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Wind Attribute Time Series Modeling & Forecasting in IRAN

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Abstract

A wind speed forecast is a crucial and sophisticated task in a wind farm for planning turbines and corresponds to an estimate of the expected production of one or more wind turbines in the near future. By production is often meant available power for wind farm considered (with units KW or MW depending on both the wind speed and direction. Such forecasts can also be expressed in terms of energy, by integrating power production over each time interval. In this study, we technically focused on mathematical modeling of wind speed and direction forecast based on locally data set gathered from Aghdasiyeh station in Tehran. The methodology is set on using most common techniques derived from literature review. Hence we applied the most sophisticated forecasting methods to embed seasonality, trend, and irregular pattern for wind speed as an angular variables. Through this research, we carried out the most common techniques such as the Box and Jenkins family, VARMA, the component method, the Weibull function and the Fourier series. Finally, the best fit for each forecasting method validated statistically based on white noise properties and the final comparisons using residual standard errors and mean absolute deviation from real data.

Keywords: Renewable Energy, Forecasting, Wind Speed and Direction Predicting, Weibull Distribution, Box and Jenkins, Vector Autoregressive (VAR), Fourier Series.

1. Introduction

Nowadays wind energy as an alternative to fossil fuels, is plentiful, renewable, widely distributed, clean, produces no greenhouse gas emissions during operation and uses little land. The effects on the environment are generally less problematic than those from other power sources. Wind power could be extracted from air flow using wind turbines or sails to generate mechanical or electrical energy. Windmills are used for their mechanical power, wind pumps for water pumping, and sails to drive ships. Large wind farms consist of thousands of wind turbines which are connected to the electric power transmission network. Many analysis show that for new constructions, onshore wind is an inexpensive source of electricity, competitive with or in many places cheaper than coal, gas or fossil fuel plants. Offshore and onshore wind speed is the main affected parts in power generation planning. Figure 1. shows total global electricity generation from wind sources and is exceeded than 520 TWh (TeraWatt hour) in 2012; where 1 TWh = 1,000 GWh = 1,000,000 MWh = 1,000,000,000 kWh.

Wind power is very reliable source of energy and is consistent from year to year but has significant variation over shorter time scales such as in season, month, week, day and hour. Power management techniques need sophisticated forecasting methods in short term prediction of wind speed as well its direction. In addition, weather forecasting permits the electricity network to be readied for the predictable variations in production that occur. There are many different techniques to forecast wind speed individually ad less efforts carried out on simultaneous prediction of speed and direction. In the literature, predicting methods categorized by physical and statistical models.

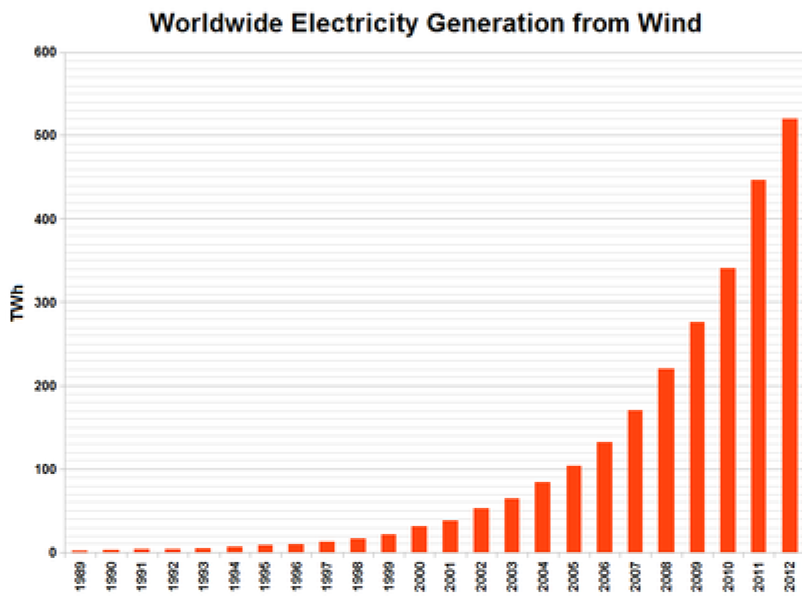

Figure 1: Global wind electricity generation trend

Physical models incorporates physical properties such as terrain, obstacles, pressure and temperature to forecast the wind speed (Lei et al., 2009; Giebel, 2003). Usually, numerical weather prediction models (NWP) are used for the large scale weather prediction. To forecast the short-term wind speed at local sites, this approach might not give the reliable results. However, it can perform equally well or better with large forecasting horizons (e.g. more than 6 h), as compared with the other statistical models (Landberg, 2001).

