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Seasonal Temporal Distribution of Forecasted Wind Speed Data in Langkawi, Malaysia

Siti Noratiqah Mohamad Deros[1]*, Arnis Asmat[1] and Shattri Mansor[2]

[1]*Faculty of Applied Sciences, Universiti Teknologi MARA UiTM), 40450 Shah Alam, Selangor, Malaysia*
[2]*Institue of Advance Technology, Universiti Putra Malaysia (UPM), 43400 Serdang, Selangor, Malaysia*

ABSTRACT

Temporal distribution of forecasted wind speed is important to assess wind capacity for wind-related technology purposes. Regional wind energy estimation needs the development of wind pattern to monitor and forecast temporal wind behaviour. Temporal wind in Malaysia mainly depends on monsoonal factor that circulates yearly and each monsoon derives distinct character of wind. This paper aims to develop a model of wind speed pattern from historical wind speed data. Then, the model was used to forecast 5-years seasonal wind speed and identify temporal distribution. Wind speed model development and forecast was performed by identifying the best combination of wind speed seasonal component using Seasonal Auto-regressive and Moving Average (SARIMA) model. Thus, three distribution models, Lognormal, Weibull and Gamma models, were exploited to further observe consistency using Kolmogorov-Smirnov goodness-of-fit test. The best fit model to represent seasonal wind distribution in each monsoon season at Pulau Langkawi, Malaysia, is Log-normal distribution (0.04679-0.108).

Keywords: Lognormal, SARIMA model, seasonal distribution, wind speed forecast

INTRODUCTION

In Malaysia, wind mainly depends on four monsoon seasons that occur throughout the year, where each monsoon brings unique and different wind behaviours (Jamaludin et al., 2010). Hence, wind studies in Malaysia involved determination of regional wind pattern including wind speed, wind distribution and wind direction (Daut et al., 2011), and for this purpose, long-term data of at least 10 years are needed (Noram et al., 2010). Most studies on wind emphasize annual wind data (Azami, Khadijah, Mahir, & Kamaruzzaman, 2009; Khadijah et al. 2009; Siti, Norizah, & Syafrudin, 2011) rather than

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E-mail addresses:
atiqahmohdderos@gmail.com (Siti Noratiqah Mohamad Deros),
arnisasmat@gmail.com (Arnis Asmat),
shattri@gmail.com (Shattri Mansor)
*Corresponding Author

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seasonal data. Siti et al. (2011) grouped annual wind speed data in Malaysia into four distinct seasons depending on the wind direction blows of each season. In other hands, Khadijah et al. (2009) and Azami et al. (2009) studied 2 years wind speed distributions to estimate wind capacity of regional study area. Nonetheless, these studies failed to project seasonal properties that highly influence wind in Malaysia. Therefore, seasonal wind study needs long-term data in order to gain sufficient information on seasonal factor.

Wind studies mainly used wind speed measurement data that are retrieved using an anemometer while wind vane records wind direction and these datasets provide timely wind measurement in hourly, daily, and monthly periods (Juan et al., 2016). This has initiated the questions on the relationships between timely wind speed and extreme wind events and how the datasets explain the long-term wind trends. Limited wind study that considers temporal and long-term data to get enough seasonal properties causes the lacking of impactful monsoonal wind study. Wind studies conducted by several researchers include determination of the best fit model to represent temporal distribution of wind in one regional area. Wind speed distribution is an important study to observe the frequency of certain wind speeds occurred to assess the cumulative wind (Zaharim, Najid, Razali, & Sopian, 2009); Azami et al. (2009) studied Weibull and Lognormal distributions to fit the wind speed data. They found that the Weibull distribution is the best fit model as compared to the Lognormal distribution to describe the behaviour of annual wind speed data. Moreover, researchers discussed the Weibull (Wengang & Igor, 2016) and Rayleigh (Maina et al., 2016) distributions to describe the wind energy potential on the basis of 5-years hourly time series wind speed data. They concluded that the Weibull distribution provides a better fit to probability distributions as compared to the Rayleigh model. However, the use of annual wind data only projects a general distribution of wind speed, and thus neglects the wind speed seasonal properties and actual wind condition in one monsoon. For example, the northeast monsoon was recorded to have the highest wind speed among other monsoon seasons that bring together abundant rainfall and may cause hurricane (Noratiqah, Arnis, & Shattri, 2012). This explains the importance of seasonal wind distribution study and long-term trend to forecast future wind scenario.

