Real-Time Prediction of the Wind Power Based on Improved Sustainable Model

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***Abstract*—Accurate prediction of wind power is an effective technology to achieve the large-scale utilization of wind energy. This article conducts in-depth research on real-time prediction of wind power based on the interim measures for the management of power prediction and prediction of wind farm published by the National Energy Board. It begins with an analysis of several typical prediction methods on single step, and gives the recommended modeling domain length, and puts forward the improved sustainable model which combines a time series model with sustainable model. We conduct several real-time predictions under different conditions with the data of wind power measured in a wind farm in Northeast China, evaluate different models combined with the corresponding marks in the files published by the National Energy Board. It proves that the improved sustainable method can improve the accuracy of prediction effectively.**

Keywords: time series models; sustainable model; real-time prediction; evaluation of prediction

I. INTRODUCTION

Wind energy as a renewable clean energy plays an increasingly important role in today's life. Turn wind energy into electricity grid can reduce the pollution of the environment and to a certain extent ease the world energy crisis today [1,2]. When wind generation is significant in a power system, wind power prediction becomes an important factor in defining the operation planning policies to be adopted by a transmission system operator (TSO), namely in accepting high wind penetration [3,4,5].

The prediction of power output from a wind park is highly important presently in Europe, where the growing penetration of wind generation has reached heavy percentages (in the range of 5% to 20%) in some countries in recent years, like Germany, Spain, Denmark, or other, and increases in these values are common targets for energy policies defined [6,7]. For instance, in Portugal by 2010, some 5100 MW of wind generators will be installed, when country peak power consumption is about 8500 MW in 2008. So, we are no longer talking of marginal effects [8,9,10].

According to preliminary statistics, China's new wind power installed capacity was close to 18 million kilowatts in 2011, total installed capacity reached 65 million kilowatts [11,12]. China is already the world's superpower in wind power equipment manufacturing and the largest country in the wind power installed capacity. But the near ground wind has features such as volatility, intermittent, low energy density and so on, makes accurate prediction of wind power becoming a big problem [13]. Therefore, to improve the prediction accuracy of wind power has become the primary task. Accurate prediction of wind power, in favor of wind power connecting to the electricity grid, making reasonable arrangement of dispatching plan, reducing the influence of fluctuation of wind power grid, ensuring the safety of power grid running smoothly, increasing the ability of wind power bidding online.

Foreign advanced prediction method using numerical weather prediction model to predict effectively, such as Denmark Prediktor prediction system and Spain LocalPred prediction system have both achieved good effect [14].

Domestic wind power has a variety of prediction methods, including the BP neural network, time series ARMA model, linear regression, sustainable prediction method and combined prediction method and so on, these methods in one step prediction precision is higher. But the accuracy is low in multi-step real-time prediction, also can not exceed the conservative ideas of sustainable prediction model [15].

This article starts from the requirements of improving prediction accuracy of wind power, combines sustainable method with time series model innovatively, constructs sustainable prediction model. This article has chosen the actual power of a wind generating set as the historical data in Northeast China from May 10 2006 to May 20 2006, we use the real-time wind power prediction under different time scales from midnight on May 20 and combine with the national energy bureau issued "interim measures for wind farm power prediction management" to analyze the results of evaluation index. Prediction results show that the improved sustainable prediction model can effectively improve the prediction precision.

II. PRACTICAL APPLICATION SITUATION

A. *Wind Farm Situation*

This article adopts the wind farm which is composed of 58 wind turbines, the rated output power of every unit is 850kw. Specifies that the four wind turbines of the wind farm (A, B, C, D), the data of output power (denoted as PA, PB, PC, PD); The total power output of four sets is denoted as P4 and the total output data of 58 wind turbines (denoted as P58).

