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Research Article

The Forecasting Procedure for Long-Term Wind Speed in the Zhangye Area

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Energy crisis has made it urgent to find alternative energy sources for sustainable energy supply; wind energy is one of the attractive alternatives. Within a wind energy system, the wind speed is one key parameter; accurately forecasting of wind speed can minimize the scheduling errors and in turn increase the reliability of the electric power grid and reduce the power market ancillary service costs. This paper proposes a new hybrid model for long-term wind speed forecasting based on the first definite season index method and the Autoregressive Moving Average (ARMA) models or the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) forecasting models. The forecasting errors are analyzed and compared with the ones obtained from the ARMA, GARCH model, and Support Vector Machine (SVM); the simulation process and results show that the developed method is simple and quite efficient for daily average wind speed forecasting of Hexi Corridor in China.

1. Introduction

Energy crisis has made it urgent to find alternative energy sources for sustainable energy supply. Since the first worldwide oil crisis in the early 1970s, energy supply has become tighter and tighter. Many countries have enacted laws to promote renewable energy supply and to reduce the fossil fuel-based energy usage. In the twenty-first century, as the prices of crude oil in the international oil market has gone up like a rocket and the oil resources has been diminishing, renewable energy, such as wind energy and solar power, has attracted more and more attention from both developed and developing countries, especially from the countries that are heavy energy consumers. In recent years, the collective installed capacity of wind power systems increase with an average annual growth rate of 24.8%. There are over 100 thousand wind turbine units have been installed. The installed capacity has reached 94.1 million kilowatts and the revenue of wind power industry has exceeded 37 billion U.S. dollars. With the pressure of reducing greenhouse-gas emissions and mitigating the impact of climate changes, both developed and developing countries have been devoting more and more efforts in renewable energy development. Amongst the affordable renewable energy sources, wind power is considered as one of the most attractive clean energy sources and has becomes the first choice for renewable energy development.

The development of wind power industry is one of the China's responses to energy challenges. As China's economic development and industrialization and urbanization are speeding up, energy demand grows rapidly so that China has become the world's second energy producing and consuming country. China, however, has relative shortage of high-quality energy sources and the majority of energy sources are fossil based, such as coal and gas, which are neither environmental friendly nor sustainable in long term. In order to fix China's energy problems, a fundamental strategy is to promote energy conservation as well as to vigorously develop new energy and renewable energy sources, such as solar energy, biomass and wind energy. Amongst these alternatives, wind power has more advantages, such as a high degree of industrial maturity, low cost of power generation, good physical and social environmental impact, and become the first choice of renewable energy sources in China. In addition, wind speed is one of the most difficult weather parameters to forecast as a result of the continuous and chaotic fluctuations of the wind, this can give rise to difficulties in the energy transportation and power balance of the network. A great number of authors have proposed different kinds of methods to forecast wind speed in [1–12]. As can be seen from the literature review, hybrid models based on first definite season index method and ARMA or GARCH have not been proposed for long-term wind speed forecasting. Consequently, in this paper the approach for wind speed prediction in the Hexi Corridor Region of China is presented.

There are four advantages of the proposed methodology. Firstly, wind speed of Zhangye area exhibit seasonality and time-varying volatility attributed to weather, pressure difference and so on. We wanted to detach seasonality that would be easily comprehensible in application. Then, GARCH model is usually applied in stock prediction, due to wind speed have uncertain changes that are similar to stock, consequently, this study adopts GARCH model to predict wind speed in the Hexi Corridor Region of China. Furthermore, ARMA and GARCH eliminated the seasonal factor effects create commendable improvements that are relatively satisfactorily for current research. The wind speed forecasting errors are in general ranging from 25% to 40% [13]. It is not only with relation to the prediction methods, but also with relation to the forecast period and wind speed characteristics of the forecast location. In general, the shorter the forecast period is and the more relax the wind speed of the forecast location are, the smaller the forecast error will be, otherwise, the larger the forecast error will be [14]. However, this study concludes that the long-term forecasting errors 27.4126% and 26.0001%. Finally, there are few papers to forecast long-term wind speed, but it is very important for the programme and dispatching of wind park. The main objective of this paper is to offer developing methods of long-term wind speed forecasting, which can provide tendency analysis and reference for wind power equipment operation and wind power system planning. However, study on long-term wind speed forecasting is rarely reported in the literature. Therefore, a simple and efficient forecasting method for long-term wind speed forecasting is significant, necessary and highly desirable for the development of the wind energy systems.

The rest of paper is organized as follows. Section 2 describes the forecasting model, including the Jonckheere-Terpstra test, the first definite season index method for eliminating the seasonal factor effects and forecasting models based on either the ARMA model or the GARCH model (ES-ARMA model and ES-GARCH model). Section 3 introduces two loss functions for evaluation of forecasting performance. Section 4 presents a case study which applies the developing forecasting procedure to the wind speed data sets obtained in the Hexi Corridor Region Zhangye city of China from 2001 to 2006 (six years) and the analysis of the results.