Wind pattern development is an important study to monitor and forecast wind including any wind-related hazards such as tsunami and hurricane. Development of wind pattern allows the forecast of wind that helps in planning effective coastal structuring activity and deep-water fishing. Seasonal wind forecast can estimate seasonal wind pattern from different properties of wind speed, distribution, and direction. Seasonal pattern studies had been done by Zuhaimy and Khairil (2005) on potential wind energy, and Noratiqah, Arnis and Shattri (2012) on seasonal wind speed model by using Seasonal Auto-regressive and Integrated Moving Average (SARIMA) models to simulate seasonal properties. The model has the ability to recognise the unique pattern of monsoonal wind and formulate the trend in one model (Soebiyanto, Adimi, & Kiang, 2010) such as seasonal wind. The trend formulates and forecasts wind speed by using SARIMA that has a high correlation with actual wind measurement.

This study attempted to forecast wind speed from 2011-2015 by formulating the seasonal forecast model using 2000-2010 wind speed data. Thus, the seasonal distribution of forecasted wind was determined as the best model to represent the temporal wind distribution in each monsoon season. The distribution models tested in this study were Gamma, Lognormal and

Weibull models, whereby the best model was determined by using the Kolmogorov-Smirnov Goodness-of-fit test.

METHOD

In this study, the 10-year data of wind speed recorded from 2000 to 2010 were provided by Malaysian Meteorological Department (MMD). The data were recorded from the anemometer devices installed at 10-meter tower from the ground. The anemometer station is located in Pulau Langkawi (6° 20 'N Latitude and 99° 44' E Longitude, 6.4 metres above the Mean Sea Level, MSL). The data format or unit is in meter per second (m/s) and grouped into Northeast monsoon, April Intermonsoon, Southwest monsoon and October Intermonsoon. The mean and standard deviation of the data of every season are tabulated in Table 1 to show the wind speed properties in each season.

Table 1
Seasonal mean and standard deviation of wind speed data from year 2000 to 2010

Year	Northeast Monsoon		April Inter-monsoon		Southwest Monsoon		October Inter-monsoon	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
2000	2.87	0.96	2.16	0.47	2.55	1.39	2.76	2.06
2001	2.55	0.81	2.12	0.48	2.43	1.34	2.17	0.71
2002	3.49	1.13	2.45	0.39	2.61	1.10	2.16	0.40
2003	2.94	0.97	2.17	0.26	2.54	0.98	3.32	1.91
2004	3.16	1.01	2.19	0.24	2.48	1.42	2.31	1.09
2005	3.28	0.99	1.93	0.31	1.75	0.46	1.54	0.39
2006	2.18	0.93	1.62	0.25	1.75	0.50	1.76	0.47
2007	2.29	0.76	1.71	0.37	1.57	0.43	1.67	0.58
2008	2.34	0.85	1.70	0.25	1.59	0.35	1.63	0.29
2009	2.31	0.76	1.76	0.46	1.79	0.72	1.65	0.47
2010	2.45	0.73	1.77	0.25	1.64	0.40	1.74	0.51

Table 1 shows the highest and consistent wind speed blow during the northeast monsoon with the mean range of 2.18-3.49 m/s from 2000 to 2010. On the other hand, the wind speed in other monsoon period is constant at the range of 1.54-3.32 m/s. However, the wind speed decreases gradually each year and this may be due to the coastal structuring that introduces frictional force on wind (Michael, 2009).