Statistical models is the most technical way in time series forecasting. Among the most notable approaches the Seasonal Auto Regressive Integrated Moving Average (SARIMA) was introduced by Box–Jenkins methods (Box & Jenkins, 2015). Torres (2005) applied the ARIMA models comparisons to anticipation short-term wind series. (Tuller, 2004) studied speed changing patterns in west of Canada. His results showed a decrease tend in average wind speed in winter. Akpinar and Akpinar (2005) carried out a forecasting analysis based on local data in Turky for five time intervals. Cheng et al.(2002) examination showed an increasing wind speed in winter and decreasing trend in summer. Ewing et al.(2006, 2008) fitted an autoregressive models and also a Generalized Auto-Regressive Conditional Heteroskedasticity conditional variance called as GARCH model to local data. Payne et al.(2009) applied the use of GHARCH-M method in different times of the wind speed fluctuations which previously were discussed. Guo et al.(2010) offered a new combinatorial model to forecast wind speed in long-range and a moving average return model in the form of Autoregressive Moving Average (ARMA) and extended back GARCH dissonance for Errors to predict and compare whit a Support Vector Machine (SVM) method. They showed that their method is simple extension and is very useful for average daily forecast for wind speed in china. Liu et al.(2013) presented a quantitative method for estimating wind speed and interval estimation of the operation of wind turbines and the predicted power output of the wind carried the technological advantage of this method due to the fluctuation of wind power forecast average wind speed. This method is applied to construct a model to predict ARMA- GARCH-M. Estimation of the operation speed and power output of a wind turbine is expected.

Neural network (NN) models is another soft computing statistical method for wind speed forecasting. NN is a methods from the artificial intelligence and machine learning fields. For instance, Li and Shi (2010) compared three different artificial neural networks (ANNs) to compare the wind speed, and they found that the selection of NN type and parameters greatly affects the performance of wind speed forecasting. Monfared et al.(2009) proposed a strategy to predict wind speed with fuzzy logic and neural network. Erasmo, used an Autoregressive Integrated Moving Average (ARIMA) model to interpret wind speed in three different regions of the Mexico based on one month time series. The neural network then obtained by an ARIMA method taking into account the non-linear trends can be identified for decreasing errors after taking in formation from sample for each of the sites to predict the wind speed which was used to form a composite model. The results compared with ARIMA and NN model separately using some common statistical indices such as Mean Square Error (MSE), Mean Absolute Deviation (MAD) and Mean

Absolute Error (MAE) which the smaller amounts shows the best fits for forecast speed of wind (Cadenas & Rivera, 2010).

Spatial-temporal models take the location information into consideration and predict the wind speed based on the speed information at the neighboring sites. Morales et al.(2010) developed a joint methodology for constructing a spatial–temporal model to forecast the wind speed. Meanwhile, wind direction is an important factor for efficient turbine control for getting the most power with a given wind speed. Based on the forecasts on wind direction, it would be possible to align the turbine with the wind direction to get the most energy output. However, research on forecasting wind direction is far less common, and the related publications for energy conversion purpose are even scarcer. Zhang et al.(2002) took a Bayesian approach to develop models for predicting wind speed, wind direction, and ambient temperature, and combined them to assess the online conductor thermal overload risk. Erdem and Shi (2011) applied four different method and they compared results on predicting wind speed and direction and then they showed the result derived from a Vector Autoregressive (VAR) method is the best forecast.

The structure of the paper is organized as follows. A brief discussion on six gereral mathematical model for wind attribute time series forecasting is presented in section 2. The proposed forecasting models are provided in section 3 along with explaining hypothesized validation techniques. Here forecasts presented individually using each common forecasting methods after calibrating them on real data. The 4th section discusses numerical results on forecasting performance measures and argues on findings. And finally, some concluding remarks are given in the last section.

2. Material and Methods

In order to hourly forecast wind attributes in the Aghdasiyeh station, we candidate five common forecasting methods that covers both the linear and angular stochastic prediction models. They are ARMA-GARCH, VARMA, the component approach, the Weibull function and Fourier series. The last two approach considered wind attribute as a given function of time. Here correlation between wind attribute and time considered for curve fitting. Although in other methods, we focused on autocorrelation analysis. In each applied method, the forecasting errors are defined as the differences between the actual wind attribute and the predicted one obtained from the forecasting models. The positive error values would imply that the model underestimates the actual wind attribute while the negative values indicate that the model overestimates the actual wind attribute. Here alternative method depicted as:

2.1 Linear Box-Jenkins time series models

The most common technique in univariate time series is on using Box and Jenkins models. Such model focused on time series pattern without reflecting the associated covariates. By using this approach it is possible to fit appropriate models to show level, trend, seasonality and random patterns on wind speed. Since the present level of wind speed (Y_t) depends on its immediate past, we describe this univariate time series Y_t by the process

$$Y_t = E\left[Y_t|\Omega_{t-p}\right] + \epsilon_t \qquad (1)$$

where $E[.|.]$ denotes the conditional expectation operator, Ω_{t-p} the information set at time $t-p$ and ϵ_t the innovations or residuals of the time series which are uncorrelated, have mean zero and play the role of the un predictable part of the time series. The most well-known model is Autoregressive Moving Average $ARMA\,(p,q)$ model which following (mean adjusted) form.

$$Y_t - \mu = \sum_{i=1}^{p} \varphi_i (Y_{t-i} - \mu) + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \qquad (2)$$

where μ is mean of time series, φ is autoregressive coeffcient and θ is moving average coeffcient. When $q = 0$ we have a pure autoregressive process and when $p = 0$ pure moving average process.

