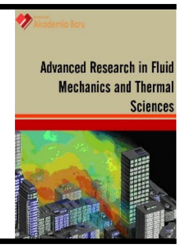
Penerbit Akademia Baru

Journal of Advanced Research in Fluid Mechanics and Thermal Sciences

Journal homepage: www.akademiabaru.com/arfmts.html

ISSN: 2289-7879



Comparison of Univariate and Bivariate Parametric Model for Wind Energy Analysis

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ARTICLE INFO

Article history:
Received 16 March 2018
Received in revised form 2 May 2018
Accepted 21 August 2018
Available online 2 September 2018

ABSTRACT

Single parameter or univariate parametric model of wind speed is essential in studying the wind energy potential of an area. But, the joint modelling of wind speed and direction is believed to be much more significant in representing wind regime. In this work, four models of the joint probability distribution of wind speed and wind direction are selected and thoroughly analysed. They are namely Weibull-finite mixture von Mises (fmvM), gamma-fmvM, inverse gamma-fmvM and Burr-fmvM. The proposed bivariate models are constructed by considering the marginal distributions of wind speed and wind direction. The marginal (univariate) case of wind speed modelling based on the conventional distribution. Four of them are selected based on the goodness-of-fit. However, finite mixture Von Mises is selected based on wind direction modelling, as it best for describing the multimodal condition of wind direction in Malaysia. This study reveals that the bivariate parametric model gives slightly higher mean wind power density (W/m^2) when compared to univariate model. Thus, the result verified that bivariate parametric model is significant in representing wind regime of an area.

Keywords:
Univariate, bivariate, wind power density

1. Introduction

Wind is a form of solar energy and is a result of the uneven atmosphere by the sun. Wind speed and wind direction varies greatly depends on the location, vegetation, and differences in terrain. For years, studies on the univariate parametric model of wind speed have been practice widely [1-7]. The wind speed regimes analysis were revealed and widely used in various fields including marine activities, bridge construction and much more. The output of wind speed studies provides sufficient information that leads to wind energy analysis in an area. Contrast with wind direction, the complexity of it nature of circular variable limit the exploration of such data. However, [8-16] in their studies have investigated the wind direction regime, the trend of wind direction and the significance of direction in wind power assessment. The literature showed the importance of wind direction and the extension of these studies is critical.

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Although the trend of jointing wind speed and wind direction in wind power assessment has begun abroad [17-21], there is no such analysis in Malaysia, at the time this paper is written. This study combines the wind speed and wind direction in a bivariate probability model to investigate the significance effect of wind direction in determining the wind power density at Mersing, Malaysia. The method of obtaining circular-linear distribution with specified marginal distributions by Johnson & Wehrly [22] has been used for this purpose. The best fit model for univariate and bivariate probabilistic model and annual wind power density for each model are discovered and used to represent the availability of wind energy potential across Mersing, Malaysia.

1.1 Wind Data Sources

Malaysia is in Southeast Asia and consists of Peninsular and East Malaysia on the northern edges of the Borneo Island, which represent Sabah and Sarawak. Malaysia is facing a hot and humid throughout the year with the temperature range from 22 to 32 degree Celsius. However, this study only focuses on Mersing area. Mersing is on the East coast of Peninsular Malaysia with geographical coordinates of (2° 26' N; 103° 50' E). Throughout the year, Mersing experiences a wet and humid condition just like others places in Malaysia. The wind in Mersing is influenced by the monsoon seasons, namely northeast monsoon with two short inter-monsoon. The northeast monsoon occurs from November till March brings higher wind speed to the peninsula. The first affected areas of the strong northeast monsoon are in the east coast areas including Mersing. Malaysian Meteorological Department provides the hourly wind speed (m/s) and wind direction (in degree, °) at 10-meter height data of Mersing. The data records is from January 2007 to July 2013.

2. Methodology

2.1 Univariate Probability Models For Linear and Circular Variables

There are four univariate parametric models for wind speed involved in this study namely; Weibull, Gama, Inverse Gama and Burr distribution. The selection are made based on the previous researches in Malaysia together with the goodness-of-fit that has been done in this study. While finite von Mises distribution is chosen for representing circular model of the wind direction.