2. The Developing Forecasting Model for Long-Term Wind Speed Prediction

The developing forecasting models are primarily for predicting long-term wind speed based on historical wind speed data (come from Meteorological Bureau in Gansu Province http://cdc.cma.gov.cn/), which usually exhibit periodic patterns and seasonal factor effects. It can be built based on the ARMA and the GARCH model with data set verification and transformation phase, so the developing models are proposed: first, we eliminate the seasonal factor effects, and then use ARMA model and GARCH model to predict, these models are called ES-ARMA model and ES-GARCH model.

Moghram and Rahman [15], review five short-term load forecasting methods. The conclusion reached is that there is no one best approach, model performance under specific conditions should be analyzed and understood and incremental improvements made based on knowledge gained [16]. The developed hybrid ES-ARMA model and ES-GARCH model are more proper forecasting technique for daily average wind speed prediction in Zhangye city of Hexi Corridor through the historical data analysis, research, and compared with other conventional forecasting methods. So from this view, the simple and efficient method is the best option for the dispatching department of wind park.

The model consists of three typical stages: (1) perform the Jonckheere-Terpstra test for checking whether the given wind speed series of 2006 have significant difference with the ones from 2001 to 2005 or not, whether they exhibit a periodic pattern or not; (2) if the series are not significant, they have periodic pattern, preprocess the series by separating the seasonal factor effects using the first definite season index method; and (3) construct an ARMA model or a GARCH model for actual forecasting the future trend of the preprocessed series. Details about these stages are given in the following subsections.

2.1. *Jonckheere-Terpstra Test*

The Jonckheere-Terpstra test is a nonparametric test for ordered differences among classes (segments of data series). It tests the null hypothesis that the distribution of the response variable does not differ among the classes. The Jonckheere-Terpstra test statistics can be computed by the following two steps.

(i) Form $R(R-1)/2$ Mann-Whitney counts $M_{i,i'}$, where $i < i'$, for pairs of rows in the contingency table as follows:

$$M_{i,i'} = \{\text{number of times } X_{i,j} < X_{i',j'},\ j = 1,\dots,n_i;\ j' = 1,\dots,n_{i'}\} + 0.5\{\text{number of times } X_{i,j} = X_{i',j'},\ j = 1,\dots,n_i;\ j' = 1,\dots,n_{i'}\}, \tag{2.1}$$

where X_{ij} is the jth response in the ith row.

(ii) Compute the Jonckheere-Terpstra test statistics by $J = \sum_{1\le i<i'\le R} \sum M_{i,i}$.

This test will reject the null hypothesis of no difference among classes for large values of J. Asymptotic P-values for the Jonckheere-Terpstra test are obtained by using the normal approximation for the distribution of the standardized test statistics. The standardized test statistics can be computed by

$$Z = \frac{J - \left(N^2 - \sum_{i=1}^{k} n_i^2\right)/4}{\sqrt{\left(N^2(2N+3) - \sum_{i=1}^{k} n_i^2(2n_i+3)\right)/72}}, \tag{2.2}$$

where k is the number of sample groups, n_i is the number of the ith sample group (SAS/STAT User's Guide). If P-values less than the significant level α, then the distributions of the response variables have significant difference, otherwise, they do not have significant difference.

2.2. First Definite Season Index Method

Suppose there is a data series $x_1, x_2, \dots, x_T$ $(T = ml)$ and can be recorded in an array format as $x_{11}, x_{12}, \dots, x_{1l};\ x_{21}, x_{22}, \dots, x_{2l}; \dots;\ x_{m1}, x_{m2}, \dots, x_{ml}$, where l is the number of columns, which denotes the number of data points in one cycle, and m is the number of rows, which denotes the number of cycles in the data series, the average value for each cycle can be calculated by:

$$\overline{x}_k = \frac{(x_{k1} + x_{k2} + \cdots + x_{kl})}{l} \quad (k = 1, 2, \dots, m). \tag{2.3}$$

Dividing the time series by the cycle average value, one can have a normalized time series as:

$$I_{ks} = \frac{x_{ks}}{\overline{x}_k} \quad (k = 1, 2, \dots, m;\ s = 1, 2, \dots, l). \tag{2.4}$$

The seasonal index for the jth data element in a cycle is defined as the average value of I_{kj} $(j = 1, 2, \dots, l)$, which are corresponding to the same time sampling point in every cycle, and can be calculated by

$$I_j = \frac{(I_{1j} + I_{2j} + \cdots + I_{mj})}{m} \quad (j = 1, 2, \dots, l). \tag{2.5}$$

Thanks to the following fact:

$$\sum_{j=1}^{l} I_j = \frac{1}{m}\sum_{k=1}^{m}\sum_{s=1}^{l} I_{ks} = \frac{1}{m}\sum_{k=1}^{m}\frac{\sum_{s=1}^{l} x_{ks}}{\overline{x}_k} = \frac{1}{m}\sum_{k=1}^{m} l = l \tag{2.6}$$

the seasonal index satisfies the normalized condition.