This section further explains the wind speed model development that is used in wind speed forecast. The forecasted seasonal wind speed distribution analysis is elaborated further so as to determine the distribution model of wind in each monsoon season. Wind pattern forecast model chosen in this study is the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model, which was adapted from Zuhaimy and Khairil (2005) who used SARIMA to model and forecast the seasonal energy demand for daily basis and found that the SARIMA model produced demand forecast that highly correlates with the actual demand. On the contrary, Caixia (2010) also modelled the seasonal wind pattern by using the Autoregressive and Moving Average (ARMA) model. However, the model developed is not flexible enough to explain the seasonal properties of wind. In this study, the seasonal wind speed model can be best developed by using SARIMA due to its flexibility to recognise the seasonal pattern of data.

The plot of monthly mean wind speed data was used to determine wind speed properties and seasonality factor in the data. The seasonality span, *T*, which is the time taken for data to repeat the pattern for the next period was also identified from the plot. According to Zuhaimi and Khairil (2005), the span was determined in month scale. Hence, the seasonality span in this study is $T=12$ due to the circulation of all monsoons that takes 12-month period. Meanwhile, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model comprises of four processes; identification, estimation, diagnostic checking and forecasting. The SARIMA model can be expressed in SARIMA $(p,d,q)\times(P,D,Q)$ form. This model consists of non-seasonal and seasonal winds represented by degree, p, q, P and Q. Seasonal integration order is represented as D, while non-seasonal integration order is represented by d. In order to identify the SARIMA model of wind speed, Equation [1] is applied.

$$\Phi_P(L^s)\phi_p(L)\Delta_s^D\Delta^d y_t = \Theta_Q(L^s)\theta(L)\varepsilon_t \qquad [1]$$

Parameter Δ_s^D is defined as the seasonal difference $(1-L^s)^D$, Δ^d as the non-seasonal difference $(1-L)^d$ and Φ as the parameter for non-seasonal autoregressive (AR). Meanwhile, ϕ is the seasonal autoregressive (SAR) parameter, Θ is the parameter for seasonal moving average (SMA) and θ is the parameter for non-seasonal moving average (MA). All the four parameters are the respective lag operator, L polynomials. The model was examined by using the penalty function criteria method based on two penalty function statistics, Akaike Information Criterion (AIC) and Schwarz/Bayesian Information Criterion (BIC) (Lee, Yoo, & Jin, 2007).

The five-year (2011-2015) wind speed forecast was implemented by using the SARIMA model developed. The forecast method was done by applying the out-of-sample method (Gokhan, 2011), in which the data were divided into two; 80% the in-sample dataset and 20% the out-of-sample dataset. The forecast horizon, $h=5$ represents the 5-years wind speed distribution forecast. To test the reliability of the SARIMA model developed, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error were calculated. The smaller error value (<0.5) shows a good data forecast.

The three distribution models (Gamma, Lognormal and Weibull distribution model) were chosen in this study based on the suitability with the wind speed data that are asymmetric, continuous and mostly positive outliers. The best-fit model had been tested on the seasonal forecasted wind speed data. Important forecasted wind speed parameter was used in this stage according to the distribution model requirement.

Gamma Distribution

A positive random variable X is said to be gamma distributed when it has the probability density, as shown in [2] below.

$$\rho(t) = \frac{\lambda^{\alpha} t^{\alpha-1}}{\Gamma(\alpha)} e^{-\lambda t}, t \geq 0 \quad [2]$$

where 0> α is the shape parameter and 0> λ is the scale parameter. The symbol $\Gamma(\alpha)$ denotes the complete gamma function. The gamma density always has only one maximum at t = (α-1)/λ > 0, and then decreases to zero when t=∞.

$$Gamma, g\ (x) = \frac{x_i^{\alpha}}{\beta^{\alpha}\Gamma(\alpha)} \exp[-\frac{x_i}{\beta}] \quad [3]$$

where $g(x)$ is the gamma probability distribution α is the scale parameter, and β is the shape parameter. The random variable is denoted by x and the normalising factor is presented as Γ.

