2017 13th IEEE Conference on Automation Science and Engineering (CASE)
Xi'an, China, August 20-23, 2017

A Rolling ARMA Method for Ultra Short Term Wind Power Prediction*

Yongxia Liu[1] and Yanyan Zhang[2]

***Abstract*— Wind power is one of the popular renewable energy in the world. And accurate wind power prediction can improve the quality of wind power integration and help to guarantee the safety of power grid system. In this paper, a Rolling Auto-regressive Moving Average(RARMA) method is proposed to improve the prediction accuracy for ultra short term wind power prediction. And for the purpose of illustrating the feasibility of the RARMA method, numerical experiments are conducted. Simultaneously, the Root Mean Square Error(RMSE), the Maximum Error(MAXE), Average Relative Error(ARE), and Prediction Accuracy Rate(PAR) are selected to compare the effect of prediction methods. The numerical results show that the RARMA method exhibits a promising prediction accuracy.**

I. INTRODUCTION

With the depletion of conventional energy and prominent of environment problem, much attention has been made to the exploitation and utilization of renewable energy by majority of the countries in the world. As a kind of clean and renewable energy, wind power has attracted keen attention. And the global wind power capacity increased with years. In China, it also grows rapidly as is shown in Fig.1[1]. However,

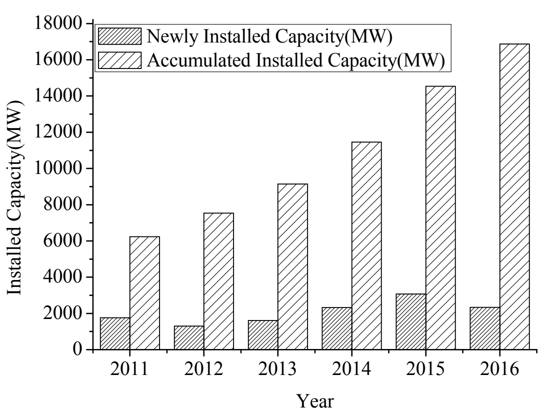

Fig. 1. The trend of newly and accumulated installed wind power in China during 2011-2016

*This work was supported by the National Key Research and Development Program of China (Grant No. 2016YFB0901900), the Fund for Innovative Research Groups of the National Natural Science Foundation of China [Grant 71621061], the 111 Project (No. B16009), and the Fund for National Natural Science Foundation of China for Major International (Regional) Joint Research Project (Grant No. 71520107004)

[1]Yongxia Liu is with the Institute of Industrial & Systems Engineering, Northeastern University, Shenyang, 110819, P. R. China yxliu1208@126.com

[2]Yanyan Zhang is with the Institute of Industrial & Systems Engineering, Northeastern University, Shenyang, 110819, P. R. China zhangyanyan@ise.neu.edu.cn

the wind abandoned rate is relatively high, it can be found from Fig.2[1]which shows the change of the rate from 2011 to 2016. This phenomenon leads to the energy waste. One reason for this is that the wind power is intermittent and with volatility. It is because the wind speed is fluctuating. Importantly, the volatility of the wind power have impact on the stability of the power grid system(PGS). And, with increasing capacity of wind power integrated in grid system, the impact also becomes obvious. Seriously, it may affect the stability of grid system. To overcome this problem, it is necessary to predict the wind power from a few minutes up to several hours in advance. Moreover, the higher of the prediction accuracy, more beneficial for the PGS making scheduling operation plan. And it is conducive to guarantee the quality of power grid[2]. In recent years, many researches

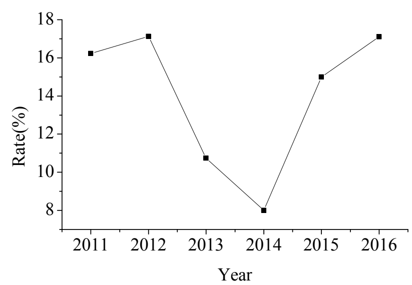

Fig. 2. Trend of wind abandoned rate from 2011 to 2016

have been carried on to obtain accurate predictions of wind power. In order to train prediction model, support vector machine regression [3], back propagation neural networks[4] and other learning based methods, generally need to take the National Weather Predict (NWP) as input data. However, Time Series Analysis(TSA) method only needs finite previous historical data. As a kind of TSA method, Auto-regressive Moving Average(ARMA) is paid more attention in practice. Such as in meteorology[6], [7], biology[8], finance[9], as well as in wind power prediction, etc. In the review paper [10] and [11], the feasibility of using ARMA methods for wind power forecasting are indicated. Especially, in [11], it is shown that ARMA method is pinpoint for ultra short term prediction(USTP). In [12], chaotic time series is adopted to conduct UST prediction, and feasibility is confirmed by the numerical experiments. In [13], the prediction performance among Wind Power Prediction Tool(WPPT), AR models and other five methods are investigated, and shown that the TSA model are suitable for USTP. Also, ARMA model has been used for predicting short term wind power in [14]. Tian et. al. proposed ARMA-GARCH model for USTP[15].