Dividing each data element x_{ks} in the time series by the corresponding seasonal index I_s as follows:

$$y_{ks} = \frac{x_{ks}}{I_s} \quad (k = 1, 2, \ldots, m;\; s = 1, 2, \ldots, l), \tag{2.7}$$

one can obtain a time series y_{ks} that has the seasonal factor effects separated.

2.3. ES-ARMA Forecasting Model

It is possible to build a linear stochastic model of a wind speed time series using the Autoregressive Moving Average (ARMA) model. An ARMA model of order (p, q) can be defined as

$$y_t - \varphi_1 y_{t-1} - \varphi_2 y_{t-2} - \cdots - \varphi_p y_{t-p} = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \tag{2.8}$$

or

$$\varphi(B) y_t = \theta(B) a_t, \tag{2.9}$$

where p is the number of autoregressive terms, and q is the number of lagged forecast errors in the prediction equation, y_i $(i = t, \;\; t-1, \ldots, t-p)$ is series that eliminating seasonal effects and a_j $(j = t, \;\; t-1, \ldots, t-q)$ is stationary white noise with zero mean.

The order of an ARMA model can be determined by using the autocorrelation function (ACF) and the partial autocorrelation function (PACF), proposed by Box and Jenkins. Autocorrelation and partial autocorrelation graphs, which provide information about the AR and MA orders, are then drawn based on the specified lag numbers. Autoregressive (AR) process order is determined from the partial autocorrelation graph and similarly MA process order is determined from the autocorrelation graph [17].

2.4. ES-GARCH Forecasting Model

2.4.1. Construction of a GARCH Model

To relax the traditional assumptions of homogeneity, in 1982, Engle [18] suggests that the conditional variance can be modeled as a function of the squared lagged residual. That is, the predictable wind speed is dependent on past value. After that, in 1986, Bollerslev [18] generalizes the conditional variances in the ARCH model by assuming that the conditional variances are not only subject to the influences caused by the squared error terms, but also to the previous conditional variances.

After the seasonal effects are separated, a wind speed time series becomes stationary. It is possible to build GARCH model; the regression model of GARCH (p, q) for the time series y_t can be described as

$$y_t = \mathbf{x}_t \boldsymbol{\gamma} + u_t, \tag{2.10}$$

where

$$u_t = \sqrt{h_t}\varepsilon_t, \tag{2.11}$$

where

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i {u_{t-i}}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}. \tag{2.12}$$

ε_t is a sequence of independent, uniformly distributed random variables with zero mean and unit variance, that is, $E(\varepsilon_t) = 0$, $\mathrm{var}(\varepsilon_t) = 1$. The model requires the following conditions:

$$\alpha_0 > 0, \quad \forall i \alpha_i \geq 0, \quad \beta_i \geq 0, \quad \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1. \tag{2.13}$$

The unobservable parameters are estimated through the Maximum Likelihood (ML) estimation. ML estimates are known to be asymptotically unbiased and efficient. The parameter estimation is based on maximizing a likelihood function for the available data [19]. Rigorous statistical hypothesis testing is applied to validate the model assumptions of the GARCH specification. The diagnosis checks verify the statistical significance and assumptions of the parameters in the GARCH model and its residuals (actual value minus predicted value) [19]. Statistical tests on the residuals include the F-statistic, Ljung-Box statistic and plots, such as the autocorrelation and partial autocorrelation.

The Akaike's Information Criterion (AIC) is a metric that can be used to select optimal model from a class of competing models. The AIC compares the accuracy of the model against its complexity measured by the number of parameters. For a model, the AIC is given by

$$\mathrm{AIC} = -2 \ln L + 2P, \tag{2.14}$$

where p is the number of parameters in the model and $\ln L$ is the natural logarithm of the maximum likelihood [20].

2.4.2. Forecasting Procedure Using the GARCH Model

The procedure consists of the following steps: (i) eliminate the seasonal effects; (ii) forecast using the least square method; (iii) conduct the ARCH test. If the result is Yes, go to step (iv), otherwise, stop. The flow chart of this procedure is shown in Figure 1.

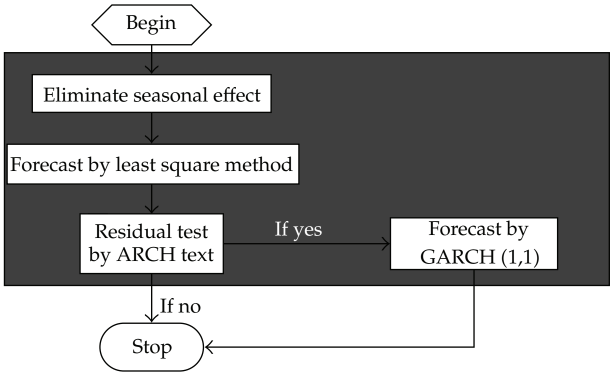

Figure 1: The flow chart of the forecasting procedure using ES-GARCH model.

