomposition (VMD), and Lorenz disturbance. First, the VMD is used to process the data to get several intrinsic mode functions (IMFs). Second, the neural network model (NN model) can be established by these IMFs of the training set, and the validation set is used to adjust the model parameters. Subsequently, given the nonlinearity of wind speed, Lorenz disturbance is added to determine the finial model, and the best Lorenz disturbance parameter and the best Lorenz disturbance sequence can be obtained by minimizing the mean absolute error of validation set. At last, the wind speed can be forecasted by the hybrid model. Taking Sotavento wind farm in Spain as an example, the results show that, the hybrid model has stable prediction performance, and the distribution characteristics of its results are consistent with the actual wind speed. The general model only focuses on improving prediction accuracy. However, on the basis of improving the forecasting accuracy, the proposed model not only enhances the prediction stability, but also restores the characteristics of wind speed. This research work provides a more scientific basis for wind power dispatching arrangement, and it is of great significance to improve the utilization rate of wind power.

INDEX TERMS Wind speed, neural network, Lorenz disturbance, VMD, hybrid model, atmospheric uncertainties.

I. INTRODUCTION

'New Energy Outlook 2017' in the Bloomberg New Energy Finance (BNFN)[1] shows that, with the cost of renewable energy decreasing, global total investment in power generation will continue to increase in the next 20 years, renewable energy presents a good growth trend. The Asia-Pacific region will be the main market for energy investment, and its total investment scale will be roughly equivalent to the sum of the rest regions, in which wind power and solar energy nearly account for 1/3 respectively. According to the global wind energy council (GWEC) [2], in 2017, the global cumulative installed capacity of wind power exceeded 539 GW, the global annual installed capacity is 52.6 GW, and the new installed capacity of Asia and China is 24.4 GW and 19.5 GW respectively. Asia has become an important market for renewable energy, and China has become the country with the largest wind power development in the world.

Wind power, with the characteristics of low cost and non-pollution, has attracted the worldwide attention, but the randomness, volatility of wind speed and intermittency of wind power make its developments face great challenges. Therefore, accurate and stable wind power prediction is essential, which not only contributes to the stability of wind power system, but also can provide a scientific basis for making dispatching plan.

There are many methods to improve the prediction accuracy of wind power, such as the data preprocessing technology, the proper prediction model and so on. At present, there are many technologies of preprocessing data, such as wavelet

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transform [17], [29], [30], empirical mode decomposition (EMD) [15], [16], [18], principle component analysis [31], [26] and cluster analysis [35]. Principle component analysis and cluster analysis are used to process the multivariate data, wavelet transform and empirical mode decomposition (EMD) are used for single variables or highly volatile data. Compared with wavelet transform, EMD not only has the advantage of multiresolution, but also overcomes the difficulty of selecting wavelet basis and determining the decomposition scale. However, EMD exists the problems of end effect and mixed mode. In order to solve the problems of EMD and wavelet transform, variational mode decomposition (VMD) is introduced. Compared with other data processing methods, VMD can decompose wind speed into several IMFs that fluctuates around a central frequency, which helps to restore its fluctuating feature during the prediction process.

At present, the forecasting methods of wind speed can be divided into the statistical method, the physical method, and the artificial intelligence method, among which the statistical method and artificial intelligence method are widely used [3]. Time series method [4]–[6], MCMC [7], [8], support vector machine (SVM) method [9], [10], [34], and neural network [11], [12], [36], are often used to make wind speed and wind power prediction. To depict the mean and fluctuation of wind speed accurately, [5] builds many time series models such as ARIMA, ARIMA-GARCH and ARIMA-GARCH (M), and the results show that ARIMA-GARCH(M) model can reflect the mean of wind speed and its fluctuating trend. SVM has obvious advantage in regression and time series prediction. Therefore, in [10], LS-SVM model is established to make wind speed prediction, then the predicted results are corrected by error. And the results shows that, compared with the single LS-SVM model, the accuracy of the corrected prediction results is improved significantly. In [26], ICA and PCA are utilized to preprocess the wind speed, then RBF neural network is used to predict the wind speed, the prediction results show that the model has a small prediction error and it can effectively display the wind speed characteristics. [32] divides the forecasting into two stages, in the first stage, the adaptive wavelet Neural network is used to do a regression for each decomposition signal, in the second stage, the feed-forward neural network is utilized to transform wind speed into wind power forecast by the nonlinear mapping. The result shows that, compared with the based model, the proposed method is more effective in wind power forecasting. The main purpose of these above methods is upgrading the algorithm itself, they neglect that the uncertain factors in atmosphere also affect the wind speed. In order to quantify the atmospheric uncertainties, the paper introduces the nonlinear system to establish Lorenz disturbance model [13], [14], which can describe the nonlinear characteristic, decrease the effect of uncertain factors, and improve the prediction accuracy.

Given the nonlinearity of wind speed, NN model with strong nonlinearity learning ability is presented. Based on the strong fluctuation of wind speed, the data is preprocessed by VMD. Considering the atmospheric uncertainties, Lorenz disturbance is introduced. To sum up, considering the characteristic of wind speed, the paper establishes a hybird model based on neural network, Lorenz disturbance and VMD.

The structure of this paper is as follows: The second section introduces the theories, which include VMD, neural network and Lorenz system. The third section introduces the wind speed forecasting process in detail, including the calculation of Lorenz disturbance sequence, data analysis and the whole prediction process. The fourth section mainly introduces the prediction results and error analysis, and the fifth section makes a conclusion and gives a prospect.

II. VMD, NEURAL NETWORK AND LORENZ SYSTEM

A. VARIATIONAL MODE DECOMPOSITION

VMD, proposed by Konstantin Dragomiretskiy and Dominique Zosso in 2014, is a self-adaptive, quasi-orthogonal, and completely non-recursive decomposition method [27]. The method uses Hilbert transform and Wiener filter to decompose the signal into several intrinsic mode functions (IMFs) of finite bandwidth. It overcomes the aliasing problem of EMD. The decomposing steps are divided into constructing the variational problem and carrying out VMD algorithm.