Log-normal Distribution

Log-normal distribution is the reference to normal distribution. A random variable is log-normally distributed if the logarithm of the random variable is normally distributed (Zaharim, 2009).

$$F(x) = \frac{1}{2}\left[1 + erf\left(\frac{\ln x - \mu}{\sigma\sqrt{2}}\right)\right] \quad [4]$$

Equation [4] shows the cumulative probability function of log-normal distribution. The mean, μ, and standard deviation, σ, of the wind speed distribution are the normal random variables of $ln(x)$, not the log-normal random for variable x.

$$Log - normal, l\ (x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{-\ln x - \mu^2}{2\sigma^2}} \quad [5]$$

The log-normal probability distribution is demoted by $l(x)$, $ln\ x$ is the random variable that is log-normally distributed with the mean (μ) and standard deviation (σ).

Weibull Distribution

The Weibull cumulative distribution function is effectively used to total up the wind speed distribution in one seasonal period (Akpinar & Akpinar, 2004). In the graphical method to estimate the Weibull shape parameter, k, and Weibull scale parameter, c, the cumulative wind speed distribution is required. These parameters may be estimated by using linear regression of the cumulative Weibull distribution (Youm et al., 2005).

$$Weibull, h\ (x) = \frac{\beta}{\alpha} (\frac{x_i}{\alpha})^{\beta-1} e^{-(\frac{x_i}{\alpha})^{\beta}} \quad [6]$$

For the Weibull probability distribution Equation [6], *h(x)* involved the scale parameter (α) and shape parameter (*β*) of the random variable *x*. However, those parameters used in the distinct model are derived from the basic descriptive statistics, especially mean and standard deviation of the variables. Thus, the model structure itself influences the fitness of the distribution instead of the data. The function of cumulative Weibull distribution is described in Equation [7] below.

$$F(v) = 1 - \exp\left(\frac{v}{c}\right)^k \qquad [7]$$

Equation [7] explains the percentage of time when the wind speed is equal to or lower than the wind speed. The shape parameter, *k*, is important to explain the site topology. For a given average speed, a lower value of *k* shows a greater variability of wind speed. It occurs due to low shape factor, which makes the wind speed range greater (Piazza et al., 2010). According to Shamshad et al. (2009), the higher value of scale parameter, *c*, indicates that the wind speed is higher, while the shape parameter, *k*, shows the wind stability. In other words, shape parameter, *k*, helps to observe the distribution, i.e. whether they are closely related to each other or not. Shape parameter may be ranked from 1 to 3, where it can be high, moderate and consistent wind variations, while scale parameter, *c*, explains how windy the study area is. Goodness of fit-test was applied to test the fitness of the three distributions by indicating the error of the distributions. A comparison with the original data sample was done using the Kolmogorov-Smirnov test in Equation [7] (Zaharim, 2009).

$$D = \min_{1 \leq 1 \leq N}\left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i)\right) \qquad [8]$$

The Kolmogorov-Smirnov test with the distribution function Y, which is the continuous distribution denoted by *F(Y)*, and the test statistic value were presented by *D*. The goodness of fit test model such as Kolmogorov-Smirnov test measures the gaps between the data sample and the distribution tested. The lower the test statistic value, the smaller the gap is (<0.5), and the fitter the distribution tested.

RESULTS AND DISCUSSION

This section is divided into two parts; the seasonal wind speed model development and forecast and the seasonal distribution model determination.

The monthly mean wind speed from 2000 to 2010 is 2.306 m/s, while the standard deviation is 0.657 m/s. The monthly mean used to plot the graph of wind speed versus month shows that the highest wind speed in Langkawi has various wind speed patterns in different times, respectively. This variation is influenced by the southwest monsoon that occurs in May to September, the transition between two monsoons in October, the northeast monsoon in November to Mac and the second inter-monsoon in April each ear. As shown in Table 2, there are four possible SARIMA models that can represent the time series data of wind speed.

Table 2
AIC and BIC values of the ARIMA model

SARIMA	AIC	BIC
(1,1,1)×(1,1,1)	0.703544	0.747660
(1,1,2)×(1,1,1)	0.707552	0.751668
(1,1,3)×(1,1,1)	0.275654	0.319770
(1,1,4)×(1,1,1)	0.702883	0.746999

However, AIC and BIC values, that work by controlling the possible error and fitting the measure using the maximum likelihood method, indicate that SARIMA (1,1,3)×(1,1,1) has the smallest value. Therefore, it is the fittest model to the data series.