3. Evaluation of Forecasting Performance

Edison Electric Institute's "Guide to Forecasting Methodology" [21] presents a brief description and examples of the major forecasting methods currently in use. These are: (1) Time Trend Forecast, (2) Time Series Forecast, (3) Informed Opinion, (4) End Use, (5) Econometric, and (6) Hybrid End Use and Econometric. The guide presents a set of criteria for evaluating for forecasting method: understandability, credibility, accuracy, cost, maintainability, and adaptability. Generally, the forecasting method used will depend on the relative emphasis placed on the criteria [16].

Two loss functions can be served as the criteria to evaluate the forecasting performance relative to wind speed value including mean absolute error (MAE) and mean relative error (MRE). The loss functions are expressed as follows:

$$\begin{aligned} \text{MAE} &= \frac{1}{T}\sum_{i=1}^{T}\left|y_t - \hat{y}_t\right|, \\ \text{MRE} &= \frac{1}{T}\sum_{i=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right|. \end{aligned} \tag{3.1}$$

The MAE measures are not very useful, because they have some relations with the original data. The MRE is widely used, and is the basic measures in this evaluation [22, 23]. We take the absolute values because the magnitude of error is more significant than the direction of error.

4. Case Study

4.1. Test Data Set

Although Hexi Corridor region in Gansu province is not the richest wind energy source in China, its reserves of wind energy is the fifth in China. Zhangye area is in the middle of Hexi Corridor and has become an important production base in Gansu Province. It potentially is a good site for developing a wind farm. Accurate prediction of long-term wind speed would be

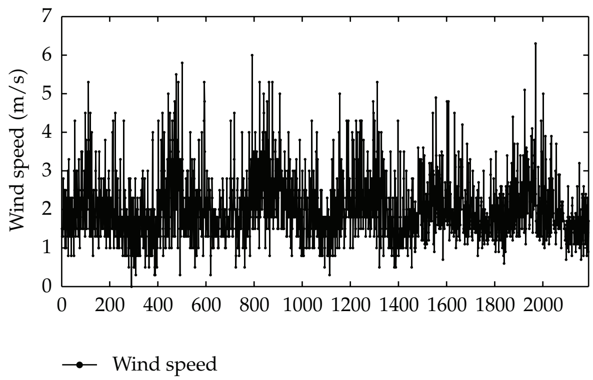

Figure 2: Plot of the wind speed values from 2001 to 2006 of Zhangye city in Gansu province.

Table 1: Season division.

Season	Period
Spring	March–May
Summer	June–August
Autumn	September–November
Winter	December–February

very helpful to aid the evaluation. Therefore, this case chooses the wind speed data obtained from the Zhangye area for a period of time as the test data set, which contains the daily wind speed values for the period of 2001–2006, as depicted in Figure 2.

The data set is divided into two parts: the first part contains the data from 2001 to 2005 and it is used for training the forecasting procedure; and the second part contains the data in year 2006 and it is used as the future wind speed values for testing the forecasting procedures. Every part is divided into four seasons: Spring, Summer, Autumn, and Winter, as shown in Table 1.

The implementation of the developing forecasting procedure and ARMA model are on a PC with one Pentium IV processor and 512 MB RAM at 1000 MHz. The software used are MATABLE and EVIEWS software package. The running times, including training and prediction, are within one minute for each test presented.

4.2. The Jonckheere-Terpstra Test

For the test data set, including the two parts, perform the Jonckheere-Terpstra test. The results of the test are tabulated in Table 2.

It can be seen from Table 2 that the difference of observed J-T statistic and mean J-T statistic is not obvious. The probability P of J-T statistic is .998. If the significant level is set to be .05, that is, equals .05, then the wind speed in each year have similar distribution as $P = .998 \gg= .05$. The results show that the data in 2006 do not have significant difference with the data from 2001 to 2005, that is to say, the wind speed data have periodic characteristic.

Table 2: The results of Jonckheere-Terpstra test.

Jonckheere-Terpstra test Grouping Variable: cs	Wind speed
Number of levels in cs	6
N	2190
Observed J-T statistic	999135.5
Mean J-T statistic	9991874.5
Std. deviation of J-T statistic	16794.834
Std. J-T statistic	−.003
Asymp. Sig. (2.tailed)	.998

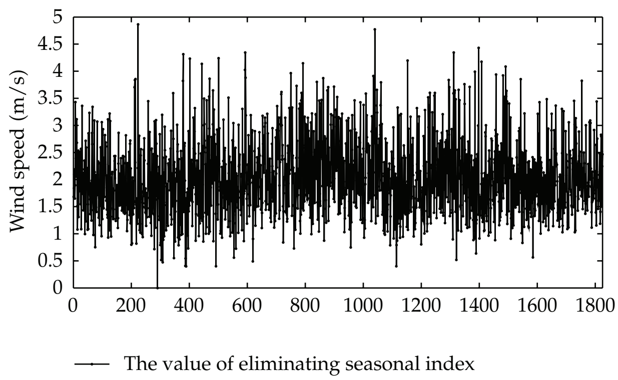

Figure 3: The wind speed from 2001 to 2006 of separating the season effects.