The steps of constructing the variational problem are as follows:

Step 1: Each mode function u_k can get its analytic signal $S(t)$ by Hilbert transform, which is

$$S(t) = [\delta(t) + \frac{j}{\pi t}]^* u_k(t) \tag{1}$$

Step 2: The analytic signal of each mode function is multiplied by the estimated central frequency, and it is moved to the base frequency spectrum $B(t)$, which is

$$B(t) = \{[\delta(t) + \frac{j}{\pi t}]^* u_k(t)\} e^{-j\omega_k t} \tag{2}$$

Step 3: Gaussian smoothing is used to solve the bandwidth of each mode function, the sum of each mode function is the decomposed signal $X(t)$ and the constraint variational problem is the minimum sum of the estimated bandwidth in each mode function, that is:

$$\begin{aligned} &\min\{\sum{}_{k=1}^{K} ||\partial_t[(\delta(t) + \frac{j}{\pi t})^* u_k(t)] e^{-j\omega_k t}||_2^2\} \\ &s.t. \sum{}_k u_k = f \end{aligned} \tag{3}$$

In the formula (3), f is the original signal.

To implement VMD, penalty factor α and Lagrange multipliers $\lambda(t)$ are introduced to transform constrained variational problems into non-constrained variational problems. Among them, the augmented Lagrange formula is as follows:

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha\sum_k\left\|\partial_t[\delta_t+\frac{j}{\pi t}*u_k(t)]e^{-j\omega_k t}\right\|_2^2 + \left\|f(t)-\sum_k u_k(t)\right\|_2^2 + <\lambda(t), f(t)-\sum_k u_k(t)> \quad (4)$$

The steps of implementing VMD is as follows:

Step 1: Initialize $\{\hat{u}_k^1\}, \{\omega_k^1\}, \{\hat{\lambda}^1\}, n \leftarrow 0$

Step 2: Upgrade $\{\hat{u}_k^1\}, \{\omega_k^1\}$

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega)-\sum_{i<k}\hat{u}_i^{n+1}(\omega)-\sum_{i>k}\hat{u}_i^{n}(\omega)+\frac{\hat{\lambda}^n(\omega)}{2}}{1+2\alpha(\omega-\omega_k^n)^2} \quad (5)$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty\left|\hat{u}_k^{n+1}(\omega)\right|^2 d'\omega} \quad (6)$$

Step 3: Upgrade λ

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega)+\tau(\hat{f}(\omega)-\sum_k\left|\hat{u}_k^{n+1}(\omega)\right|) \quad (7)$$

Step 4: Repeat the step 2-3 until the convergence condition (8) is reached, then the renewal ends with getting several narrow band IMF.

$$\sum\nolimits_k \left\|\hat{u}_k^{n+1}-\hat{u}_k^n\right\|_2^2 / \left\|\hat{u}_k^n\right\|^2 < e \quad (8)$$

B. NEURAL NETWORK

Artificial neural network is a simplified computational model that simulates the design of human brain, which is characterized by its strong nonlinear mapping ability. This model contains a large number of neurons organized in a hierarchical way for calculation. A classical neural network consists of three layers: input layer, output layer and hidden layer. Compared with the traditional linear algorithm, the advantages of artificial neural network mainly lie in its self-learning function, associative storage function and the ability to search optimal solutions quickly. Wind speed sequence has nonlinear characteristic, so the neural network can embody the nonlinear process of wind speed well. In the paper, data is divided into training set, validation set and test set, the neural network algorithm flow is shown in figure 1.

In this paper, four neural network models are selected, which is long short-term memory(LSTM) neural network [19], [33], back propagation(BP) neural network [20], [21], radial base function (RBF) neural network [22], [23] and Elman neural network [24], [25] respectively. LSTM neural network solves the problem of long-distance dependence and it is suitable for processing time series data. BP Neural Network has the ability to popularize. RBF Neural Network has the advantages of simple structure, fast learning, overcoming local minimum problem and approaching arbitrary nonlinear function. Elman Neural network not only has a fast convergence speed, but also has strong associative memory and optimized computing ability. They are all based on the structure of a three-layer neural network. On the premise of satisfying the accuracy, the basic principle is to minimize the number of hidden layer nodes. The various parameters used in the neural network are shown in table 1.

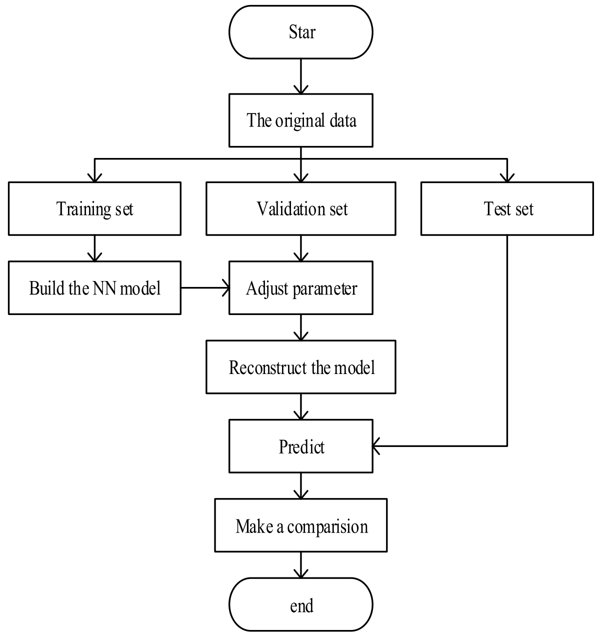


FIGURE 1. The flow chart of neural network prediction.