The forecasting of seasonal wind speed data later was done using the SARIMA (1,1,3)×(1,1,1) model. Results of the forecasting data produced low error with 0.3186 root mean squared error (RMSE), 0.265 mean absolute errors (MAE) and 11.644% mean absolute percentage error (MAPE). This shows the accuracy of the SARIMA (1,1,3)×(1,1,1) model to represent the wind speed data. Figure 1 shows the plot of mean wind speed data versus 2002 to 2015 during the southwest monsoon. The forecasting started after the first period of the sample. Only 2002 and ahead of the forecast data were produced after the adjustment to get an accurate forecast. The forecasted data of the wind speed generated from the wind speed model developed are described in Figure 1.

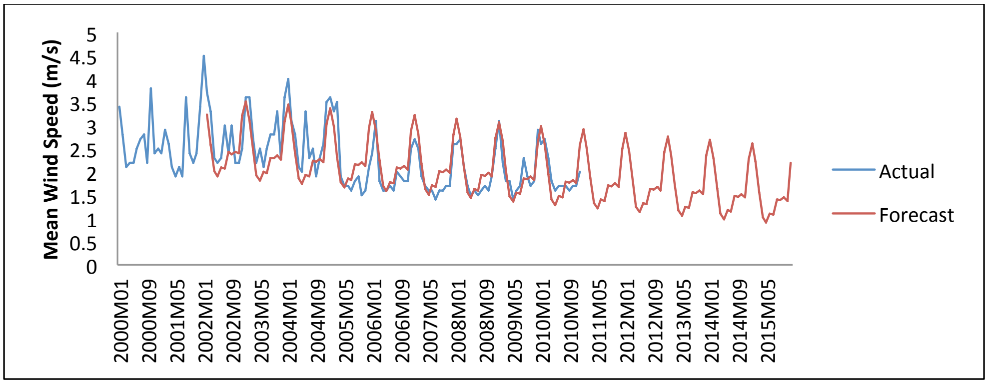

Figure 1. Actual vs. forecasted monthly wind speed data

As shown in Figure 1, there are temporal wind speed trend patterns of the actual and forecasted wind speed data. Figure 1 shows the forecasted wind speed that is represented by the red line, while the pattern of actual wind speed is represented by the blue line. The peak line shows the highest wind speed and it can be observed that wind speed is significantly high during the months of December, January and February of each year. Then, the wind speed gradually decreases through the year, as can be observed from the plot. However, we can also observe that the highest wind speed of the consequence year is not as high as the wind speed of the previous year.

The descriptive statistics of seasonal wind speed forecasted is tabulated in Table 3. The highest mean wind speed is during the northeast monsoon, while the lowest is during the April Inter-monsoon. This is due to the fact that the distance travelled by wind from the Indian Ocean during the southwest monsoon introduced a higher friction force on wind (Michael, 2009).

Hence, in order to identify the distribution that satisfies the wind speed criteria, the Kolmogorov-Smirnov goodness-of-fit test was performed and the results are presented in Table 3. It can be observed that, of all season, the best fit distribution is the Log-normal distribution. Fit distribution should have (0.5) that indicates the small gap or difference between the distribution and original data sample.

Table 3
AIC and BIC values of the ARIMA model

Seasonal	Kolmogorov-Smirnov Goodness-of-fit test		
	Gamma	*Log-normal*	*Weibull*
Northeast monsoon	0.04993	0.04679	0.06504
April inter-monsoon	0.07078	0.06997	0.084
Southwest monsoon	0.13875	0.108	0.17185
October inter-monsoon	0.13508	0.10165	0.14595

Table 3 shows that among three models tested, the Log-normal distribution model produced the lowest gap value among all the seasonal wind speed data in each monsoon season. This was followed by the Gamma distribution model and finally the least fit model for seasonal wind speed distribution is the Weibull model. Then, the distribution analysis performed by the Log-normal model shows that the Northeast monsoon is the season with the most fit data value (0.04679) compared to the Gamma (0.04993) and Weibull (0.06504) distribution models. This finding differs from the study by Eugene et al. (2011) who found that the wind speed is best represented by the Weibull distribution model. This may be due to the 10-minute mean wind speed data used that are more constant compared to the daily mean. In addition, the Weibull model has no ability to estimate extreme wind speed changes, the task that is best performed by the Lognormal distribution model (Burton et al., 2001).