4.3. *Eliminating the Seasonal Effects Using the First Definite Season Index Method*

Modeling seasonal time series has been one of the main research endeavors for decades. In the early 1920s, the decomposition model along with seasonal adjustment was the major research focus due to Persons [24, 25] work on decomposing a seasonal time series [26]. The significant assumption in many different seasonal adjustment approaches is that seasonality can be separated from other components of the time series. That is to say, the seasonal time series can be decomposed into a seasonal component I_s and a nonseasonal component $y_{ks} : y_{ks} = x_{ks}/I_s$. The nonseasonal component can be further predicted by many methods. Seasonal adjustment is a process that estimates the seasonal component called seasonal factors and then dividing the original series by seasonal factors for multiplicative models or additive models. Applying the first definite season index method described in Section 2.2, the wind speed series that has the seasonal effects eliminated is obtained and plotted in Figure 3. This preprocessed wind speed series become smooth and is ready for building a linear stochastic model using ARMA or GARCH model.

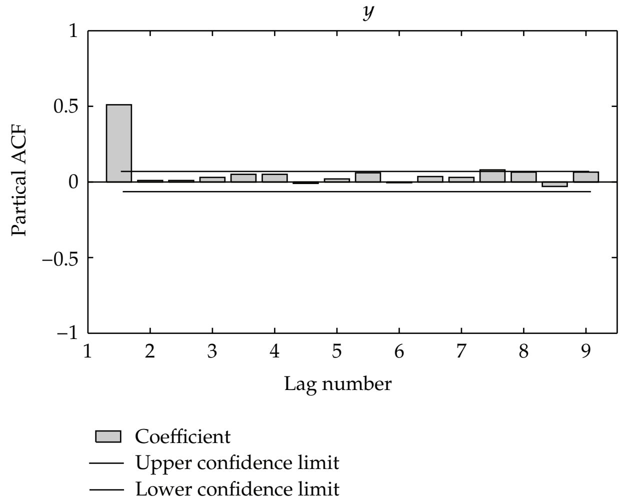

Figure 4: The partial autocorrelation function of determining p.

4.4. Building a Linear Stochastic Model

4.4.1. Forecasting Procedure Using the ES-ARMA Model

(A) Construction of the ARMA Model

Based on the autocorrelation and partial autocorrelation graphs shown in Figures 4 and 5, two observations can be made: (1) the autocorrelation coefficients function (ACF) values vary significantly from zero to three lags and then statistically rapidly declines to zero; and (2) the partial autocorrelation coefficient function (PACF) value begins with a very high value at one lag and then statistically rapidly decrease to zero. Based on these two observations, the order of the ARMA model can be determined as $q = 3$, $p = 1$, that is, ARMA (1, 3).

(B) Forecasting Result

Figure 6 shows the predicted wind speed value by applying the ES-ARMA model.

4.4.2. Forecasting Procedure Using the ES-GARCH Model

(A) Construction of GARCH Model

GARCH model in EVIEWS soft is used to forecast the preprocessed wind speed series of Zhangye city. According to the flow chart of applying GARCH model shown in Figure 1, firstly, we used the least square method to estimate wind speed data; secondly, we preformed the ARCH test over the residuals by analyzing the autocorrelation and partial autocorrelation of the residuals and looking at the values of the F-statistics, which is not strong. It has been found that the residuals have ARCH effect. The results of the ARCH test are given in Table 3. We then drew the residuals' histogram, which follows student's distribution. Moreover, when the parameters are estimated, in general we have checked that all of them are significant, according to the ARCH test; Consequently, the optimal lag order of conditional

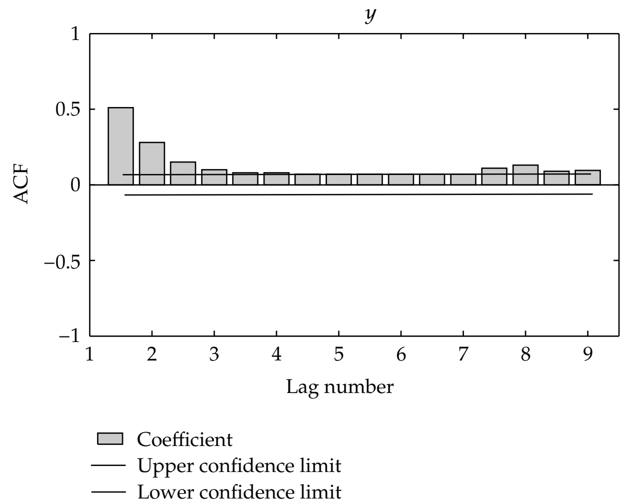

Figure 5: The autocorrelation function of determining q.