TABLE 1. The parameters of neural network.

neural networks	Activation function	network structure
LSTM	Sigmoid	1-25-1
BP	Sigmoid	1-18-1
RBF	Gaussian	1-25-1
Elman	Sigmoid	1-18-1

C. LORENZ SYSTEM

In 1963, E.N. Lorenz, a famous meteorologist, firstly discovered chaotic motion to solve mathematical model equations when studying the regional microclimate. While researching in Rayleigh Bernard convection of the regional microclimate, he intercepted the first three of Fourier series to simplify the solution of the nonlinear ordinary differential equation, and Lorenz equation was obtained as follows:

$$\begin{cases} \frac{dx}{dt} = -\sigma(x-y) \\ \frac{dy}{dt} = -xz+rx-y \\ \frac{dz}{dt} = xy-bz \end{cases} \quad (9)$$

TABLE 2. The actual fluid motions of lorenz system in the conditions of $\sigma = 10, b = 8/3$ and different r.

Rayleigh number r	Actual fuid motion
$0 < r < 1$	Heat conduction
$1 < r < 13.97$	Convection
$13.97 < r < 24.74$	Transient chaos
$r > 24.74$	Chaos

In the formula (9), x, y, z is the state variable of Lorenz system, in which, x is the turning rate of convection, y expresses as the horizontal direction temperature difference of upper and lower convection, and z indicates the deviation degree of vertical direction temperature difference caused by convection. σ, r and b are positive real numbers of unit dimension, σ represents the Prandtl number, r expresses Rayleigh number, b is related to the range of the climate region.

The solution of Lorentz equation is closely related to the initial conditions, and table 2 is the actual fluid motion state in different Rayleigh numbers. Selecting the initial condition as (0, 1, 0) and fixing the parameters σ and b, namely $\sigma = 10, b = 8/3$, different Rayleigh Numbers r is set to observe the Lorenz attractor morphology r. Figure 2 is Lorenz attractor morphology respectively in $r = 0.6$, $r = 12$, $r = 26$ and $r = 48$. The formation of wind is the nonlinear process of atmospheric power system, so this paper mainly studies Lorenz system in chaos state

III. WIND SPEED PREDICTION

A. LORENZ COMPREHENSIVE DISTURBANCE FLOW

According to table 2 and figure 2, with the change of initial conditions and Rayleigh number, Lorenz attractor presents different motion states. When r is 24.74, Lorenz system starts to go into chaotic state. Considering the influence of Lorenz system in chaotic state on wind speed, the concept of Lorenz disturbance sequence (LDS) is proposed. The steps of calculating Lorenz disturbance sequence are as follows:

Step 1: Solve the Lorenz equation. The initial condition of Lorenz equation is set as (0, 1, 0), and the parameter is selected as $\sigma = 10, b = 8/3, r = 28$.

Step 2: Standardize the data, the Min-Max method is to eliminate the influence of dimensionality. The equation is as follows:

$$x_t' = \frac{x_t - x_{\min}}{y_{\max} - x_{\min}}, \quad y_t' = \frac{y_t - y_{\min}}{y_{\max} - y_{\min}}, \quad z_t' = \frac{z_t - z_{\min}}{z_{\max} - z_{\min}} \tag{10}$$

where, $x_t, y_t, z_t, t = 1, 2 \ldots n$ is the numerical solution of Lorenz equation, $x_{\min}, y_{\min}, z_{\min}$ and $x_{\max}, y_{\max}, z_{\max}$ are respectively the minimum and maximum values of x, y, z.

Step 3: Calculate the Lorenz disturbance sequence. The Chebyshev distance of the normalized data is as the Lorenz disturbance sequence. The Chebyshev formula is

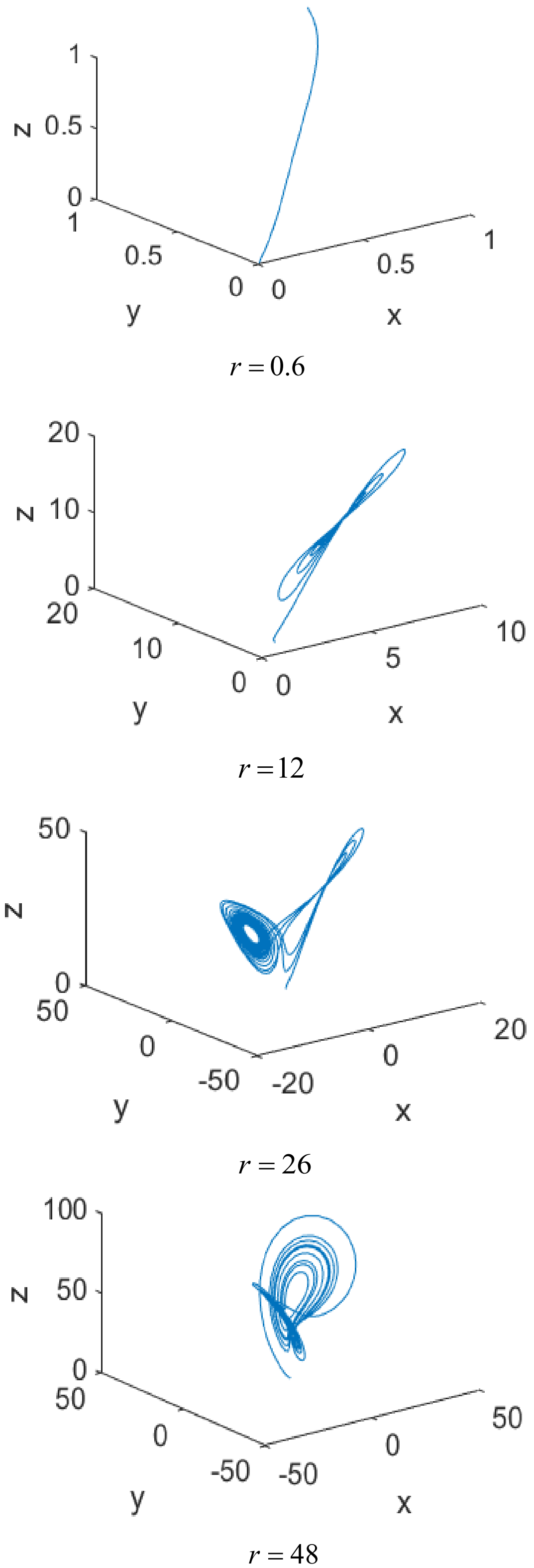


FIGURE 2. Lorenz attractor morphology in different Rayleigh Numbers.

as follows:

$$D(C_t - C_0) = \max(|x_t - x_o|, |y_t - y_o|, |z_t - z_o|) \tag{11}$$

where, C_t is, C_0 is (x_0, y_0, z_0).