2.1.1 Weibull distribution

The probability density function is expressed as

$$f(v) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} v^{\alpha-1} \exp\left(-\frac{v}{\beta}\right) \quad (1)$$
$$for\ 0 \le v < \infty$$

2.1.2 Gamma distribution

The probability density function is expressed as

$$f(v) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} v^{\alpha-1} \exp\left(-\frac{v}{\beta}\right) \quad (2)$$

2.1.3 Inverse gamma distribution

The probability density function is expressed as

$$f(v)=\frac{\beta^p}{\Gamma(p)}v^{-p-1}\exp\left(-\frac{\beta}{v}\right) \tag{3}$$

2.1.4 Burr distribution

The probability density function is expressed as

$$f(v)=\frac{aqv^{a-1}}{b^{a-1}\left[1+(v/b)^a\right]^{1+q}} \tag{4}$$

2.1.5 Finite mixture von mises distribution

For wind direction data which is a kind of circular data, von Mises distribution (equivalent to the normal distribution for linear data) is the model of choice in most applied problems [23] and being commonly used by researchers [10,14,16,20,24-26]. For a circular multimodal data set or data with more than one mode, finite mixture of von Mises distribution is selected as it flexibility and best explain for this type of data. The probability density function is expressed as

$$f_\theta(\theta)=\sum_{j=1}^{H}\frac{\omega_j}{2\pi I_0(\kappa_j)}\exp\left[\kappa_j\cos(\theta-\mu_j)\right] \tag{5}$$

For:

H is the number of components in the mixture; $\kappa_j \geq 0$ and $0 \leq \mu_j < 2\pi$ is the parameter; $0 \leq \omega_j \leq 1, (j=1,2,......,H)$ and $\sum_{j=1}^{H}\omega_j=1$. While μ_j is the mean direction parameter and is the concentration parameter with $I_0(\kappa_j)$ denoting the modified Bessel function of the first kind and order zero and defined as

$$I_0(\kappa_j)=\frac{1}{\sqrt{2\pi}}\int_0^{2\pi}\exp\left[\kappa_j\cos\theta\right]d\theta=\sum_{k=0}^{\infty}\frac{1}{(k!)^2}\left(\frac{\kappa_j}{2}\right)^{2k} \tag{6}$$

The best model for each studied station may vary to another station based on the goodness-of-fit test which is R^2 determination coefficient and Akaike Information Criterion (AIC) for the univariate model, as shown in Equation (7) and Equation (8).

$$R^2=\frac{\sum_{i=1}^{n}\left(\hat{F}_i-\bar{F}\right)^2}{\sum_{i=1}^{n}\left(\hat{F}_i-\bar{F}\right)^2+\sum_{i=1}^{n}\left(F_i-\bar{F}\right)^2} \tag{7}$$

where
F_i is a cumulative data function and

$\hat{F}_i$ is the estimate cumulative distribution function

$$\overline{F} = \frac{\sum_{i=1}^{n} \hat{F}_i}{n}$$

$$AIC = -2\log(L) + 2k \tag{8}$$

where *L* is the likelihood model function and *k* is the number of parameters in the model [27].

AIC is a method which compare several models simultaneously. It will compare the number of missing information for each model that fitted data. The model with smallest number of missing information will be selected as the best model that represent data. While R^2 determination coefficient will represent the highest percentage of variation can be explained in a model. Consistent with that, the highest value of R^2 determination coefficient and lowest value of Akaike Information Criterion (AIC) will be selected as the represented model for that particular station.

2.2 Bivariate Probability Model for Linear and Circular Variables

The analytic forms for the joint distribution of linear and angular variables are described and assessed with Johnson and Wehrly of model. The Johnson-Wehrly is a well-known of bivariate distribution and it has been used by numerous researchers of circular variables [17,20] . It probability density is defined by

$$f_{v,\theta}(v,\theta) = 2\pi g(\xi) f_v(v) f_\theta(\theta) \tag{9}$$

For:

$0 \le \theta < 2\pi$; $-\infty < v < \infty$ and $g(\xi) = 2\pi\left[F_v(v) - F_\theta(\theta)\right]$

The proposed models for this study are the all four models for linear variables which are match to the finite mixture of von Mises distribution for the circular variable.