On the basis of the electric power dispatching department for the different needs of op eration mode, wind power prediction is divided into day pr ediction and real-time prediction. Day prediction is to point to predict the future 24 hours at 96 time points of the wind power value. The real-time prediction refers to use every time point to predict future 4 hours at 16 ti me points of the wind po wer value. This paper mainly studies the real-time prediction and applies A table wind power generating unit as the main research object.

B. Evaluation

In this pa per, the evaluation of real-time prediction of wind power is based on the prediction assessment indicators of grid wind farms from national energy administration, as follows:

Accuracy:

$$r_1 = \left[1 - \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\frac{P_{MK} - P_{PK}}{Cap}\right)^2}\right] \times 100\% \qquad (1)$$

In which, r_1 is prediction planning curve accuracy; P_{MK} is the average value of the actual power of K ti mes; P_{PK} is the average value of prediction power of K times; N is the total numbers of such periods of the day assessment (about 96 points - from the inspection); Cap is boot capacity of wind farms.

Qualified rate:

$$r_2 = \frac{1}{N}\sum_{K=1}^{N} B_K \times 100\% \qquad (2)$$

In which,

$$\left(1 - \frac{P_{MK} - P_{PK}}{Cap}\right) \times 100\% \geq 85\%, B_K = 1,$$

$$\left(1 - \frac{P_{MK} - P_{PK}}{Cap}\right) \times 100\% < 85\%, B_K = 0.$$

RMS error:

$$r_3 = \sqrt{\frac{\sum_{k=1}^{N}\left(\frac{P_{MK} - P_{PK}}{Cap}\right)^2}{N-1}} \times 100\% \qquad (3)$$

Document [1] requires the error of real-time prediction of the grid wind power should be less than 15%, the RMS error of predicted results should be less than 20% throughout the day.

III. Classical Prediction Model Introduction and Analysis of The Results

A. Time Series Models

Time series data with time advancing have a certain correlation between each other, prediction model is established depending on the correlation of data variables before and a fter and the distribution of the random disturbance item. Time series application flow chart as shown in Fig.1.

Implementing stationarity test on the raw data of A unit, finds the data do not meet the stability requirements, after the first-order differential to the data, gains test results as shown in Fig.2, the ADF has a value of -25.35358 is less than -3.438672. So we have 99% certaint y that the data has reached smoothly.

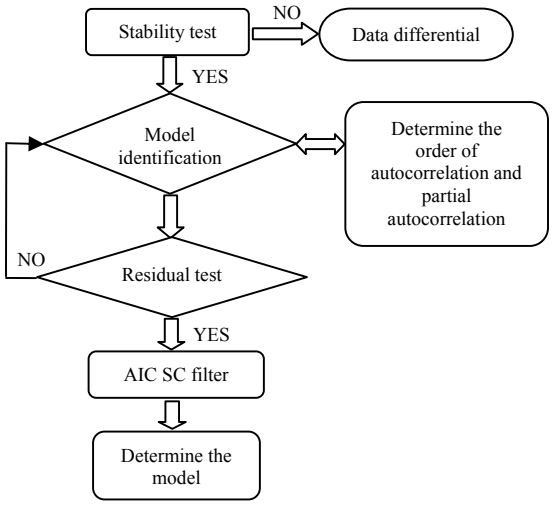


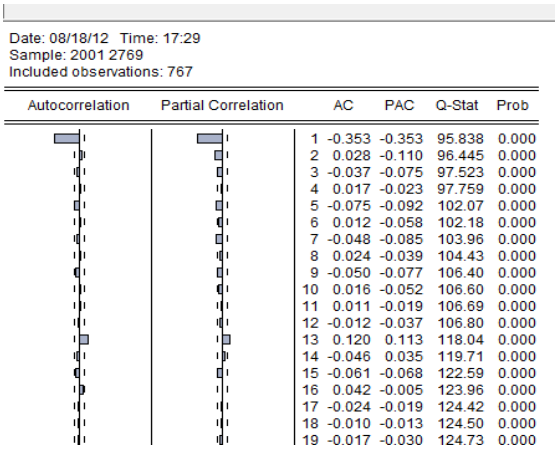
Figure 1. ARMA Model's Foundation Process

Null Hypothesis: D(Z) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=19)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-25.35358	0.0000
Test critical values:	1% level	-3.438672	
	5% level	-2.865103	
	10% level	-2.568722	

*MacKinnon (1996) one-sided p-values.