It may happen that squared residuals exhibit significant serial correlation. It indicates that errors are not independent although they are serially uncorrelated. Residuals are called then conditionally heteroscedastic and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models have been proved to be very successful at modeling the serial correlation in the second moment of the underlying time series. The variance equation of the process is expresses as follows:

$$\epsilon_t = z_t \sigma_t \quad ; z_t \sim D(0,1) \qquad (3)$$

$$Var(\epsilon_t|\Omega_{t-1}) = E(\epsilon_t^2|\Omega_{t-1}) = \sigma_t^2 = K + \sum_{j=1}^{a} \alpha_j \sigma_{t-j}^2 + \sum_{i=1}^{b} \beta_i \epsilon_{t-1}^2 \qquad (4)$$

$$= K + \alpha(B)\sigma_{t-1}^2 + \beta(B)\epsilon_{t-1}^2 \qquad (5)$$

where z_t are iid random variables with zero mean and unit variance and D is their probability density function. Common choices for density function D are normal distribution, student-t distribution and generalized error distribution. Thus, under the $GARCH(a, b)$ model, the conditional variance of ϵ_t, σ_t^2 depends on the squared residuals in the previous b periods, and the conditional variance in the previous a periods.
In general seasonal models may be applied after de-seasonalizing a given time series. In such cases behaviors of wind speed in repeated time intervals could be presented in the form of a SARMA model after evaluating and determining seasonal effects. For example wind speed behavior may be repeated on every morning.

2.2 Multivariate time series models

If one wish to forecast a stationary series not only based upon its own past realizations, but additionally taking realizations of other stationary series into account, then the model nominated as a vector autoregressive process (VAR, for short)(Suri, 2011). For this purpose we use the VAR method using vector retrograde.

$$\emptyset(B)Y_t = \delta + \theta(B)\varepsilon_t \tag{6}$$

The error terms ε_t are assumed to be white noise processes, which may be contemporaneously correlated, but are uncorrelated with any past or future disturbances.

2.3 Component approach

Some of researchers believe that wind direction (D) and speed or velocity (V) should be analyzed together using angular variables (José et al., 2008). In the component model, the first step is to find out the prevailing wind direction. Based on it, the lateral and longitudinal components of the wind speed can be calculated. In order to find the prevailing wind direction, the following approach is utilized.

$$\bar{D} = \begin{cases} tan^{-1}\left(\frac{S}{C}\right) & S > 0, C > 0 \\ tan^{-1}\left(\frac{S}{C}\right) + \pi & C < 0 \\ tan^{-1}\left(\frac{S}{C}\right) + 2\pi & S < 0, C > 0 \end{cases} \tag{7}$$

where $\bar{D}$ is the mean direction. S is the summation of the sine values of the angles of wind vectors with respect to the north axis (i.e. S = $\sum_{i=1}^{n} sin\ D_i$), and C is the summation of the cosine values of the angles of wind vectors with respect to the north axis (i.e. C = $\sum_{i=1}^{n} cos\ D_i$).

After finding the mean direction, next step is to decompose the wind speed vectors into lateral and longitudinal components. In order to do so, the following formulas are used

$$v_{y_t} = V_t cos\ (D_t - \bar{D}) \tag{8}$$

$$v_{x_t} = V_t sin\ (D_t - \bar{D}) \tag{9}$$

where v_{y_t} is the longitudinal component of the wind speed, v_{x_t} is the lateral component of the wind speed, D is the angle of wind vector with respect to north axis, and $\bar{D}$ is the mean direction.

Using a single prevailing wind direction would help simplify the underlying component model thus resulting in more parsimonious models. Several researchers construct the component models based on the concept of a single prevailing wind direction (José et al., 2008). One reason for decomposing the wind vector into the lateral and longitudinal components is to reduce the interaction between these two components. Decomposing the wind speed into two orthogonal components based on the prevailing wind direction could help to build two separate ARMA models to represent the lateral and longitudinal components. After finding the lateral and longitudinal components, the next step is the employing ARMA model for the forecast. After ARMA model is constructed and verified, forecasts are obtained for the lateral and longitudinal components respectively. Based on the forecasted components, the corresponding wind direction can be found as follows,

$$D_t = tan^{-1}\left(\frac{v_{x_t}}{v_{y_t}}\right) + \bar{D} \tag{10}$$

where D_t is the forecasted wind direction for time period t. The forecast for the corresponding wind speed can be found by the following equation,

$$V_t = \sqrt{(v_{x_t}^2 + v_{y_t}^2)} \tag{11}$$

Using this approach, it is possible to obtain the forecasts for wind speed and direction simultaneously.

2.4 The Weibull curve fitting

The word Weibull comes from the name Valvdy Weibull as a well-known statistician whose probability density function is a continuous function and has good flexibility in statistical modeling. If the time series can fit the joint correlation structure between wind speed and time, the Weibull function may be fitted to data set. In such circumstances the Weibul function is as Eq. 12.

$$V_t = a * b * t^{b-1} * e^{-at^b} \quad (12)$$

Where a and b are constant non-negative parameters and could be estimated using ordinary least square method by statistical curve fitting software. The calibrated Weibull curve should have normally distributed residuals around zero with constant variance.