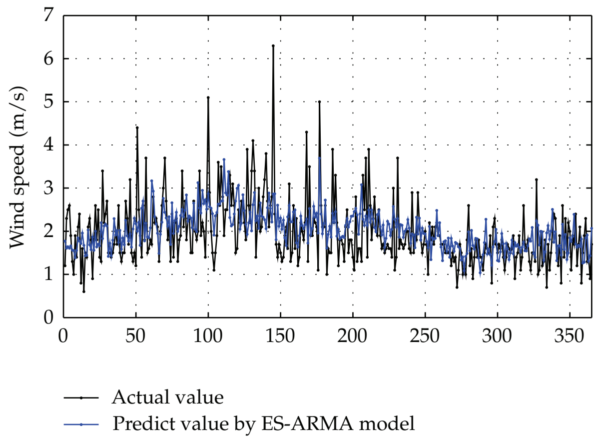

Figure 6: The comparison of actual value and forecast value of ES-ARMA model.

variance has been selected by the AIC, in all cases, the criteria agree and lead to the choice of $p = q = 1$. Therefore we chose GARCH (1,1) model to predict the future wind speed as. Figure 7 presents the predicted wind speeds using the ES-GARCH model.

4.5. Evaluation of Forecasting Results

We evaluate the variance forecasting ability of ARMA (1,3) and GARCH (1,1), ES-ARMA (1,3) model and ES-GARCH (1,1) model that have been eliminated the seasonal effects. Two loss functions (MAE and MRE) are considered as the evaluation methods of variance forecasts and the results are reported in Tables 4 and 5. These two loss function values of ES-ARMA (1,3) model and ES-GARCH (1,1) model are almost smaller than those of ARMA (1,3) and GARCH (1,1) model except the MRE of Summer by ES-ARMA model. This indicates that ES-ARMA (1,3) model and ES-GARCH (1,1) model have superior volatility forecasting

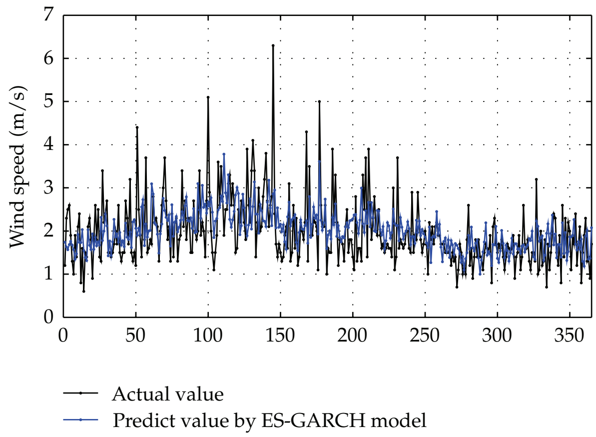

Figure 7: The comparison of actual value and forecast value of ES-GARCH model.

Table 3: ARCH test.

F-statistic	2.357606	Probability		0.124818
Obs*R-squared	2.357220	Probability		0.124704
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.722515	0.034614	20.87338	0.0000
RESID^2(−1)	0.032836	0.021386	1.535450	0.1248
R-squared	0.001078	Mean dependent var		0.747041
Adjusted R-squared	0.083768	S.D. dependent var		0.833057
S.E. of regression	0.797402	Akaike info criterion		2.259945
Sum squared resid	1383.610	Schwarz criterion		2.288566
Log likelihood	−2460.250	F-statistic		20.98596
Durbin-Watson stat	1.936123	Prob (F-statistic)		0.000000

ability for the case. Although ES-ARMA model only improves **4.673**% compared with ARMA model, the forecasting values of ARMA model become a stationary line in Figure 8, and it is impossible to reflect the future trends and changes of wind speed. That is to say, this forecasting model is not persuasive. However, ES-ARMA model and ES-GARCH model give similar prediction trends for wind speed and improve their forecasting accuracy effectively. In addition, traditional SVM can be used to forecast wind speed, it is obvious that its accuracy is lower than the proposed models as seen in Table 6.

4.6. Discussions and Analysis

The forecasting errors are defined as the differences between the actual wind speed and the predicted one obtained from the forecasting models (ES-ARMA model and ES-GARCH model). The positive error values would imply that the model underestimates the actual wind speed while the negative values indicate that the model overestimates the actual wind speed. Our explanation to why the preprocessing eliminated seasonal effects helps is that seasonal variation of the time series with seasonality may account for the preponderance of its total change. Models that ignore these seasonal patterns will results in a high error

Table 4: The errors of ARMA model and ES-ARMA model.