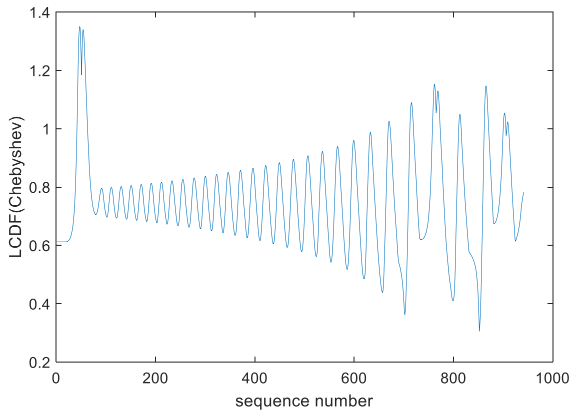


FIGURE 3. The LCDF distribution of Chebyshev distance.

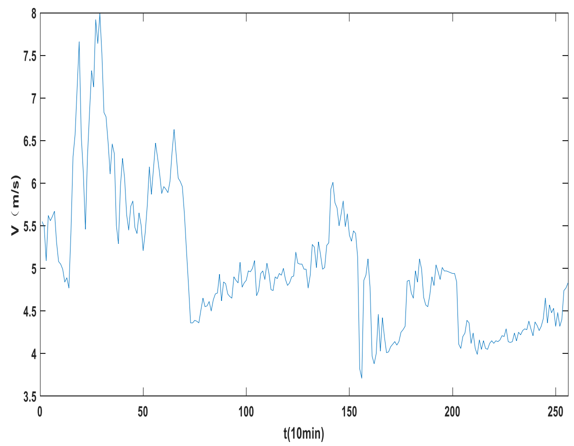


FIGURE 4. Wind speed distribution.

Figure 3 is the Lorenz disturbance sequence calculated by the Chebyshev formula.

B. WIND SPEED PREDICTION BASED ON LORENZ DISTURBANCE AND VMD

1) ORIGINAL SEQUENCE ANALYSIS

This chapter selects the Spanish Sotavento wind farm data [28] as an example analysis. The sampling interval time is 10 minutes, the sample size is 256, the first 65% sample is selected as the training set, the next 17.5% is the validation set, the rest is the test set. Figure 4 is the wind speed series, which shows that wind speed has a strong randomness and volatility, and it is a non-stationary sequence.

2) DECOMPOSE THE ORIGINAL SEQUENCE

Wind speed, as time series data, has strong fluctuation. VMD decomposes it into multiple components around its corresponding central frequency, which can highlight the fluctuation characteristic and alleviate the lag caused by time series modeling. In figure 5, original sequence is decomposed into several intrinsic mode functions by VMD, which reduces the randomness of wind speed fluctuations.

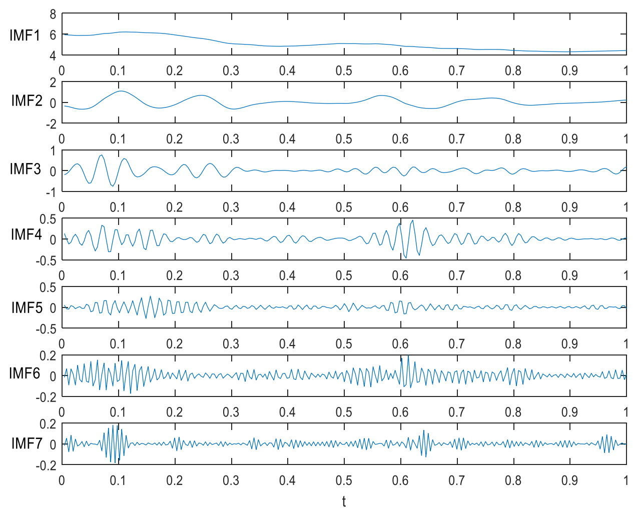


FIGURE 5. VMD of wind speed.

3) WIND SPEED FORECASTING PROCESS

In this paper, Matlab is used as analysis tool, VMD and neural network are used to predict wind speed, LDS is used to correct the predicted result of validation set, then wind speed prediction result can be optimized. The steps of modeling are as follows:

Step 1: Decompose the original series. The unstable original sequence is decomposed into 7 intrinsic mode functions by VMD.

Step 2: Establish model. IMFs of train set are used to build neural network model (LSTM, BP, RBF, and Elman). Neural network model optimized by VMD is called V-NN, and LSTM, BP, RBF and Elman perfected by VMD are respectively called as V-LSTM, V-BP, V-RBF and V-Elman.