The Lognormal distribution model projects the different mean and standard deviation of different monsoon seasons. This leads to the different frequencies and cumulative wind in an individual monsoon. Based on the forecasted wind derived in the SARIMA and Lognormal distribution models, the seasonal wind speed can be expressed as in Figure 2 below.

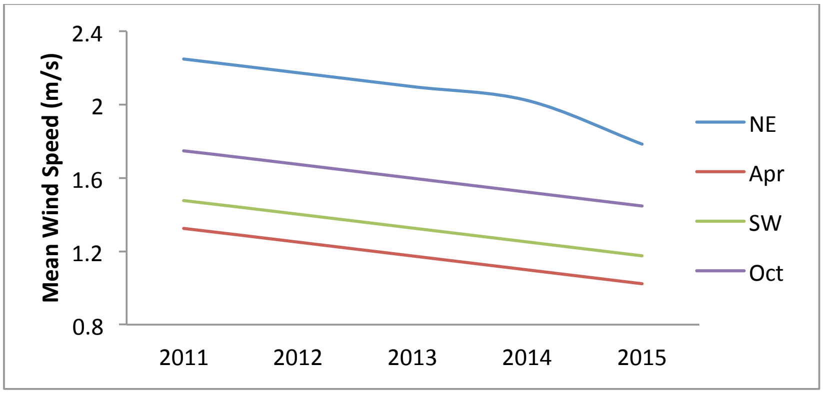

Figure 2. Seasonal Forecasted Mean Wind Speed (m/s) Distribution for 2011 to 2015

Figure 2 shows that the northeast (NE) monsoon acquires the highest mean wind speed with an average between 1.8 to 2.3 m/s, followed by October intermonsoon, Southwest monsoon and the lowest wind speed was estimated to be in April intermonsoon between 0.9 to 1.3 m/s. The monthly mean wind speed data explain the frequency and cumulative wind in one monsoon season, as summarised in Table 4.

Table 4
Seasonal forecasted mean wind speed, standard deviation, the period and cumulative wind on each monsoon season

Monsoon	Mean, μ (m/s)	S. Deviation, σ	t (day)	Cumulative wind (m/s)
Northeast	2.458	0.348	755	9070.028
April intermonsoon	1.514	0.316	150	1673.145
Southwest	1.667	0.317	765	11923.645
October intermonsoon	1.938	0.316	155	1944.162

Wind speed distribution provides frequency and cumulative information of each monsoon season. Table 4 shows the cumulative wind speed provided in each monsoon season derived from seasonal mean wind speed and the period taken by each monsoon season. This shows that the northeast monsoon possesses a high mean wind speed, and also a high standard deviation value. This high standard deviation value means that the wind speed data in the northeast monsoon are not consistent and highly spread above or below the mean value. This is the main reason of the low cumulative wind speed derived during the northeast monsoon compared to the southwest monsoon that apparently has lower mean wind speed. The time period taken by the southwest monsoon that possesses 10 days longer than the northeast monsoon also contributes to the higher cumulative wind speed produced during its season. The cumulative wind for the April and October intermonsoon highly depends on the mean wind speed and time period taken by each monsoon season. The consistent mean value, due to the low and equal standard deviation value, did not affect the cumulative wind of both intermonsoons.

CONCLUSION

Low goodness-of-fit test statistics value means the smaller the gaps among the data samples. The results of the three distribution models tested on the forecasted wind speed data show that the log-normal distribution model is the fittest model to represent wind speed distribution of all seasons. This is due to the lowest gap among the data samples distributed by the Lognormal distribution model in all the seasons.

Both mean and standard deviation of wind can help to determine the best location and appropriate wind-related technology devices to be installed. Cumulative wind is useful to estimate the amount of wind derived by each monsoon season for wind technology planning and design. Nevertheless, cumulative wind can also help in coastal structure observation and development.

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