Figure 2. The Result of First Difference



Date: 08/18/12 Time: 17:29
Sample: 2001 2769
Included observations: 767

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.353	-0.353	95.838	0.000
		2	0.028	-0.110	96.445	0.000
		3	-0.037	-0.075	97.523	0.000
		4	0.017	-0.023	97.759	0.000
		5	-0.075	-0.092	102.07	0.000
		6	0.012	-0.058	102.18	0.000
		7	-0.048	-0.085	103.96	0.000
		8	0.024	-0.039	104.43	0.000
		9	-0.050	-0.077	106.40	0.000
		10	0.016	-0.052	106.60	0.000
		11	0.011	-0.019	106.69	0.000
		12	-0.012	-0.037	106.80	0.000
		13	0.120	0.113	118.04	0.000
		14	-0.046	0.035	119.71	0.000
		15	-0.061	-0.068	122.59	0.000
		16	0.042	-0.005	123.96	0.000
		17	-0.024	-0.019	124.42	0.000
		18	-0.010	-0.013	124.50	0.000
		19	-0.017	-0.030	124.73	0.000

Figure 3. MODEL'S RECOGNIZING

TABLE I. EXAMINATION SHEET OF AIC SC

Detection value	**ARI（1,1）**	**ARI（2,1）**	**ARIMA（3,1,0）**
AIC	13.049	13.083	13.105
SC	13.021	13.029	13.023

By Fig.3, we can determine the order number is 3 from the autocorrelation coefficient and the partial autocorrelation coefficient, make AIC and SC test on ARI(1) and ARI(2). Test results are shown in Tab.1, we can conclude that ARIMA(3,1,0) is the final model.

B. Linear Regression Model

Linear regression is a kind of prediction method that tends to causal analysis. So take advantage of the correlation analysis of historical data of wind power to predict, the stationarity of historical data and the modeling domain length of the linear regression model are greatly affecting the precision of the prediction.

As a result, the linear regression model application flow chart as shown in Fig.4.

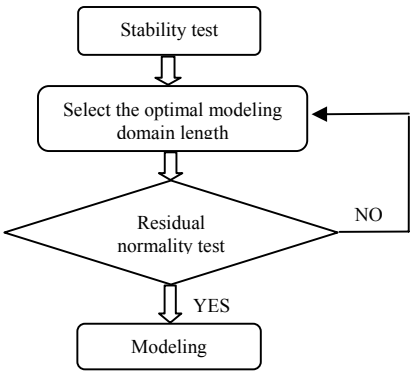


Figure 4. LINEAR REGRESSION MODEL'S FOUNDATION PROCESS

The following to explore the relationship between the step length selection of the modeling domain and the precision, as shown below.