(a) Weibull – finite mvM
(b) Gama - finite mvM
(c) Inverse Gama - finite mvM
(d) Burr - finite mvM

While for the bivariate model, the best-fit model determined by the highest R^2 determination coefficient and lowest value of root-mean-square error (RMSE). The circular-linear correlation describe the degree of relationship between circular and linear variable in a model. The highest value should be the best.

The bivariate relationship between the mean direction (circular) with wind speed (linear) is measured by the linear-circular correlation coefficient, *r* [28]. It is given by

$$r = \sqrt{\frac{r^2{}_{xc} + r^2{}_{xs} - 2r_{xc}r_{xs}r_{cs}}{1 - r^2{}_{cs}}} \tag{10}$$

where, $r_{xc} = \cos(x, \cos\theta)$, $r_{xs} = cor(x, \sin\theta)$, $r_{cs} = cor(\cos\theta, \sin\theta)$

2.3 Wind Energy Assessment

The theoretical wind power density, P_0 is given by

$$P_0 = \frac{1}{2}\rho_k v^3 f_v(v) \tag{11}$$

As in this study, the variability of wind speed and wind direction are considered, the evaluation of wind energy in such location is considering the wind power density distribution. This is represented by the following relation.

$$P = \iint \frac{1}{2}\rho_k v^3 f_{v,\theta}(v,\theta)\,d\theta\,dv \tag{12}$$

For Malaysia case, the value of air density [29], $\rho_k = 1.16 kg/m^3$. The Monte Carlo method which considering iteration techniques is used for obtaining numerical solutions to the double integration in Equation (9). The value of wind power density is in W/m^2.

3. Results and Discussion

3.1 Univariate Analysis for Wind Speed

The selection of proposed univariate model is based on the result of R^2 determination coefficient and AIC as in Table 1 below. Based on the result, Gamma distribution is selected as the proposed univariate model for wind speed data in Mersing.

Table 1
R^2 determination coefficient and AIC

Proposed univariate model	R^2 value	AIC value
Weibull	0.9673	15849
Gamma	0.9924	13521
Inverse Gamma	0.9489	16064
Burr	0.9578	18328

Figure 1 shows the annual mean speed for Mersing data. The highest mean is 2.9201 m/s for the year of 2008 and the lowest is in year 2012 with the value of 2.5776 m/s. The overall trend seems that the mean speed are consistent with no extreme values.

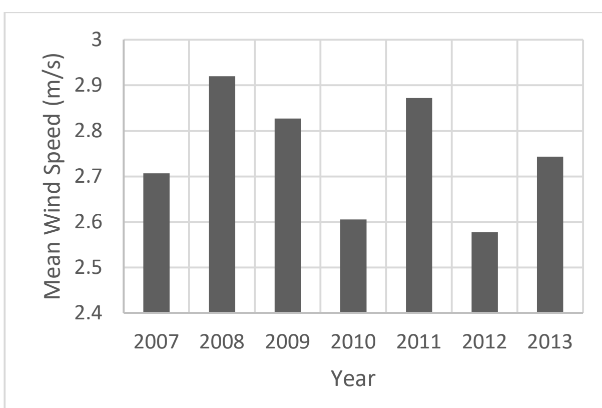

Fig. 1. Annual mean wind speed (m/s)

The value of wind power density for the univariate model (Gamma distribution) is as shown in Figure 2. The highest wind power density for the univariate model is in the year of 2013 with 25.4892 (W/m^2), while the lowest is 14.296 (W/m^2) for 2012. The result for 2012 is concurrent with the mean wind speed of that particular year which is the lowest among all. However, the highest value of mean wind speed in the year 0f 2008, does not guarantee that the highest wind power density for that year.

