Research of Wind Power Prediction Based on the Auto-Regressive Model

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Abstract—**This paper discusses in detail the reason for the inaccurate result from the present system for wind farm output power prediction. Time series analysis method was applied for improving existing problem in prediction model and treatment method of basic data. Improving self-regressive mathematical model was established and taken the model identification. Using SPSS software simulates and further assists model identification and using given wind farm historical output power data to forecast one and multi-wind power unit output power in odd-number days and a week. Finally, this paper compares and analyses the getting prediction power and expound the next step work that improves the wind power prediction accuracy.**

Keywords-wind power prediction; time series analysis; self-regressive mathematical model; simulation

I. INTRODUCTION

Wind power technology is current renewable energy utilization of the most mature technology and the most large-scale development and commercialization development prospects. With the development of wind power technology development, its malpractice appears gradually. Intermittency and fluctuation of wind power itself unique determines the power of intermittent and fluctuating. In order to satisfy the power supply demand, ensuring the reliability of the stable operation of the power grid and power supply system, so, we need to effectively plan and schedule for the power supply system. While the wind power intermittent itself unique and uncertainty, increase the difficulty of grid scheduling and the reserve power capacity. In order to solve the distribution problem of instability and reduce the power grid reserve capacity cost, we must predict the output power of large-scale wind farms. Through real-time accurate prediction for wind power generation, power dispatching department can advance the sch eduling plan according to the wind power change in order to ensure the power balance and the safety operation of the power grid, and adjust accordingly to effectively mitigate the adverse impact of wind power on power grid and effectively reduce the operation cost and improve the efficiency of wind power generation. Therefore, how to forecast the wind power as accurately as possible is an urgent problem to be solved.

II. AR MATHEMATICAL MODELING

We apply the stochastic process theory and mathematical statistical methods to study statistical regularities followed by random data sequence. Random data is arranged based on chronological sequence. It possesses good predictability using time series analysis to analyze smooth time series data. The ARMA model consists of two models of the AR (p) model and the MA (q).

A. ARMA Model Identification Criteria

If stationary series x (t) is tailing the autocorrelation function, partial autocorrelation function for the censored sequence, x (t) is the AR sequence. If stationary series x (t) is the autocorrelation function of the truncation, partial autocorrelation function is tailing sequence, then, x (t) is the MA sequence. If the autocorrelation function and partial autocorrelation function of stationary series x (t) is all tailing, x (t) is the ARMA series. Where the self-correlation function is $\rho_k = r_k / r_0$. The self-covariance function is $r(k) = \frac{1}{n}\sum_{t}^{n-k}(x_{t+k} - \bar{x})(x_t - \bar{x})$, among, $\bar{x} = \frac{1}{n}\sum_{t=1}^{n} x_t$ is the sample mean. Based on model identification criteria, we analyze data and complete the establishment of the mathematical model.

B. Model Identification

For example, wind power data of certain wind power plant; we adopt historical data to model from May 10 to May 30, 2006 and for the test data on May 31. We use the historical data to draw a line chart from May 10 to May 30, 2006, Figure. I show:

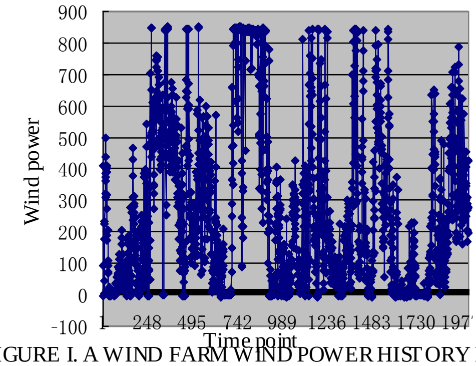

FIGURE I. A WIND FARM WIND POWER HISTORY DATA.

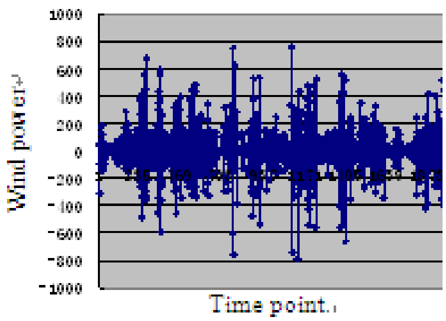

FIGURE II. A FIRST-ORDER DIFF.

As can be seen from the Figure I, the data has large fluctuations and is not stable related time series data, and therefore, we need to make odd transform for data and difference calculation. We take first-order differential operation for the data, the point data shown in figure 2.

By a first-order differential diagram, we can know, the value of wind turbine power is always in the vicinity of a constant random fluctuation, and fluctuations are of the range bounded, no clear trend and cycle characteristics, we regard it as smooth sequence. Therefore, we can further analyze and model based on this data.