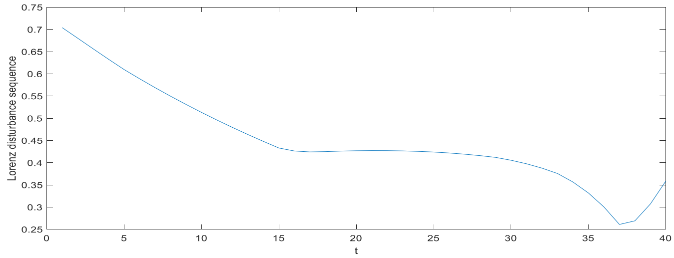
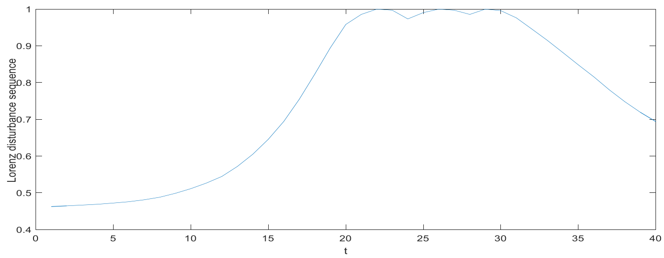
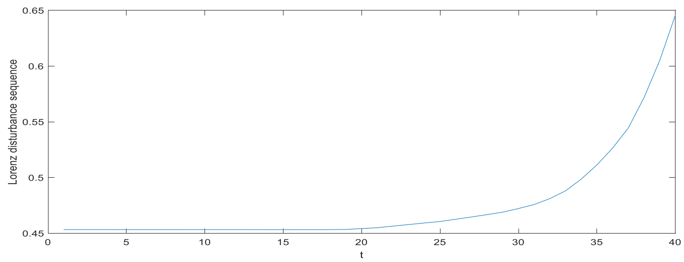
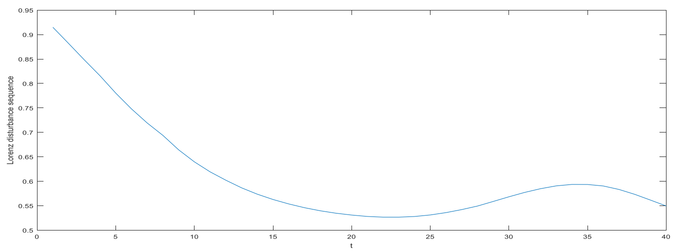
Step 3: Adjust the parameters of NN model. The model of training set is used to predict the validation set, and the parameters is adjusted by the predicted value of training set.

Step 4: Determine the best Lorenz disturbance parameter and Lorenz disturbance sequence. Given the influence of atmospheric uncertainties on wind speed, LDS is used to modify the prediction results of validation set, and its minimum mean absolute error is utilized to make sure of the best Lorenz disturbance parameter and the best Lorenz disturbance sequence. The correcting formulation is as follows:

$$V_{LD} = V + lL \tag{12}$$

In the formula (12), V_{LD} is the corrected prediction value of validation set, V is its preliminary prediction result of validation set, l represents Lorenz disturbance parameter, and its positive and negative represent the enhancement or attenuation of LDS, L denotes LDS. When the predicted value is less than actual wind speed, l is positive, whereas, l is negative. The models based VMD and Lorenz disturbance are all called as LD-V-NN model. V-LSTM, V-BP, V-RBF and V-Elman corrected by LDS are named as LD-V-LSTM, LD-V-BP, LD-V-RBF and LD-V-Elman respectively.

TABLE 3. The best disturbance coefficient and disturbance sequence.

Model	l_{best}	The best disturbance sequence
LD-V-LSTM	-0.1224	
LD-V-BP	0.1429	
LD-V-RBF	0.3469	
LD-V-Elman	-0.2653	

Step 5: V-NN model is adopted to forecast the test set value, then the result is modified by the best LDS of Step 4.

$$v_{LD} = v + l_{\text{best}} L_{best} \tag{13}$$

In equation (13), v is the preliminary predicted value of test set, v_{LD} is its modified predicted value, l_{best} represents the best Lorenz disturbance parameter, and L_{best} represents the best Lorenz disturbance, l_{best} and L_{best} are determined by the step 4.

According to the minimum Mae, the best Lorenz disturbance coefficient and the best Lorenz disturbance sequence are determined, as shown in table 3.

IV. WIND SPEED PREDICTION RESULTS AND ERROR ANALYSIS

A. WIND SPEED PREDICTION RESULT

Figure 7 shows the wind speed prediction results, in which the black solid line is the actual wind speed, the green dotted line is the prediction results of NN model, the blue line with o is the prediction results of V-NN model, and the red line with $*$ is the prediction results of LD-V-NN model. Figure (a) is the prediction results based LSTM neural network, figure (b) is the predicted values on basis of BP neural network, figure (c) is the forecasting lines grounded upon RBF neural network, figure (d) is the predictive curves founded on Elman neural network. In figure (a), the predicted results of LSTM model are obviously lagged the actual values, the fluctuation amplitude of prediction results is greater than that of actual values. With LSTM model compared, V-LSTM model solves the lag problem of predictive values, and the predicted curve of LD-V-LSTM model is closer to the actual values. Compared with V-LSTM model, the prediction values of LD-V-LSTM model are all smaller, and its errors are decreased. In figure (b), the prediction results of BP Neural network have a greater fluctuation amplitude than the original wind speed sequence, and their fluctuation trend lags behind that of the original sequence distinctly. In V-BP model, the fluctuation amplitude and trend of prediction values are basically consistent with those of the original sequence, but the predicted values are all less than the actual values. In LD-V-BP model, the fluctuation trend, amplitude and size of predicted values agree basically with the actual sequence.

In figure (c), the predictions of RBF model are far from the actual curve, and the most evident one is at the end of prediction values. The prediction tendency of V-RBF is similar to that of actual wind speed, but its predicted values are below the actual values. In LD-V-RBF model, the characteristics of predicted values are not only similar to the actual one, but the numeric size is closer to the real value. In the middle segment, there is a certain consistency between the predicted trend of Elman model and the actual trend, but the prediction effect is not good at the end segment. The forecasting fluctuation trend of V-Elman accords with the actual one, the values and the tendency predicted by LD-V-Elman are completely identical with the real one.