2.5 Fourier series

In mathematics, a Fourier series is a way to model a periodic function or time series as the sum of simple sine and cosine terms. More formally, it decomposes any periodic function or periodic time series into the sum of a (possibly infinite) set of simple oscillating functions, namely sines and cosines in the form of:

$$V_t = \frac{a_0}{2} + \sum_{n=1}^{\infty}[a_n \cos(\omega_n t) + b_n \sin(\omega_n t)] \quad (13)$$

Here, ω_n is harmonics of the Fourier series in radians and the coefficients a_0, b_n, a_n could be derived based on the length of the interval ($2l$) using Eq. 14-16.

$$a_0 = \frac{l}{2l}\int_{-l}^{l} V(x)dx \quad (14)$$

$$a_n = \frac{1}{l}\int_{-1}^{1} V(x)\cos(\frac{n\pi}{1}x)dx \quad (15)$$

$$b_n = \frac{1}{l}\int_{-l}^{l} V(x)\sin(\frac{n\pi}{l}x)dx \quad (16)$$

The calibrated Fourier series should have normally distributed residuals around zero with constant variance.

2.6 Forecasting performance measures

Before any forecasting, the candidate series should convey white noise properties that means residuals have normal distribution white zero mean and small constant variance. There are many metrics to measuring statistical forecasting performance. The most important ones are mean-absolute error (MAE), median-absolute error, residual variance and mean-squared error (MSE). When residuals are white noise processes (deploys form normal distribution with zero mean and a constant small variance), hence model has calibrated characteristic. Here we focused on white noise characteristic with a constant residual variance (σ_ε^2) that can be estimated form data set by:

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{n}\sum_{t=1}^{N}(e_t - \bar{e})^2 \quad (17)$$

We also ease MAE as alternate performance measure using Eq. 18.

$$\text{MAE} = \frac{\sum_{t=1}^{N}|y_t - \hat{y}_t|}{N} \quad (18)$$

where y_t is the realized value at time period t, $\hat{y}_t$ is the forecast pertaining to that period, and N is the number of data points.2

3. Forecasting methods

This research considers 72-hour-ahead forecasts of maximum wind speed over the Aghdasiyeh in Tehran (capital of Iran) in the period from April 1, 2014 through April 25, 2014, initialized at 00 hours local time. Wind speed and direction registered every hours. Here the dataset contains observations at surface airway observation stations. Maximum wind speed is defined as the maximum of the hourly "instantaneous" wind speed over the previous one hours, where an hourly "instantaneous" wind speed is a 3-minute average from the period of three minutes before the hour to on the hour. Data were available and used for 25 days, and data for the next three days focused in prediction.

Table 1: A typical view to raw data gathered from 2014/4/1 1:00 to 2014/4/25 23:00

Time-Hour	Speed (m/s)	Direction (°)
…	…	…

4/1/2014 5:00	2.3	0.890
4/1/2014 6:00	2.2	1.828
4/1/2014 7:00	3.2	2.193
…	…	…
4/1/2014 22:00	1.6	1.822
4/1/2014 23:00	2.2	1.929
4/2/2014 0:00	2.3	2.170
…	…	…
4/25/2014 23:00	1.9	1.258

Fig. 2 shows the wind speed series. Although the series is dominated by variation, there is no repeated peaks which suggest that there is no seasonality within each year. Skewness is also evident in the series, with occasional large values not matched by extremes in the lower direction because of the lower bound of zero. In order to try to gain further insight into the seasonality, we evaluated plot of the wind speed observations against the day of the year. The plot did not show any evidence of seasonality in both the level and variance of the series.