III. AR SIMULATION MODELING

We apply SPSS software to simulate self-correlogram and assist further to make model identification, autocorrelation shown in Figure 3 and Figure 4:

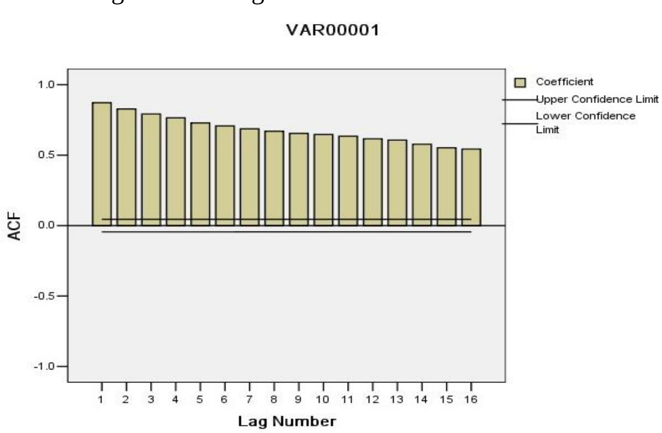

FIGURE III. AR CORRELATION.

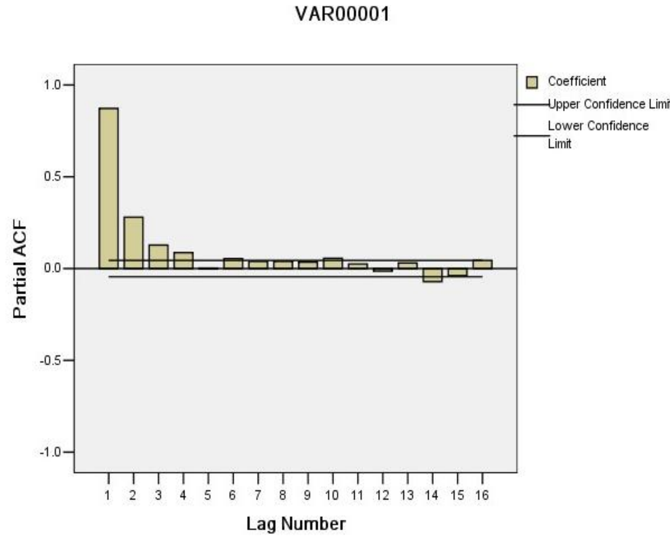

FIGURE IV. MA CORRELATION.

As can be seen from Figure 3, model AR (P) analyzed for auto-correlation function of stationary sequence x (t) which is derived from data analysis is tailing. The correlation of partial autocorrelation function correlation established by the MA model is censored, namely, AR (P) model accord with time series analysis and establish AR (p) model, take a P=2.

A. Establishing Autocorrelation Function

We establish the stationary model

$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots\ldots + \phi_p x_{t-p} + \varepsilon_t$, and multiply at the equal sign by $x_{t-k}, \forall k \geq 1$, and then obtain its expectations, gain the equation:

$$E(x_t x_{t-k}) = \phi_1 E(x_{t-1} x_{t-k}) + \ldots\ldots + \phi_p E(x_{t-p} x_{t-k}) + E(\varepsilon_t x_{t-k}), \forall k \geq 1$$

According to the conditions of the AR (p) model, we can get $E(\varepsilon_t x_{t-k}) = 0, \forall k \geq 1$, so we can get the recurrence formula of self-covariance function:

$$r_k = \phi_1 r_{k-1} + \phi_2 r_{k-2} + \ldots\ldots \phi_p r_{k-p}$$

Because of $\rho_k = r_k / r_0$, r_k is divided by the variance function r_0, and gain recurrence formula of self-correlation function $\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + \ldots\ldots + \phi_p \rho_{k-p}$.

We can calculate on the data basis of the above formula obtained and obtain $\bar{x}$, r_k, ρ_k, and then $\phi_1, \phi_2, \ldots\ldots \phi_p$.

Using SPSS software analysis, we get simulation results shown in Figure 5:

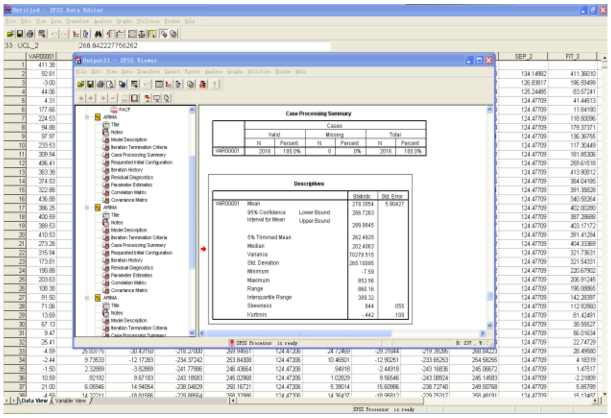

FIGURE V. SPSS SIMULATION RESULT.