The predicted fluctuation amplitude and trend of NN model are inconsistent with these of actual wind speed, NN model optimized by VMD resolves these problems exactly. Given the atmospherical uncertain factors, LDS is added into the V-NN model, which modifies the predictive results, improves the predicting precision, and shows the fluctuation characteristics of wind speed. Not only does LD-V-NN model take consideration of improving the prediction accuracy, but also it quantifies the uncertainties in the atmosphere. Thus, the proposed method has distinct advantage in wind speed prediction.

B. MODEL EVALUATION OF WIND SPEED PREDICTION

There are many indexes to make model evaluation, such as goodness of fit R^2, mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE) and so on. In this paper, three indexes of MAE, MSE and MAPE are selected to evaluate the model. The formula of MAE, MSE, MAPE is as follows:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t - \hat{y}_t\right| \tag{14}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \tag{15}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(y_t - \hat{y}_t)}{y_t}\right| \tag{16}$$

In which, $y(t)$ and $\hat{y}(t)$ represent the actual value and the predicted value of wind speed at time t, the sample size is n.

Table 4 shows the model evaluation indexes. For several NN models, all MAEs are smaller than 0.23, their MSEs are all smaller than 0.06, their MAPEs are all smaller than 0.06. For several V-NN models, all MAEs are smaller than 0.18, all MSEs are smaller than 0.04, and their MAPEs are 0.05. In these LD-V-NN models, MAEs are all smaller than 0.07, MSEs are all smaller than 0.007, MAPEs are all smaller than 0.02. Table 5 shows the decline percentage of evaluation indexes. Taking NN model as the criterion, these evaluation indexes of V-NN model and LD-V-NN model are declined, in which the evaluation indexes of LD-V-NN model are decrease more greatly, and its prediction accuracy is obviously improved. According to table 4 and table 5, these indexes of LD-V-NN model are far less than these of NN model, so the prediction performance of proposed model has been greatly improved, and the method is effective for wind speed prediction.

TABLE 4. The model evaluation of wind speed prediction.

	Specific model	MAE	MSE	MAPE
NN	LSTM	0.1075	0.0193	0.0248
	BP	0.1348	0.0270	0.0311
	RBF	0.2024	0.0534	0.0466
	Elman	0.2207	0.0587	0.0515
V-NN	V-LSTM	0.0824	0.0104	0.0190
	V-BP	0.0891	0.0097	0.0203
	V-RBF	0.1655	0.0301	0.0380
	V-Elman	0.1720	0.0312	0.0402
LD-V-NN	LD-V-LSTM	0.0651	0.0068	0.0149
	LD-V-BP	0.0351	0.0019	0.0081
	LD-V-RBF	0.0304	0.0019	0.0070
	LD-V-Elman	0.0295	0.0014	0.0068

TABLE 5. The decreasing proportion of model index.

Standard model	Comparative model	MAE	MSE	MAPE
LSTM	V-LSTM	23.33%	46.36%	23.33%
	LD-V-LSTM	39.48%	64.75%	39.90%
BP	V-BP	33.87%	64.10%	34.56%
	LD-V-BP	73.93%	92.82%	74.08%
RBF	V-RBF	18.24%	43.58%	18.54%
	LD-V-RBF	84.98%	96.46%	85.07%
Elman	V-Elman	22.06%	46.91%	21.97%
	LD-V-Elman	86.61%	97.66%	86.73%

C. ERROR ANALYSIS OF WIND SPEED PREDICTION

Table 6 is the error analysis of wind speed prediction, the error range of LSTM model is in $[-0.2721, 0.3935]$, that of V-LSTM model is in $[-0.2276, 0.1919]$, that of LD-V-LSTM model is in $[-0.2606, 0.1375]$. The errors of BP model distribute around $[-0.5044, 0.2744]$, and these of V-BP model distribute in $[0.2349, -0.0305]$, these of LD-V-BP distribute in $[-0.1280, 0.0900]$. The error range of RBF, V-RBF and LD-V-RBF is respectively in