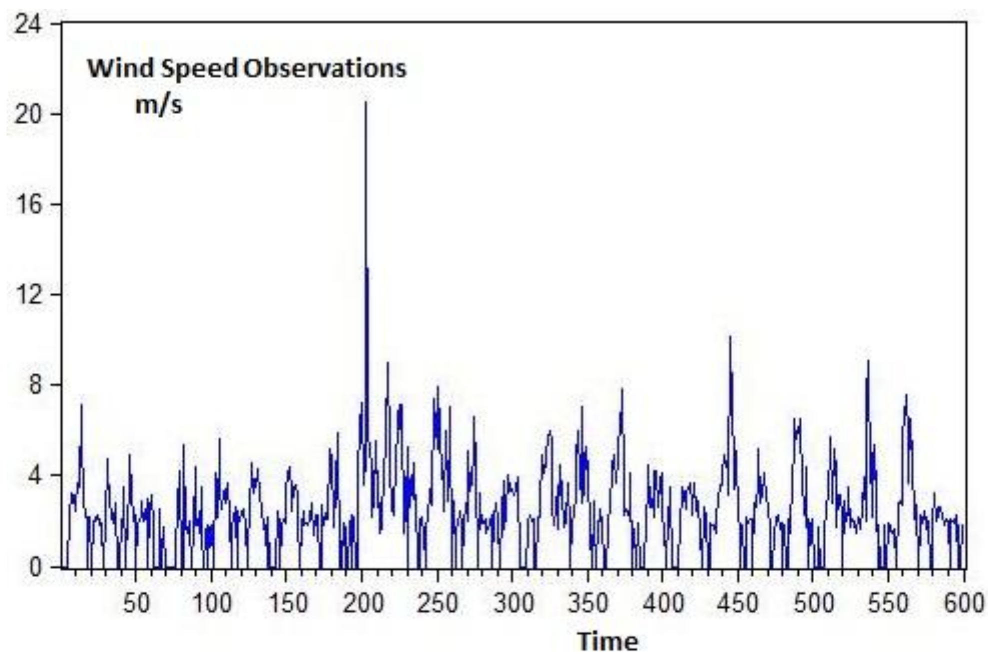

Figure 2: Hourly wind speed time series

3.1. The Box-Jenkins Prediction Approach

We estimate the components model following the approaches described in Section 2.3. In order to examine stationary condition on speed time series, we applied the unit root test augmented Dickey-Fuller test. Such hypothesis testing estimated the t student statistics equal to -4.570. Consequently, the null hypothesis of the time series has a unit root.

The correlogram of the time series in Figure 3 is obtained. This figure shows that the null hypothesis of no first-order autocorrelation is rejected based on the Q-statistic with a p-value less than 0.001.

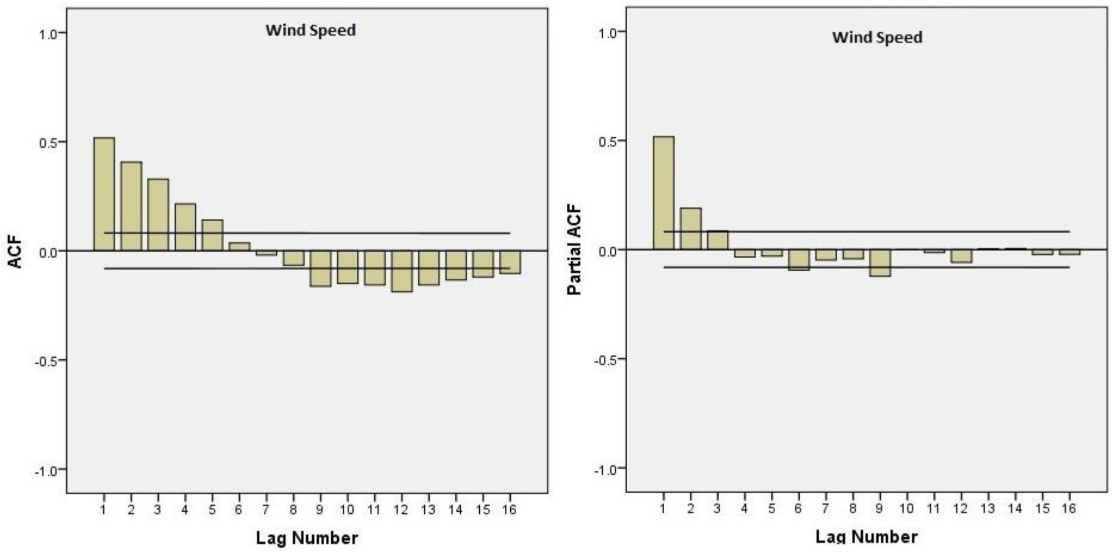

Figure 3: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of wind speed observations

Using SPSS, the best model covered both seasonality and autoregressive moving average estimated by SARMA (1,0,1) (1,0,0). The residual of this model presented in Figure 3 4and shows no spike in ACF and PACF of residuals. Then one can conclude that wind speed deploys from the follow mentioned seasonal Box-Jenkins model.

$$V_t = 2.51572638398 - 0.0901222425949V_{t-1} + 0.752889188438\, V_{t-24} + 0.067852062087\, V_{t-25} + u_t - 0.260175u_{t-1} \quad (19)$$

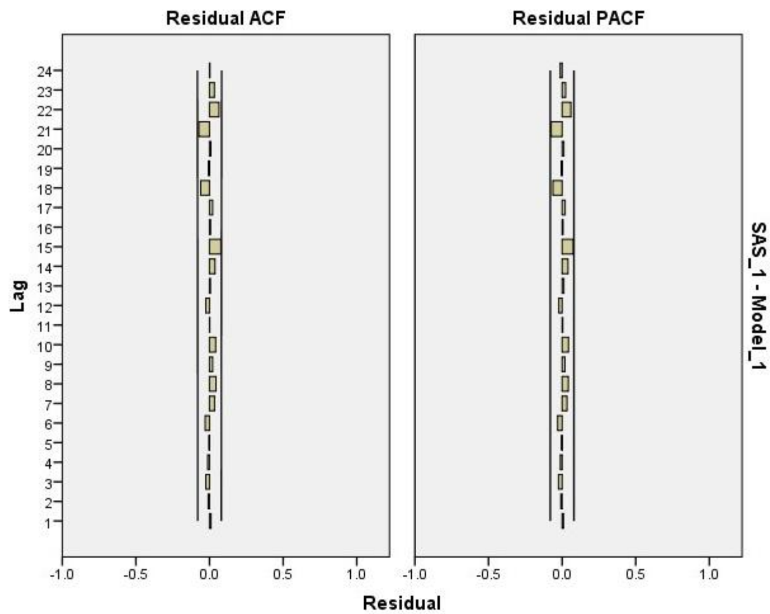

Figure 4: ACF and PACF of fitted SARMA (1,0,1) (1,0,0) to time series residuals

Figure 5 presented the observed value versus the predicted amounts based on the estimated model. In the Figure the red colored line is the observed wind speed and the solid blue line is the fitted time series.