	ARMA model			ES-ARMA model	
	MAE	MRE		MAE	MRE
Spring	0.527913	34.6678%	Spring	0.488744	31.3714%
Summer	0.669174	25.4236%	Summer	0.616475	27.4234%
Autumn	0.562325	27.9945%	Autumn	0.51789	27.4116%
Winter	0.515766	40.4048%	Winter	0.342647	25.6505%
Total error	**0.569286**	**32.086**%	Total error	**0.485655**	**27.4126**%

Table 5: The errors of GARCH model and ES-GARCH model.

	GARCH model			ES-GARCH model	
	MAE	MRE		MAE	MRE
Spring	0.685473	38.4771%	Spring	0.508807	30.3502%
Summer	0.85133	36.1763%	Summer	0.635077	24.7349%
Autumn	0.720126	34.0685%	Autumn	0.552815	27.3681%
Winter	0.437071	27.7405%	Winter	0.301493	21.5989%
Total error	**0.674836**	**34.2643**%	Total error	**0.500040**	**26.0001**%

and poor forecasting accuracy. The process of deseasonalizing removes these large seasonal variations from the original data, so helps improving the modeling accuracy.

It is also shown in Tables 4 and 5 that the proposed forecasting procedure using the ES-GARCH model gave the minimum MRE, the forecasting procedure using the ES-ARMA model gave the moderate MRE, whereas, ARMA and GARCH model gave the maximum MRE. Also, it has been observed that the proposed forecasting procedures using the ES-ARMA and ES-GARCH models lead to **4.673**% and **8.2642**% reductions in total MRE respectively in comparison with the ARIMA and GARCH model as shown in Figures 9 and 10. Furthermore, Table 6 indicates that the proposed two models are better than traditional SVM.

It has potential economic benefits for the proposed approaches, which has been used for the estimation of the reserve of effective wind energy in the Zhangye city with the Hexi Corridor region of China. The wind energy can be predicted using the following formula: $W = \rho v^3 A/2$, where W is wind energy in J, ρ is air density in $\mathrm{kg/m^3}$, v is wind speed in m/s, A is wind energy density in $\mathrm{w/m^2}$, which is the wind energy flow through the cross-sectional area that is perpendicular to the wind speed within a unit time.

When ES-GARCH is used for the prediction of wind energy in real-world wind power systems, a significant difference can be expected. For instance, based on the annual reserve energy of wind in Hexi Corridor region in China, when the wind energy is used to replace the steam power, although ES-GARCH improves 8.2642%, if ES-GARCH model is used, it can be expected to save **1606.2** million kilowatts of steam power, which are equivalent to the reduction of **469,551.8** tons coal annually. Moreover, it can be expected to reduce CO_2 emissions by **123,026** tons, SO_2 emissions by **6775.4** tons, and nitrogen oxide emissions by **6001** tons. This can yield an economic cost saving of **3685.3** million to **4625** million RMB annually.

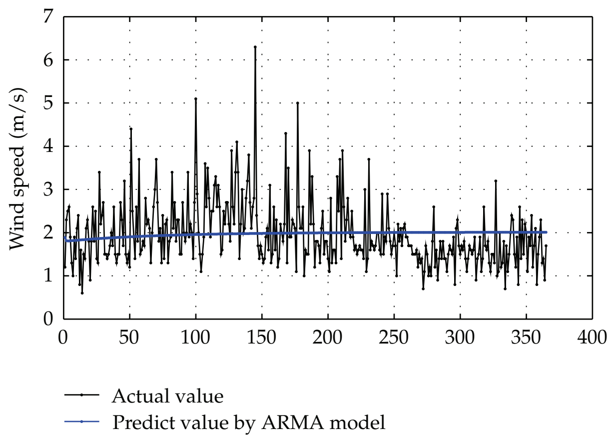

Figure 8: The comparison of actual value and forecast value of ARMA model.

Table 6: The errors of Support Vector Machine (SVM).

	SVM model	
	MAE	MRE
Spring	0.601531	31.0383%
Summer	0.684802	32.998%
Autumn	0.421253	26.6653%
Winter	0.567566	40.8079%
Total error	**0.568519**	**32.8925%**

5. Conclusions

The development of wind power industry is the important choice of China's response to energy challenges. China has become the world's second energy producing and consuming country, but generally speaking, China has relative shortage of high-quality energy sources, energy consumption is dominated by coal, environmental pressure, the energy supply system faces major challenges. To solve China's energy problems, the fundamental thing is to overall transform the economic development approach to promote energy conservation, at the same time, adhere to diversified development, vigorously develop new energy and renewable energy. Compared with solar energy, biomass and other renewable energy sources, wind power has a high degree of industrial maturity, low cost of power generation, good physical and social environmental impact, and so forth, should be the first choice of renewable energy development in future in China.