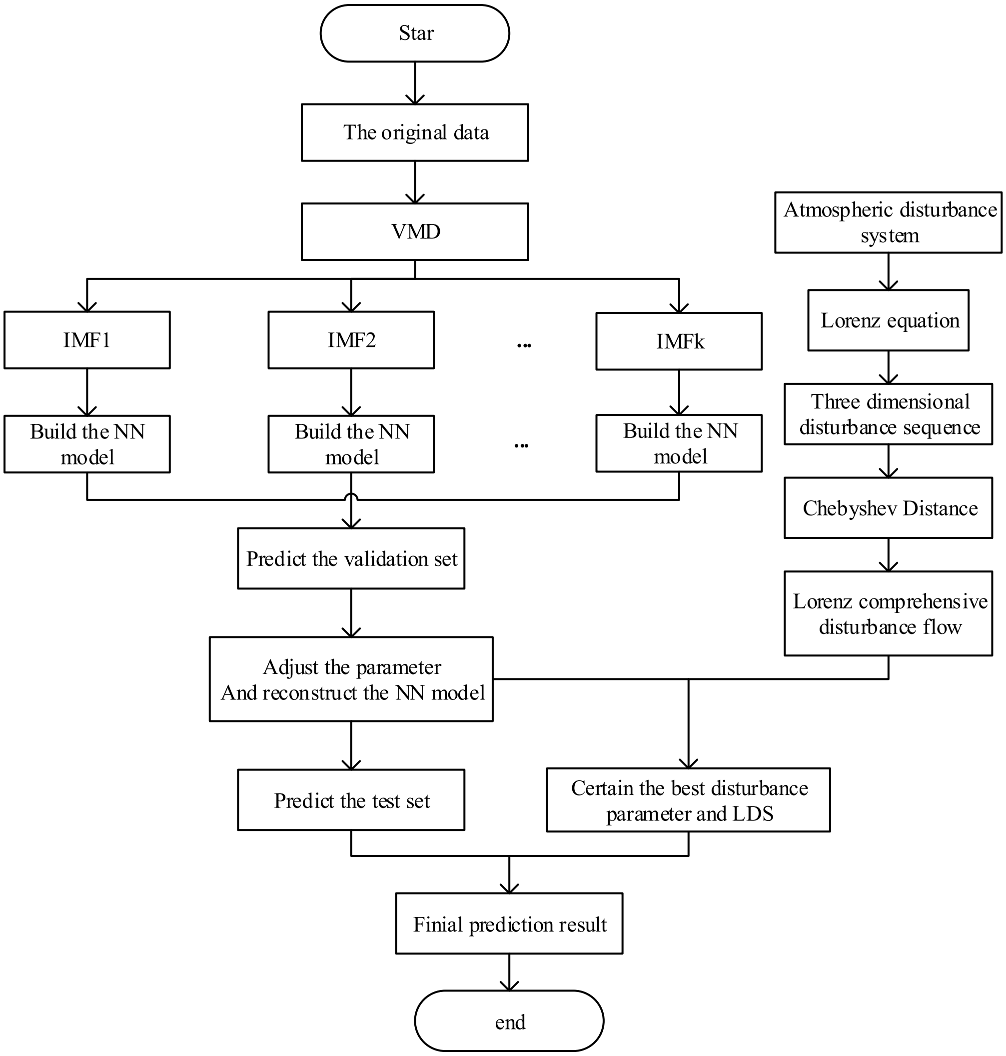


FIGURE 6. **The flow chart of wind speed prediction.**

$[-0.5105, 0.3081]$, $[-0.3293, -0.0355]$ and $[-0.1310, 0.0653]$. The errors of Elman fluctuate in $[-0.4008, 0.3866]$, these of V-Elman fluctuate in [0.0650, 0.2715], these of LD-V-Elman fluctuate in $[-0.1049, 0.1174]$. Compared with NN model, the error fluctuation interval of V-NN model and LD-V-NN model are decreased, but the error of LD-V-NN model is reduced much more than that of V-NN model. Judging from the error distribution range, the errors of LD-V-NN model have a smaller fluctuation amplitude, thus, LD-V-NN model has stabler prediction performance.

Combined with table 6 and figure 8, the average error of LSTM model is 0.0328, its standard deviation is 0.1359. Compared with LSTM model, the error range of V-LSTM model is significantly reduced, its measures of dispersion are also decreased, the mean, measures of dispersion, fluctuation range of error in LD-V-LSTM all make a great reduction. There is a large error extremum in BP model, its errors has strong random fluctuation and great measures of dispersion, and its standard deviation is 0.1625. With BP model compared, the standard deviation, error extremum and error range of V-BP model are reduced, the error of LD-V-BP model fluctuates stably around 0 and its mean and standard deviation are both close to 0. In RBF model, its average error and standard deviation are respectively -0.1613 and 0.1675, and its errors have large fluctuation range and strong measures of dispersion. The range and intensity of error fluctuation in V-RBF model is smaller than these of RBF model. The predicted errors of LD-V-RBF model fluctuate around 0, which has small fluctuation range and measures of dispersion. The mean and standard deviation of error in Elman model are 0.1613 and 0.1582 respectively. Compared with Elman model, the fluctuation range and the fluctuation tendency in V-Elman model and LD-V-Elman are decreased evidently. In addition, the average error of LD-V-Elman is about 0, and its fluctuation is stable. Taking NN model as the standard, the errors of V-NN model reduce the fluctuation range

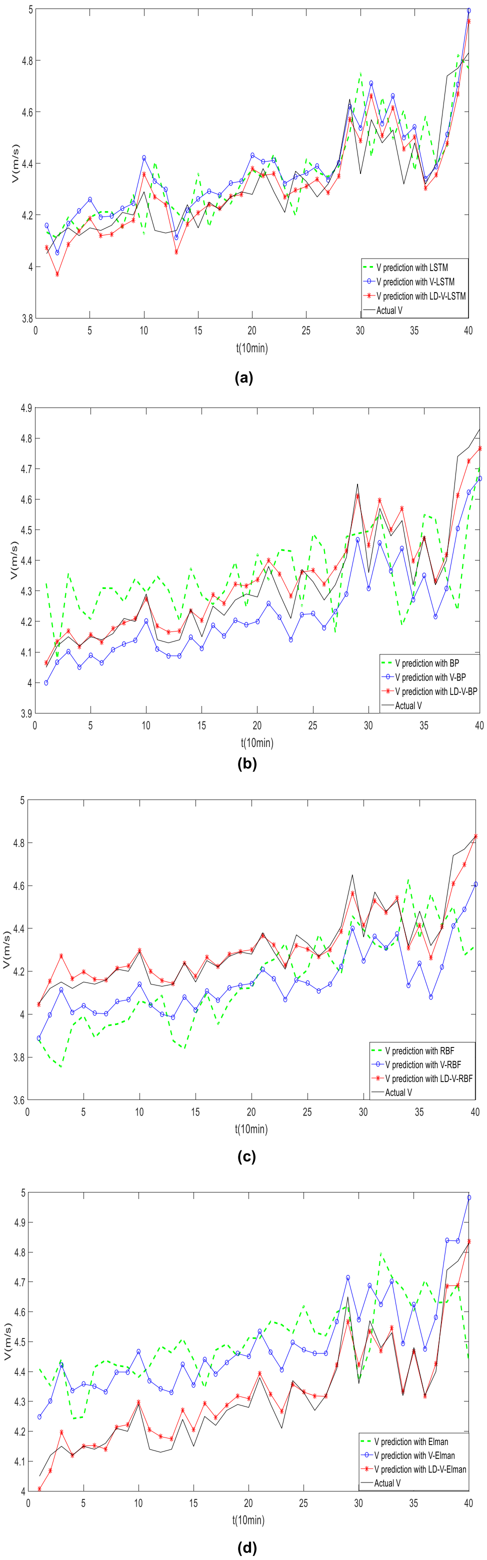


FIGURE 7. The prediction result of neural network model. (a) The prediction result of LSTM. (b) The prediction result of BP. (c) The prediction result of RBF. (d) The prediction result of Elman.