In order to examine the presence of Autoregressive conditional heteroskedasticity (ARCH) models we followed Engle ARCH hypothesis testing using the Eviews software. Here the Lagrange multipliers (LM) estimated by $nR^2 = 0.17$ which showed no significant trace on ARCH effects and we conclude there is no significant volatility and there is no reason to predict conditional variance.

Consequently, the mean of wind speed is defined by Eq. 19 as a function of exogenous variables, which consists of the lagged dependent and independent variables and other pure exogenous variables.

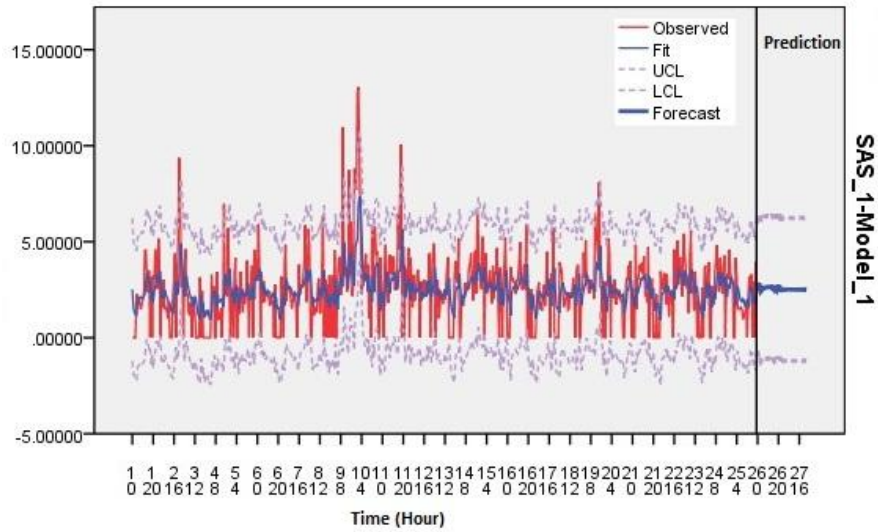

Figure 5: Observation versus the predicted values based on versus SARMA (1,0,1) (1,0,0)

3.2. Multivariate time series models

The Vector ARMA (VARMA) as a multivariate version for the ARMA model is applied on the times series data as an alternative for prediction. Here, we combine the wind attributes (speed and direction) to predict the future values of wind attributes. So, based on Akaike Information Criterion (AIC), Schwarz-Bayesian Information Criterion (SBIC) and Hanna-Quinn Information Criterion (HQIC) measures, the Eviews showed us the VAR(2) as the best model. The general equation for the most fitted model for wind speed and direction can be expressed by Eq. 20 and 21 respectively.

$$V_t = 0.84 + 0.33V_{t-1} + 0.13V_{t-2} \quad (20)$$

$$D_t = 39.98 + 4.33\, V_{t-1} + 0.31D_{t-1} + 8.52V_{t-2} + 0.11\, D_{t-2} \quad (21)$$

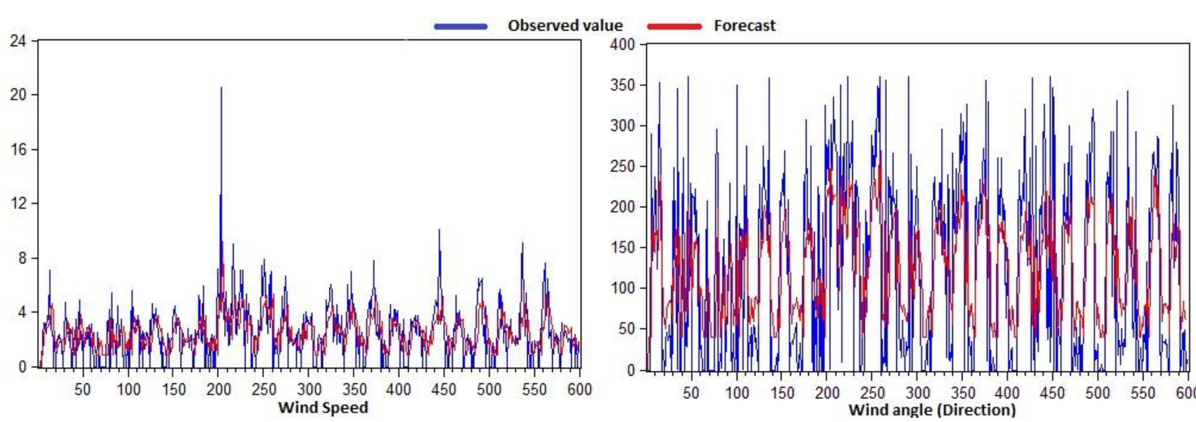

Figure 6: Observation versus the predicted values based on the Multivariate time series models