Although wind speed generally shows nonlinear, nonstationary and chaotic characteristics, it has been found based on the analysis of existing wind speed data that the wind speed of the Hexi Corridor region in China is periodic with one cycle per year. Seasonal variation is one of the most commonly encountered phenomena in many fields, such as electricity load, wind speed. How to best model and forecast the variation is a key task in planning and other related decision-making activities. This paper provides both approaches separated seasonal factors to predict wind speed of Zhangye area, the simulation results indicate the adequacy of the proposed models used in wind speed forecast. This procedure can enhance volatility forecasting ability of the well-known ARMA and GARCH model. Moreover, two

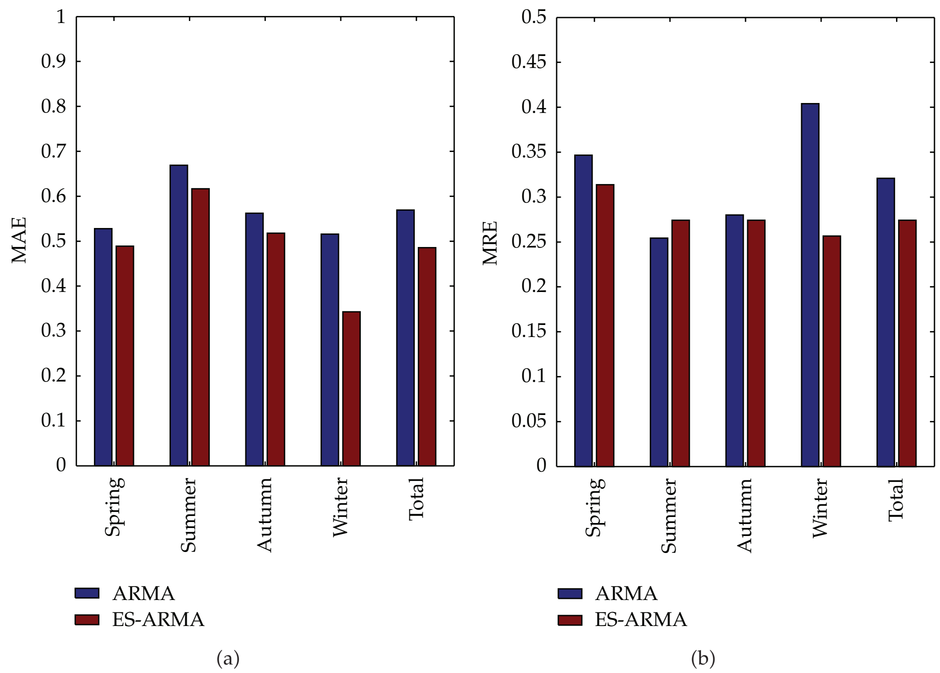

Figure 9: MAE and MRE comparison of ES-ARMA model and ARMA model.

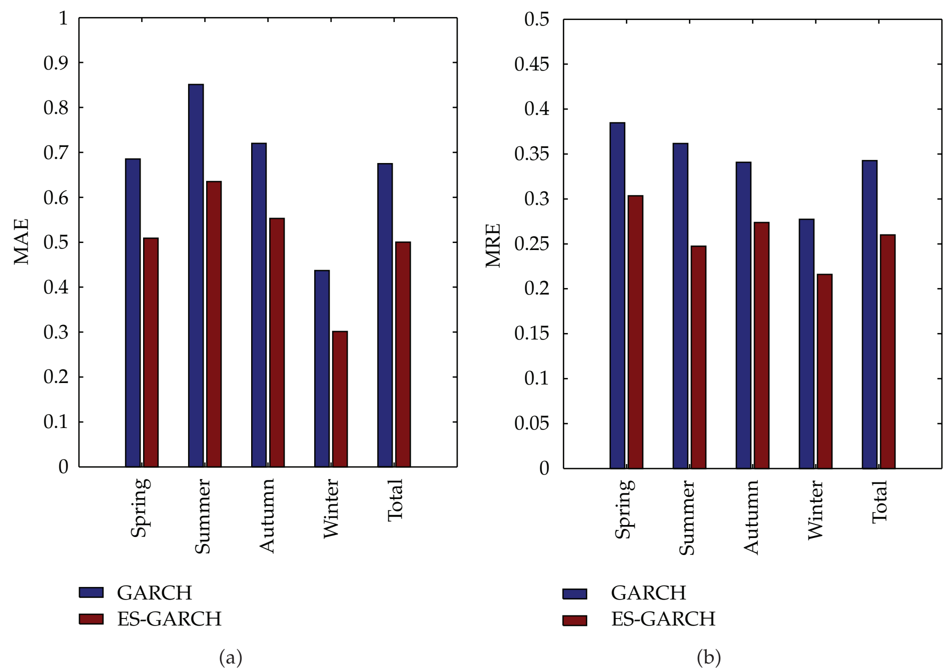

Figure 10: MAE and MRE comparison of ES-GARCH model and GARCH model.

loss functions (MAE and MRE) are used as the criteria for measuring the forecasting performance. Based on the loss functions, the results show that the new forecasting procedure using either the ES-ARMA model or the ES-GARCH model can give better performance. Consequently, this study has been able to touch on the effective methods to perform the long-term prediction problems.

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