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Wind speed forecasting based on ARFIMA-EGARCH model

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ABSTRACT

Because of the important technological and economic impacts of wind speed on wind power generation and the increasing as a renewable energy source in many countries of wind power, providing accurate wind speed prediction algorithms has become increasingly significant to the planning of wind speed plants, the scheduling dispatchable generation and tariffs in the day-ahead electricity market and the operation of power systems. In this paper, a strategy, which adopts ARFIMA-EGARCH model is presented for wind speed forecasting. The results show that ARFIMA-EGARCH model, which combines both the long memory time series and the conditional heteroscedastic processes, possesses higher accuracy than the classical approach towards wind forecasting.

KEYWORDS

ARFIMA-EGARCH;
Wind speed forecasting;
Evaluation criterion.

INTRODUCTION

More accurate forecasting of wind speed has a significantly importance in wind power resources management due to the role of management and operation of wind farms, wind energy generation, and many important applications in shipping, aviation, and the environment. The forecasting problem of wind speed has become an attractive research and many approaches and practitioners have been proposed to many methods in order to achieve a high-accuracy forecasting in the past decades. Considering the uncertainty of wind speed makes troubles in them, Li et al. proposed a wind speed forecasting method based on time-series adopt EGARCH models as asymmetric specifications and GARCH-GED for distribution assumptions.

To deal with time series heteroskedasticity, there are two popular techniques, which is autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) in prevalent[9-16]. However, the conditional techniques suffer some defects.

To overcome these problems, a new time series method combined with ARFIMA and EGARCH models is proposed in this paper. It can not only overcome the nonnegativity constraints on the parameters of traditional GARCH model, but also reflects the asymmetric effects of positive, negative impact, have great flexibility. Further testing of the residual sequence using the Lagrange multiplier method revealed the presence of heteroscedasticity apparent. After verification, heteroscedasticity of residuals are available through the

EGARCH-M-GED (autoregressive conditional heteroskedasticity) model to fit, finally established the ARIMA - EGARCH-M-GED model. The model solves the RBF neural network to all the characters into digital, put all reasoning into the numerical problems, avoid the loss of information, thus further precise error.

BASIC PRINCIPLE OF ARFIMA-EGARCH MODEL

Let $\{y_t\}_{t=0,\pm1,\cdots}$ be a zero-mean stochastic process needed to be modele. The most typical linear specification for conditional mean, which is the autoregressive $AR(p)$ model and the moving average $MA(q)$ model that can be mixed to have the $ARMA(p,q)$ model can be expressed as

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t , \qquad (1)$$

or

$$\Phi(L)(y_t - \upsilon) = \Theta(L)\mu_t , t = 0, \pm1, \cdots, \qquad (2)$$

where y_t is the time series needed to be modeled, c is a constant term of the ARMA model, r is the number of autoregressive orders, m is the number of moving average orders, ϕ_i is i th autoregressive coefficients, θ_j is j th moving average coefficients and ε_t is the error term at time period t. L is the backward operator such that

$$L^k(y_t) = y_{t-k},\ \Phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i,\ \Theta(L) = 1 - \sum_{j=1}^{q} \theta_j L^j ,$$

$\Phi(L)$ and $\Theta(L)$ are polynomials with all roots outside the unit circle and share no common factors.

The time series $\{y_t\}_{t=0,\pm1,\cdots}$ is said to have long-memory property and it may be modeled by the ARFIMA(p,d,q) model whose memory parameter, d, belongs to the closed interval $[\nabla_1, \nabla_2]$, with $-0.75 < \nabla_1 < \nabla_2 < \infty$, described as

$$\Phi(L)(1-L)^d (y_t - \upsilon) = \Theta(L)\mu_t , t = 0, \pm1, \cdots. \qquad (3)$$

Generally, a $GARCH(p,q)$ model for the conditional variance of innovations ε_t can be expressed as

$$\sigma_t^2 = k + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 , \qquad (4)$$

with constraints, $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1,$

where

$\alpha_i \geq 0 (i = 1, 2, \cdots, p)$,

$\beta_j \geq 0$, $(j = 1, 2, \cdots, q)$, $k > 0$.

Nelson and Cao found that the nonnegativity constraints in the linear GARCH model are too restrictive. It imposes the nonnegative constraints on the parameters, α_i and β_i. But there are no restrictions on these parameters in the EGARCH model ([1]). In the EGARCH model:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left[|\varepsilon_{t-i}| / \sigma_{t-i} - \gamma_i \varepsilon_{t-i} / \sigma_{t-i} - \sqrt{\frac{2}{\pi}} \right]$$

$$+ \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2) \qquad (5)$$

The combination of models in expressions (3), (4), and (5) yields to the ARFIMA-EGARCH Model.

WIND SPEED FORECASTING BASED ON ARFIMA-EGARCH MODEL

In this paper, the data analysis and processing are completed by using Eviews6.0. Unit root testÿdifferential stability analysis and sequence correlation analysis the intervention ARFIMA-EGARCH model's fitting and forecasting are completed by using Eviews 6.0.