3.3. The Component Prediction Model

As an alternative method for forecasting wind speed and direction the angular method applied to data sets. Here at the mean direction estimated as $\bar{\theta}\bar{D} = 6.25$ based on Eq. 7. Then the wind speed vector decomposed into lateral and longitudinal components using Eq. 8.
The best Box-Jenkins model to predict the longitudinal and lateral direction estimated by a first order and 2nd order autoregressive respectively. Consequently, Eq. 22 and 23 presented the best model to formulate wind speed components.

$$v_{x_t} = 0.18 - 0.04 v_{x_{t-1}} \tag{22}$$

$$v_{y_t} = 0.006 - 0.06 v_{y_{t-1}} - 0.07 v_{y_{t-2}} \tag{23}$$

Finally, future values of wind attributes (speed and direction) at any period of time could be predicted based on the aforementioned equations of 10 and 11 using the estimated predictions of wind speed components.

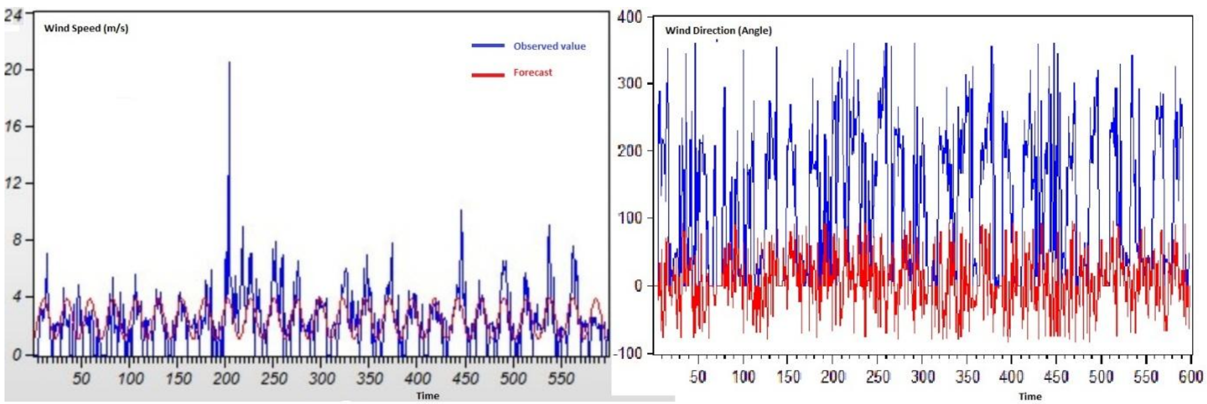

Figure 7: Observation versus the predicted values based on the Component Prediction Model

3.4. The Weibull Prediction Model

The forth alternative uses the Weibull model to forecast wind speed based on wind direction. Our analysis starts with checking the independence assumption between the wind speed and wind direction. Rather than employing the traditional formula for calculating correlation between the two variables. For estimating the Weibull coefficients, we employ the MATLAB curve fitting tool box. The estimated parameters derived as $a = 0.0127$ and $b = 1.656$. Consequently, the best fitted Weibull function to the data set is:

$$V_t = 0.0127 * 1.656 t^{0.656} . e^{-0.0127 t^{1.656}} \tag{24}$$

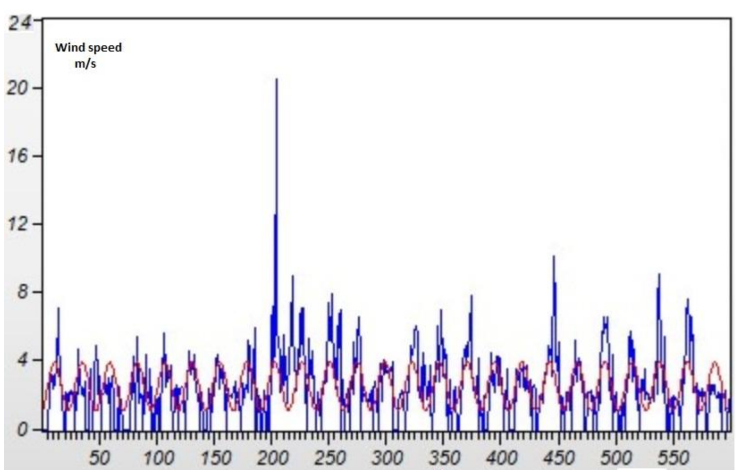

Figure 8: Observation versus the predicted values based on the Weibull

3.5. The Fourier Series Prediction Model

As discussed in Section II, daily wind speed series may possess a seasonal pattern. For another alternative seasonal version of time series, we turn to the model presented in Eq. 13 for hourly data set. The model parameters estimated on MATLAB curve fitting toolbox and presented in expression 25.

$$V_t = 2.498 - 1.378\,\mathrm{Cos}(0.2621t) + 0.3486\sin(0.2621t) \qquad (25)$$

In order to trace fittings, Figure 6 illustrates predicted versus observed amounts.