From the Figure, we obtain the value of the upper bound 289.8845 and lower bound values 266.7263 at the 95% confidence interval.

B. *Wind Power Prediction of Single-day and One Week*

We use AR (p) to predict 96 point-in-time sequence wind power data for the 1st wind turbines of certain wind farm from 0:00 to 23:45 on May 31, shown in Table 1:

We use AR (p) to gain wind power forecast value and the actual value of 58 wind turbine for certain wind farm, line graph shown in Figure 6:

TABLE I. AR(P) MODEL FOR FORECAST OF WIND POWER DATA.

Time Point	Power Prediction	Time Point	Power Prediction	Time Point	Power Prediction
1	214.46	33	175.2	65	144.12
2	172.13	34	333.33	66	171.19
3	213.76	35	168.81	67	184.11
4	263.7	36	333.33	68	193.96
5	208.98	37	175.98	69	333.33
6	163.43	38	333.33	70	333.33
7	206.88	39	218.65	71	175.27
8	237.07	40	148.37	72	333.33
9	229.88	41	165.56	73	333.33
10	204.65	42	173.9	74	333.33
11	202.94	43	146.02	75	333.33
12	197.02	44	161.55	76	172.79
13	204.06	45	185.88	77	213.2
14	212.89	46	174.36	78	182.47
15	226.14	47	333.33	79	183.25
16	196.69	48	160.34	80	188.58
17	156.59	49	333.33	81	208.69
18	184.32	50	199.06	82	219.55
19	185.86	51	333.33	83	151.29
20	181.57	52	333.33	84	182.79
21	207.74	53	333.33	85	333.33
22	197.95	54	240.67	86	333.33
23	190.11	55	226.57	87	198.43
24	198.56	56	333.33	88	333.33
25	139.15	57	333.33	89	204.39
26	83.15	58	263.94	90	207.71
27	128.06	59	185.89	91	333.33
28	92.29	60	333.33	92	333.33
29	144.13	61	138.16	93	333.33
30	151	62	216	94	220.93
31	125.9	63	152.84	95	218.81
32	160.9	64	191.18	96	181.14

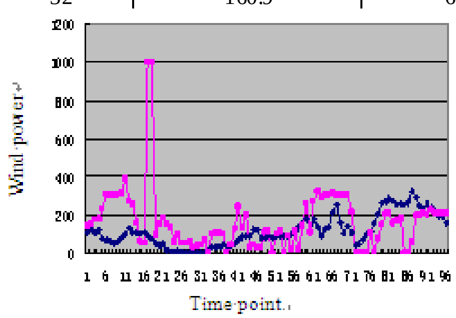

FIGURE VI. COMPARISON OF 58 WIND TURBINE WIND POWER FORECAST VALUE AND THE ACTUAL VALUE.

IV. SIMULATION MODELING RESULTS

According to accuracy rate formula of the wind farm power forecasting

$$r_1 = (1 - \sqrt{\frac{1}{N}\sum_{k=1}^{N}(\frac{P_{Mk} - P_{Pk}}{Cap})^2}) \times 100\%$$

And the pass rate is calculated

$$r_2 = \frac{1}{N}\sum_{k=1}^{N} B_k \times 100\%$$

Based on prediction results, we analyze comparatively for prediction data and the actual data from the two aspects of accuracy and pass rate, as shown in Table 2 and Table 3:

TABLE II. MAY 31ST 00:00 TO 23:45 FORECAST ACCURACY.

Wind Turbine	Accuracy	Pass rate
No1	77.29%	86.32%
No2	76.34%	87.49%
No3	75.64%	84.53%
No4	79.47%	82.48%
4Wind Turbine	80.42%	79.53%
58 Wind Turbine	80.94%	76.48%

TABLE III. MAY 31ST 00:00 TO 23:45 IN JUNE 6TH FORECAST ACCURACY.

Wind Turbine	Accuracy	Pass rate
No1	77.05%	81.86%
No2	76.55%	87.57%
No3	74.92%	83.82%
No4	79.79%	81.89%
4Wind Turbine	80.32%	79.52%
58 Wind Turbine	80.14%	76.54%

We analyze the forecast data obtained through simulation modeling, the modeling and analysis of time series method is suitable for linear problems. When the prediction step is relatively larger, it reflects good predictability. With the increase of the predicted time, the superiority of the time-series analysis model is increasingly apparent. Moreover, with the increase of the predicted time, the advantage of the ARMA model is gradually increasing and improve more obvious. Therefore, time series method is to be more effective for forecast the output power in the short-term real-time forecast.

ACKNOWLEDGEMENTS

This work was supported by the Science and Technology development plan project of Department of Science and Technology of Jilin Province (120130169), China.

This work was supported by the Science and Technology Research Project in 12th Five-Year Periods of Department of Education of Jilin Province (2013, 304), China.

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