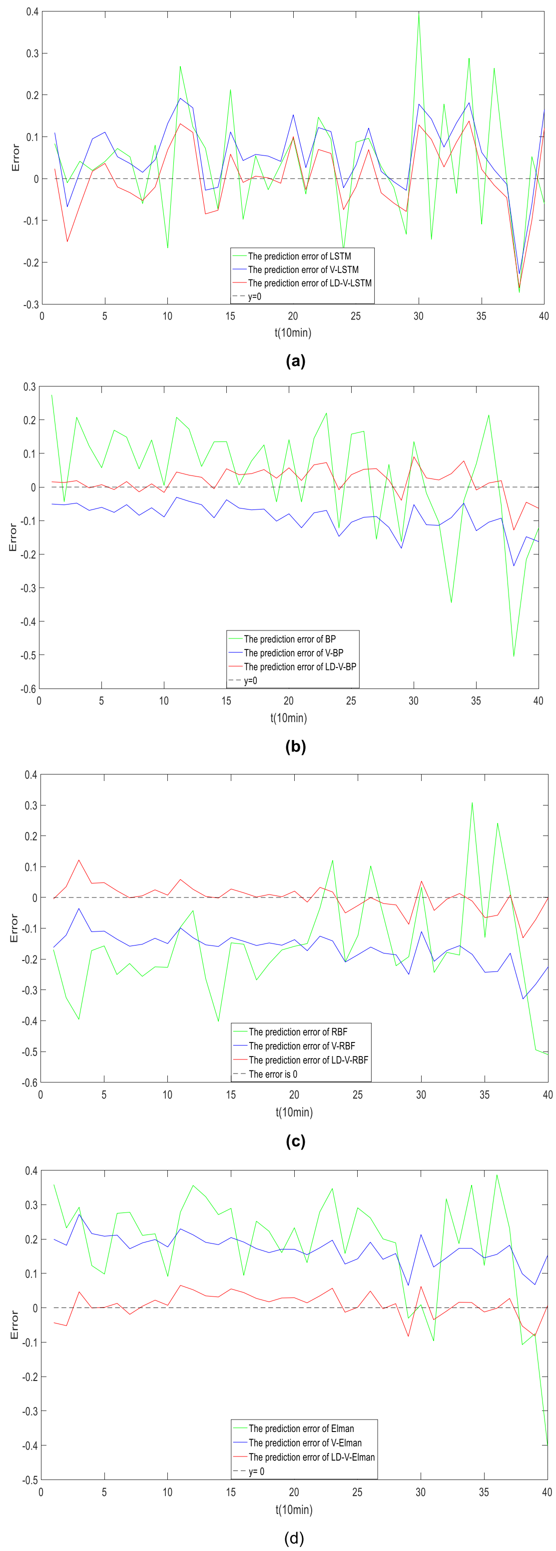


FIGURE 8. Error distribution of neural network. (a) The error of LSTM. (b) The error of BP. (c) The error of RBF. (d) The error of Elman.

and the fluctuation intensity, the average error of LD-V-NN model is closer to 0, its standard deviation is less, which reduces the size and the fluctuation range of prediction error. After adding the Lorenz disturbance, the atmospheric uncertainties are fully consideration, which decreases the error size and measures of dispersion. Therefore, the proposed

TABLE 6. Error analysis of speed prediction.

Model	Error			
	Mean value	Minimum	Maximum	Standard deviation
LSTM	0.0328	-0.2721	0.3935	0.1359
V-LSTM	0.0586	-0.2276	0.1919	0.0843
LD-V-LSTM	0.0034	-0.2606	0.1375	0.0835
BP	0.0360	-0.5044	0.2744	0.1625
V-BP	-0.0891	-0.2349	-0.0305	0.0425
LD-V-BP	0.0182	-0.1280	0.0900	0.0406
RBF	-0.1613	-0.5105	0.3081	0.1675
V-RBF	-0.1655	-0.3293	-0.0355	0.0530
LD-V-RBF	-0.0003	-0.1310	0.1217	0.0440
Elman	0.1852	-0.4008	0.3866	0.1582
V-Elman	0.1720	0.0650	0.2715	0.0403
LD-V-Elman	0.0092	-0.0832	0.0653	0.0364

model, LD-V-NN model, perfects the prediction precision by reducing the error, and improve the stability of prediction performance by decreasing the measures of dispersion.

In summary, compared with NN model, the results of V-NN model reflects the fluctuation trend of wind speed, and the fluctuation range of prediction errors is also decreased. The predicted value of LD-V-NN model is closer to the actual wind speed, the fluctuation tendency and intensity of predicted value are similar to the real one, and the prediction error fluctuates around 0. Therefore, compared with NN model, LD-V-NN model has better precision and more stable prediction performance.

V. CONCLUSION AND PROSPECT

Taking Sotavento wind farm in Spain as an example, hybrid model based on neural network is proposed. The results show that, compared with the single neural network model, the hybrid model has great stability and high prediction accuracy, the distribution characteristics of predicted values are on line with their actual features. This research uses VMD technology and neural network to restore the wind speed characteristics, and adopts Lorenz disturbance sequence to perfect the accuracy and stability of wind speed prediction. Therefore, the proposed method can provide more scientific and more accurate basis for wind power dispatching arrangement, and help to improve the development and utilization of wind energy, then improve the economic benefits of wind power.

Based on the improved effect of LDS and VMD on the model, we will start from two aspects in the next research plan: (1) VMD is combined with other traditional algorithms to reflect wind speed fluctuation. (2) Lorenz disturbance is added to other wind power prediction models to verify the general adaptability of atmospheric disturbance system in correcting the predicted values and improving the prediction stability.

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