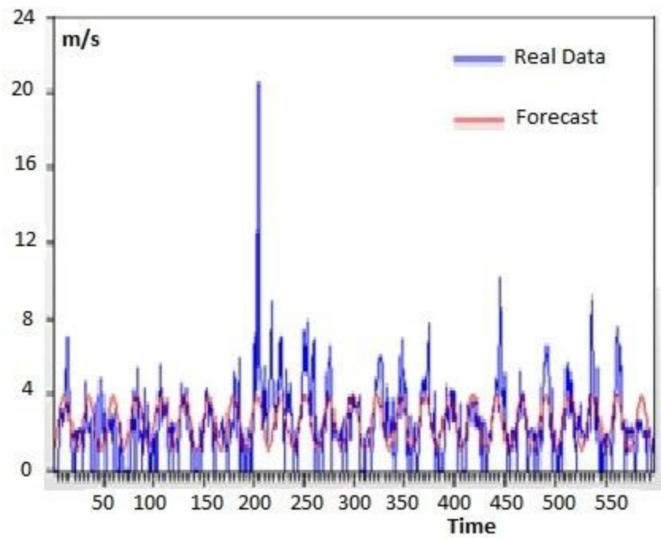

Figure 9: Observation versus the predicted values based on the Fourier series

4. Forecasting Discussion and Model Performance analysis

We now estimate the one day ahead forecasts based on the four alternative methods. Forecasts amounts in Table 2 provides wind attributes' forecast for the next 24 hours.

Table 2: Forecasting amounts based on the four alternative methods

Time ahead	The Box-Jenkins for wind speed	Multivariate models (VARMA) for wind speed	Multivariate models (VARMA) for wind direction	The longitudinal component of wind speed V	The lateral component of wind Direction
1	1.75	1.49	51.37	1.09	-30.45
2	1.25	1.11	57.27	2.37	78.85
3	1.87	1.68	63.75	2.08	43.51
4	1.95	1.83	81.16	2.17	0
5	2.04	1.81	73.47	1.56	-24.42
6	1.33	1.13	59.07	2.27	15.02
7	1.89	2.21	135.83	2.42	-51.70
8	2.03	2.48	143.07	2.81	-73.55
9	2.64	2.93	156.48	2.78	69.47
1.	2.55	3.16	201.93	1.88	-9.16
11	2.14	2.54	154.39	2.75	58.73
12	2.46	2.85	166.71	2.16	27.62
13	2.22	3.00	207.74	2.84	27.14
14	2.41	3.10	192.82	2.91	-29.34
15	2.88	3.17	161.28	3.11	50.31
16	3.11	3.03	137.28	1.91	66.89

17	2.37	2.06	92.92	2.34	54.52
18	2.23	1.88	76.55	1.38	0
19	1.39	1.19	62.63	1.09	0
20	1.02	0.82	40.08	2.72	39.66
21	2.01	1.74	50.92	2.74	60.60
22	2.62	2.97	171.97	2.55	-41.00
23	2.69	2.70	118.64	2.29	-18.99
24	2.48	2.13	89.16	2.55	-36.23

The predicted amounts show that all the mentioned prediction method could act as efficient tool for wind attribute forecasting. There is no statistically significant differences between population means in terms of t student pair wise comparison test (p-value>0.8). Maximum deviation for wind speed prediction occurred on 14 hours ahead which is less than 0.69 m/s.

A general analysis on the forecasting performance based on the results obtained for the same wind observation data set is reported across all models. To further analyze the forecasting method, a summary of standard performance measures in terms of MAE and $\hat{\sigma}_{\varepsilon}^{2}$ provided in Table 3.

Table 3: Performance measures for the four alternative forecasting methods

Forecasting Method	**Performance Measure**	
	MAE	$\hat{\sigma}_{\varepsilon}^{2}$
The Box-Jenkins for wind speed	1.17	1.65
Multivariate models (VARMA) for wind speed	1.24	2.82
Multivariate models (VARMA) for wind direction	7.382	8.922
The longitudinal component of wind speed V_x	1.57	2.16
The lateral component of wind speed V_y	1.66	2.32
The Weibull function	2.49	3.91
The Fourier series	1.24	2.96

This table show that first alternative nominated as The Box Jenkins model has fewer amounts in performance measures and could be considered as the best alternative for forecasting method in the given site.

5. Conclusion

Generally, intermittency act as critical event in electricity generation derived from wind power. This crucial problem tend to apply forecasting method for wind attributes in a given geographical area. To run such estimate quantitatively, we provide six most common methods for wind speed and direction prediction. All the alternative models were tested statistically for validation purpose via white noise properties. Then all models that support white noise errors, compared together based on forecasting performance measures of mean absolute error (MAE) and variance of residuals. Results show that the Box-Jenkins model presented in Eq. 19 could be act as the best alternative in wind speed prediction in the Aghdasiyeh station.

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