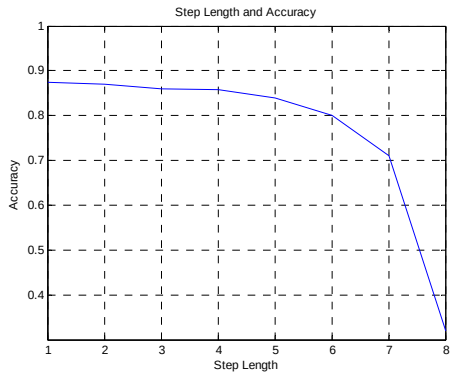


Figure 5. STEP LENGTH - ACCURACY PROFILE

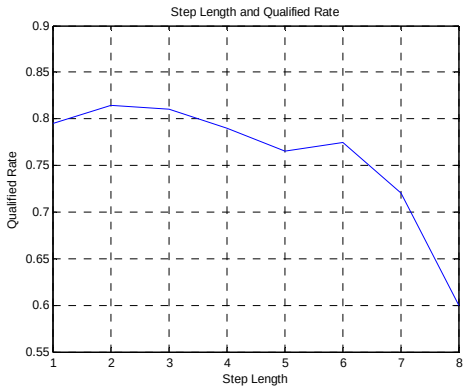


Figure 6. STEP LENGTH - QUALIFIED RATE PROFILE

You can see from figure, the accuracy rate and the qualified rate of prediction show a trend of decreasing with the increase of length of modeling domains. Therefore, let the length of the modeling domain be 2.

C. Sustainable Model

Sustainable prediction is to make the actual value of prediction time point in historical data as one or a set of predicted values. In multi-step prediction, the prediction trend will not change as prediction waveform change. To ensure that the error will not scroll with data accumulated step by step.

The sustainable model is more widely used in the wind power prediction, the method is simple and has high precision, has become the benchmark for the pros and cons of prediction methods of wind power. Makes real-time prediction of wind power for A unit at each time point in the May 20, lets the actual value of wind power of the time point as the predictive values of the next 16 points in time, accuracy analysis as shown in Tab.2.

D. Combination Prediction Model

The combination prediction model uses the information provided by each individual model, uses an appropriate

method to assign weights, weighted average to the predictive value of a single model, than derives the predictive value, makes model get higher prediction accuracy.

There are several ways to determine the weights of the combination prediction, this article uses cooperative game method which is from the point of view of game theory, depending on the individual prediction methods for the players of combination prediction, the "results" of cooperation for the sum of squared errors of the combination prediction, the individual prediction model is allocated in accordance with the cooperative game Shapley Value method, to obtain the weights of combination prediction. Following we can see the time series ARIMA(3,1,0) model, the linear regression model and the sustainable model portfolio prediction accuracy in Tab.2.

TABLE II. THE COMPARATION OF FOUR TYPICAL MODELS PRECISION

Model	Period	Accuracy (%)	Qualified rate (%)	RMS error (%)
ARIMA (3,1,0) model	***Once***	77.885	43.750	22.840
	One day	88.089	76.418	12.302
Linear regression model	***Once***	84.933	68.750	15.561
	One day	86.963	72.223	13.465
Sustainable model	***Once***	78.722	43.750	21.976
	One day	87.649	72.809	12.757
Combination model	***Once***	80.572	56.250	20.064
	One day	87.785	74.678	12.616

Tab.2 shows that under the same conditions as wind power prediction, single prediction can not evaluate the precision of the model is good or bad, but day prediction is more reasonable, ARIMA(3,1,0) model and the combination prediction model have higher accuracy.

IV. IMPROVED SUSTAINABLE MODEL

A. *Improved Sustainable Prediction Model Principle*

The sustainable model directly uses the actual value as predictive value, can avoid the prediction error into the back of the rolling prediction because of recursive prediction, but it is difficult to express the trend of the time data in the future, also considers using historical data to predict only one point has been very mature, has higher precision and be able to reflect the change trend of the future moments better. AR model just can take the correlation between the data into account; coincide with the strong correlation of wind power prediction in a short period of time. Thus, we propose improved sustainable model combined the AR model with the sustainable model and make one-step predictive values of the AR model as the real-time prediction predictive values of 16 time points.

B. *Improved Sustainable Predict Case Study*

The prediction accuracy of the ARIMA(3,1,0) model is the highest seen by the above time series models, therefore, we get ARIMA(3,1,0) improved sustainable method, ARIMA(3,1,0) model obtains the prediction power value from the historical data before the predicted point and makes it as a real-time prediction predictive value of 16 points in 4 hours. Real-time prediction for one day of 96 times prediction, every prediction establishes an AR model, can obtain the evaluations such as the accuracy、the qualified rate and the RMS error in every time and in one day and so on.