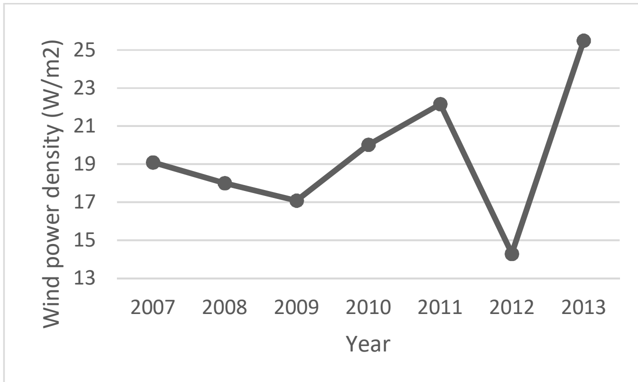

Fig. 2. Wind power density of univariate model (W/m^2)

3.2 Univariate Analysis for Wind Direction

By considering the parameter estimates of *kappa* and *weightage*, estimation for density probability function of finite mixture von Mises (H=6) model is derived as

$$\begin{aligned} f_\theta(\theta) = & \frac{0.276666}{2\pi \mathrm{I}_0(12.25072)} \exp\left(12.25072 \cos(\theta - \mu_1)\right) + \\ & \frac{0.065021}{2\pi \mathrm{I}_0(14.95576)} \exp\left(14.95576 \cos(\theta - \mu_2)\right) + \\ & \frac{0.046866}{2\pi \mathrm{I}_0(10.62431)} \exp\left(10.62431 \cos(\theta - \mu_3)\right) + \\ & \frac{0.317662}{2\pi \mathrm{I}_0(19.55538)} \exp\left(19.55538 \cos(\theta - \mu_4)\right) + \\ & \frac{0.16176}{2\pi \mathrm{I}_0(14.04048)} \exp\left(14.04048 \cos(\theta - \mu_2)\right) + \\ & \frac{0.132026}{2\pi \mathrm{I}_0(14.95576)} \exp\left(14.95576 \cos(\theta - \mu_2)\right) \end{aligned}$$

Another analysis for wind direction is by investigating wind rose. The wind rose represents the relative frequency and strength of winds from different directions. Figure 3 represents wind rose for the year of 2013. The dominant direction for wind in Mersing is from west-southwest (WSW) and from north-northeast, about 0° to 50° and 200° to 270°. In addition, the wind rose shows that the wind direction for 2013 is categorized as “calm”. Fig 3 shows the wind rose for the year of 2013.

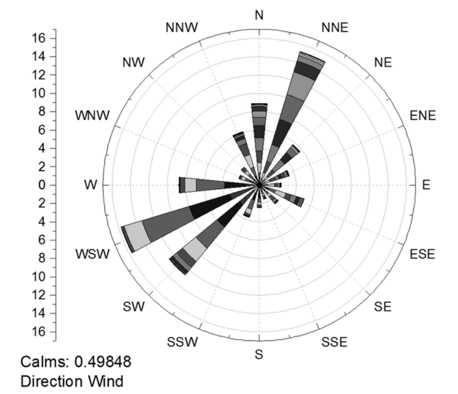

Fig. 3. Wind rose for the year 2013, Mersing, Malaysia

3.3 Bivariate Analysis for Wind Speed and Wind Direction

While for the bivariate model, inverse Gamma- finite mvM shows the highest R^2 determination coefficient with the lowest RMSE among all. This result appoints Gamma- finite mvM as a significant proposed bivariate model for wind data in Mersing. The details results are as shown in Table 2.

Table 2
R^2 determination coefficient and RMSE

Proposed bivariate model	R^2 value	RMSE value
Weibull-finite mvM	0.8847	10.305
Gamma- finite mvM	0.8913	10.282
Inv Gamma- finite mvM	0.8446	10.368
Burr - finite mvM	0. 7152	10.689

For this study, gamma is the best-fit for wind speed distribution and for the bivariate model, the best-fit is also represented by gamma with jointing of finite mixture von Mises. This finding is only true for Mersing station as the main study in this paper. However, in general [20] reveals that, the bivariate best-fit model is not provided by the corresponding univariate best fit model for wind speed.

The best bivariate model that can best explained data in Mersing, Malaysia is selected with the highest value of R^2 and lowest value of root-mean-square error (RMSE). The value of R^2 is larger than 0.8 for each fitted distribution, which is considered good in describing the variation in a model. While the lowest value of RMSE is shown in would be the best.