Stationarity test

It is well known that the application of ARFIMA model requires that time series are stationary. But not every measured is suited for a dimension estimate. Thus time series has to be stationary to decide whether the data requires differencing. For the non-stationary time series, unit root test often be used as a diagnostic tool for obtaining stationary series since one of the early motivations for unit root tests was precisely to help determine whether to use forecasting models in differences or levels in particular applications (e.g., Dickey, Bell, and Miller, 1986). In this paper, we test the sequence of stability by Eviews6.0. Figure 1 is the ADF test statistics value and the corresponding critical value which are obtained using the Eviews6.0. From Figure 1, It is easy to see that the obtained statistics data is on the rejection region when the ADF test is in 1%, 5% and 10%, and the series has no root unit sequence. Thus the series is a stationary series.

ADF Test Statistic	-18.62377	1% Critical Value*	-3.4393
		5% Critical Value	-2.8647
		10% Critical Value	-2.5685

Figure 1 : Unit root test for the three order difference sequences of wind

Model identification of time series

According to the ARMA (p, q) model schemes which were proposed by Box and Jenkins, the autocorrelation function of time series and partial autocorrelation function of the actual behavior and the theory of behavior are match. The correlation coefficient and partial correlation coefficient is obtained by Eviews (see TABLE 1). Thus we can conclude that $p = q = 1$. The sequence can be used

TABLE 1 :

order	AC	PAC	Q-Stat	Prob
1	−0. 333	−0. 333	298. 65	0
2	−0. 016	−0. 143	299. 37	0
3	−0. 032	−0. 098	302. 09	0
4	0. 032	−0. 019	304. 88	0
5	−0. 066	−0. 078	316. 77	0
6	0. 003	−0. 056	316. 8	0
7	−0. 031	−0. 071	319. 4	0
8	0. 01	−0. 044	319. 67	0
9	−0. 04	−0. 073	324. 03	0
10	0. 012	−0. 048	324. 44	0
11	0. 027	−0. 001	326. 39	0
12	−0. 034	−0. 045	329. 55	0

ARMA (1, 1) model fitting.

Parameter estimation

The parameter estimation of the time series model is obtained by Eviews 6.0. The results are shown in

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG(GARCH)	2.800403	0.373479	7.498160	0.0000
C	208.1287	21.95947	9.477854	0.0000
AR(1)	0.915097	0.006211	147.3337	0.0000
MA(1)	-0.204525	0.011382	-17.96949	0.0000
		Variance Equation		
C(5)	0.497593	0.061283	8.119587	0.0000
C(6)	0.417238	0.008068	51.71364	0.0000
C(7)	0.943322	0.005932	159.0195	0.0000

R-squared	0.778214	Mean dependent var	278.4922
Adjusted R-squared	0.777883	S.D. dependent var	264.9861
S.E. of regression	124.8862	Akaike info criterion	11.98856
Sum squared resid	31349090	Schwarz criterion	12.00805
Log likelihood	-12065.48	Hannan-Quinn criter.	11.99571
F-statistic	1175.462	Durbin-Watson stat	2.231800
Prob(F-statistic)	0.000000		
Inverted AR Roots	.92		
Inverted MA Roots	.20		

Figure 2 : The parameter estimation of ARFIMA(1,1,1)

Figure 2

As shown in Figure 3, the coefficient estimates is

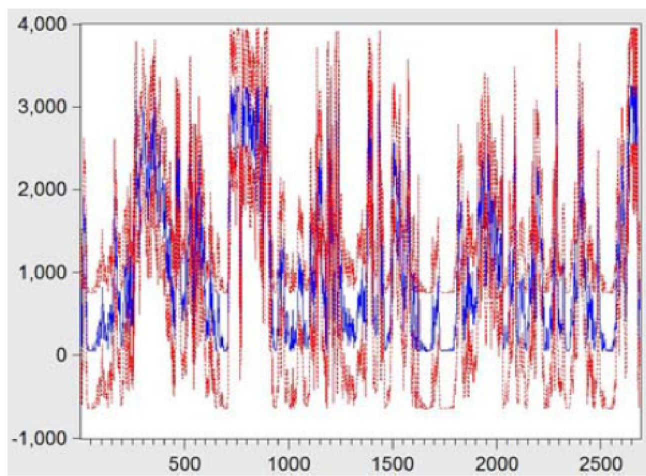

Figure 3 :

$\phi_1 = 0.946695$ÿ $\theta_2 = -0.130142$. Thus we can get the time series model

$$\Phi(L)(1-L)^d (y_t - \upsilon) = \Theta(L)\mu_t, t = 0, \pm 1, \cdots$$

where $\phi(L) = 1 - 0.915097L$ ÿ $\theta(L) = 1 + 0.204525L$.

Fitting all data, we can obtain the following curves:

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