1) Accuracy comparison between improved sustainable model with ARIMA(3,1,0) model and the sustainable method.

Compare the evaluations in one time prediction and in one day prediction using improved sustainable method such as Tab.3 and Tab.4.

TABLE III. THE COMPARATION OF IMPROVING SUSTAINABLE MODEL AND ARIMA(3,1,0) MODEL'S PRECISION

Model	Accuracy (%)	Qualified rate (%)	RMS error (%)
ARIMA(3,1,0) model	94.290	100.000	5.897
Improved sustainable model	95.241	100.000	4.915

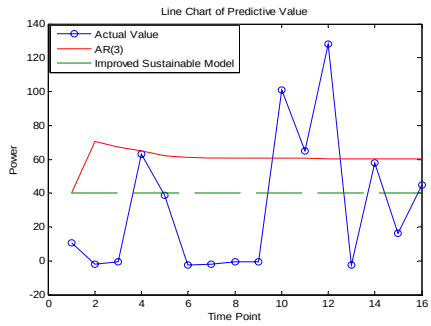


Figure 7. THE COMPARATION OF IMPROVING SUSTAINABLE MODEL AND ARIMA(3,1,0) MODEL'S PRECISION

TABLE IV. THE COMPARATION OF IMPROVING SUSTAINABLE MODEL AND SUSTAINED MODEL'S PRECISION

Model	Accuracy (%)	Qualified rate (%)	RMS error (%)
Sustainable model	87.649	72.809	12.757
Improved sustainable model	88.101	76.16	12.289

Seen from Tab.3 and Fig.7, improved sustainable model avoids the second-stage prediction error of the ARIMA(3,1,0) model, improves the prediction precision.

2) The accuracy analysis of improved sustainable model under different conditions.

In order to avoid the impact of causal factors, we take power data from the B, C, D unit, 4 units and 58 units to validate the one-day prediction accuracy of improved sustainable method under different operating conditions.

TABLE V. THE COMPARATION OF IMPROVING SUSTAINABLE MODEL AND SUSTAINED MODEL'S PRECISION OF GENERATOR B

Model	Accuracy（%）	Qualified rate（%）	RMS error（%）
Sustainable model	87.043	74.936	13.382
Improved sustainable model	87.474	75.322	12.937

TABLE VI. THE COMPARATION OF IMPROVING SUSTAINABLE MODEL AND SUSTAINED MODEL'S PRECISION OF 4 GENERATORS

Model	Accuracy（%）	Qualified rate（%）	RMS error（%）
Sustainable model	88.654	78.351	11.718
Improved sustainable model	89.014	80.284	11.346

TABLE VII. THE COMPARATION OF IMPROVING SUSTAINABLE MODEL AND SUSTAINED MODEL'S PRECISION OF 58 GENERATORS

Model	Accuracy（%）	Qualified rate（%）	RMS error（%）
Sustainable model	91.934	85.052	8.330
Improved sustainable model	91.975	85.954	8.288

From the above tables shows that the accuracy of improved sustainable method is higher than the sustainable method under different conditions, which can effectively improve the accuracy of real-time prediction of wind power.

V. CONCLUSION

The article proposes improved sustainable method which is based on the higher precision characteristics of sustainable model in the multi-step real-time prediction of the wind power, and it is validated that improves the accuracy of real-time prediction effectively under different operating conditions. National Energy Board documents wind farm power prediction assessment indicators for the standard, accuracy is about 0.4% higher than the sustainable method and the qualified rate is about 1.2% higher. It has a strong practical value.

In the field of wind power prediction, there are still many problems waiting to be solved, such as the increase in prediction accuracy of wind power can not be unlimited, if not, how much the increase of the maximum critical limits can be, what factors influence these issues in turn and so on? In subsequent studies, we will have a targeted research in the accuracy ceiling of wind power prediction.

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