According to investigate messages from wind power plant(WPP), USTP(predicting horizon is 6 hours ahead) has great significance for real-time scheduling of power grid. Thus, in this paper, under this motivation, attentions is paid for the USTP, and ARMA methods are adopted. To improve the accuracy, Rolling ARMA(RARMA) is proposed.

This paper is organized as follows. ARMA methods for wind power prediction is given in section 2. Next, the numerical experiment are carried on to verify the feasibility of the RARMA method. Finally, we draw conclusions in section 4.

II. WIND POWER PREDICTION METHODS

On the basis of previous studies, Box and Jenkins elaborated systematically the principles and methods of ARMA model in 1970[16]. In this section, ARMA method for wind power prediction will be given, and put forward a Rolling ARMA(RARMA) to improve the prediction precision.

A. ARMA Methods

Assume $\{x_t | t = 1, 2, \cdots\}$ to be stationary time series, and $\{x_t\}$ is an ARMA(p,q) process, then the model is

$$(1-\varphi_1 B-\cdots-\varphi_p B^p)x_t = (1+\psi_1 B+\cdots+\psi_q B^q)\varepsilon_t \quad (1)$$

where $\varepsilon_t \sim WN(0, \sigma^2)$, B is an operator satisfying $Bx_t = x_{t-1}$. $\varphi_p \neq 0$ and $\psi_q \neq 0$, where p and q are the order of auto-regressive and moving average part respectively. Specially, (1) is an MA process when for all p have $\varphi_p = 0$. And if for all q, $\psi_q = 0$, it is an AR process.

Assume the original series is $\{z_t\},\ t = 1, 2, \cdots$, following gives the algorithm for establishing the predicting model of the wind power.

Step1: Data pre-processing. According the process, we remove outliers and delete duplicate data from $\{z_t\}$, remembered as $\{y_t\}$.

Step2: Stationary Test. Augmented Dickey-Fuller(ADF) test is adopted to judge whether the series $\{y_t\}$ is stationary. If not, go to step3, otherwise, go to step4.

Step3: Difference processing. Backward difference is used to make $\{y_t\}$ stationary. It can be described as follows.

$$x_t = \bigtriangledown y_t = y_t - y_{t-1} \quad (2)$$

Step4: ARMA model identification. Judge initial scope of p and q based on the auto-correlation function(ACF) and partial ACF(PACF).

Step5: Parameter estimation. In this step, we mainly compute the parameters of ARMA(p,q) model.

Step6: White noise test. Do white noise test for ARMA model, if success, carry on the prediction, otherwise, go to the step4.

The algorithm flowchart is shown in Fig. 3.

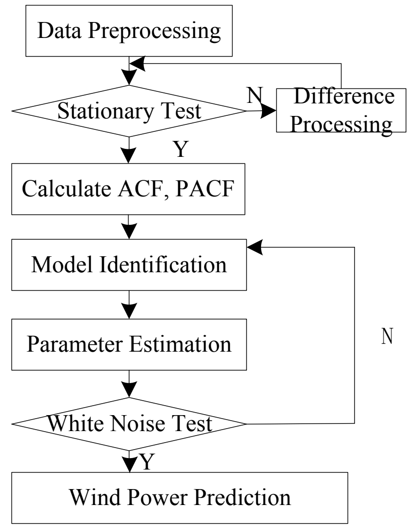

Fig. 3. ARMA algorithm flowchart

B. Rolling Prediction ARMA

Traditional ARMA method is easy to operate, and can precisely predict the future value if the series is stationary process. However, the wind power may be limited sometimes for the PGS demand, and also, the wind power is unstable, which lead to lower the prediction accuracy. To improve the prediction accuracy, the rolling strategy adopted in predictive control[17] is used. In this paper, a RARMA is proposed for improving the wind power predicting accuracy. The rolling strategy is described as follows. When we predict the wind power of the upcoming 6 hours, after one hour prediction ending, the forecasting model is reformulated again, where the current prediction is added to the training data.

III. NUMERICAL EXPERIMENTS

A. Data Sources and Selecting

The wind power data adopted in this paper is collected from a WPP. The data is from April 1^{st}, 2015 to May 31^{st}, 2015, and the data collection interval is 15 minutes. Take the wind power of April as example, the tendency of the series is shown in Fig. 4. Both from Fig. 4(a) and Fig. 4(b), it is not hard to find that the daily change of wind power is approximately a stationary process.

In this paper, we pay more attention to wind power USTP, that means, we predict the next 6 hours of wind power. For the sake of illustrate the validity of the method, we select data of April and May to carry on the experiments, respectively. For each month, we take the data of last day as the test data, and of the previous days for training the model. Simultaneously, the test data is divided into four time period of which include data of 6 hours. Thus, four groups numerical experiment are conducted for each month. The selection of training and testing data is shown in Table I. It is noteworthy that when conduct the experiment of the second stage(S2) , the data of the first stage is put into training data, and so on.