The average correlation between wind speed and wind direction are generally between 0.40 and 0.61, except for the year of 2012. Therefore, in conclusion, the correlation between wind speed and wind direction is somewhat moderate. The circular –linear correlation can be seen in Figure 4.

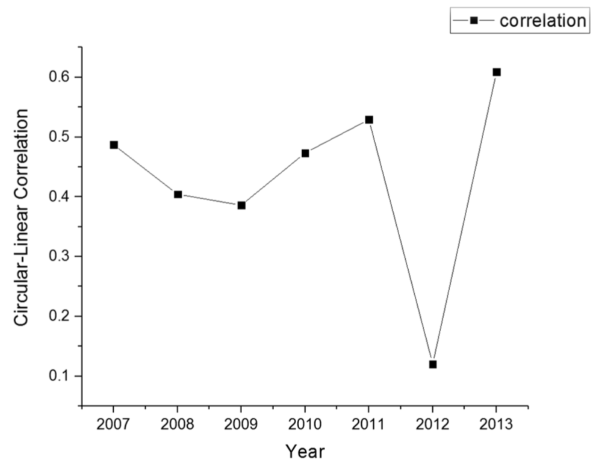

Fig. 4. Circular-linear correlation between wind speed and wind direction

3.4 Wind Energy Assessment

Annual wind power density (W/m^2) for Mersing, has been analyzed and the result as in Fig 5. Based on the mean value, there is 1.808261 percent increasing on bivariate model compare to univariate probabilistic model for Mersing annual wind power density. However, data for the year 2007 and 2013 show some decrease for about 0.5801 and 5.7612 respectively. The decline for the year 2007 is considered small, but for 2013 it may be caused of the data is from January to July only which has missed the northeast monsoon data of November and December as this monsoon bring higher wind speed. The inconsistent wind power density (W/m^2) between univarite and bivariate model indicates that the higher wind speed is not concurrent with the dominant direction of the wind which is parallel with[8] verification that there is a gradual change in the direction of the wind in their studies.

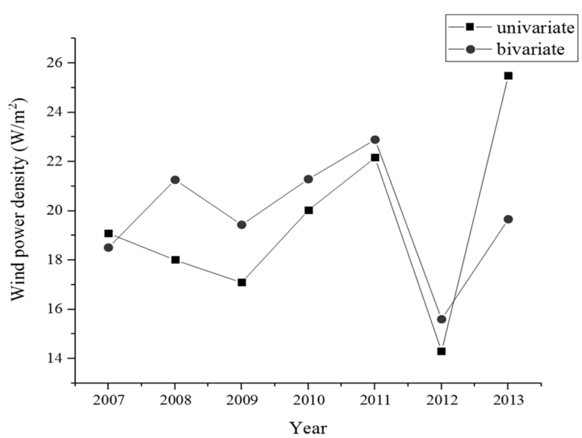

Fig. 5. Wind power density (W/m^2) for Mersing, Malaysia

4. Conclusion

This study reveals that based on the R^2 and AIC values, Gamma probability distribution is the best univariate model to explain the wind speed data of Mersing. While for the bivariate model is described by Gamma- finite mixture of von Mises probability distribution. Although the correlation between wind speed and wind direction is not strong, the average or r is 0.429917; this shows that there is the significant correlation between them. It affirms that for an optimum wind power density yields, the direction of the wind has an effect.

The significance of wind direction in the bivariate model is as shown by the wind power density (W/m2) results in this study. On average, the bivariate parametric model shows about 1.808261 percent increment on wind power density (W/m2) compare to univariate model. Thus, it indicates that there is significant effect of considering wind direction as an important variable and jointing it with wind speed to be considered in the wind power density analysis.

Acknowledgments
The authors would like to thank Universiti Kebangsaan Malaysia, Universiti Teknikal Malaysia and Ministry of Higher Education for providing the scholarship award to the principal author to carry out this project. The authors are also indebted to the Malaysian Meteorological Department for providing hourly wind speed and wind direction data.

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