Application of a New Method 'AGM' to Estimate Weibull Parameters for Low Wind Speed

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Abstract- Wind speed estimation for Weibull parameters can be attained using a variety of different methods. As a matter of fact, according to previous research, the outlined method is more effective in areas where the speed is between medium and high. While Malaysia is located within an equatorial region that experiences low wind speeds, the country's natural resources are not restricted in any way. This research is focused on developing a suitable method for forecasting wind speed in low-speed areas due to the findings of the previous research. An investigation has been carried out in order to determine the most effective methods of making predictions to make better decisions. χ^2, the first goodness of fit (GOF) test shows that the new Alternative Graphical Method (AGM) method comes in second place behind the PDM method, with a 7 per cent difference between the two. However, when it comes to the use of the second GOF, known as KS, the AGM method is once again in second place behind PDM, but this time by a significantly smaller margin of 1.8 per cent. As a result, according to the results of the last GOF (AD) also comes in second place, with forecast performance this time 3.7 per cent superior compared to the PDM method. According to these findings, the proposed new method (AGM) achievement is capable of making predictions that are more accurate than those made by existing techniques, which is a significant step forward.

Keywords- renewable energy; wind speed; Weibull distribution; method; Alternative Graphical Method.

1. Introduction

Utilising renewable energy (wind) for power production is not something new [1], [2]. Numerous nations have employed it successfully, and its growth is very rapid [3]–[5]. To date, no method can describe 100% as the best way to predict wind speed. This inaccurate seems to be because wind speeds are incredibly variable [6]. According to [7], the selection of the best method varies according to the total number of data, type of data used, suitability of the customisation method and lastly, depends on the type of distribution suitable for an area. This statement is also supported by [7]–[9]. Meanwhile, in Malaysia, most of the studies that have been conducted are more focused on using existing methods to obtain parameters for predicting wind speed [10]–[15]. Then, in conclusion, some researchers will then arrange the methods according to the best order to be applied for a particular area. So the implication is that many studies cannot make accurate estimates following existing methods. Methods to predict wind speed need to be investigated as wind speed in Malaysia is different compared to other countries with different speeds. This difference is due to the wind speed in Malaysia is slow.

The Weibull distribution was selected for this study based on the literature findings [15]–[18]. Furthermore, the findings show that Weibull has been used for a long time and is a benchmark for wind research. In addition, this distribution has also gained international recognition. Moreover, the main factor is that this distribution corresponds to the wind speed data at the Mersing study location. On top of that, this location is frequently recommended since it has one of Malaysia's highest wind speed potentials [19], [20].

Weibull distribution has two parameters, namely shape parameter (k) and scale parameter (c). Usually, the value of k is between 1.5 and 3 [21], [22] while the value of c is between the values 1.1 to 1.3 of wind speed value [22]. Once the wind speed distribution is identified, the following procedure is to select the method. According to [23], [24], there are generally two methods commonly used by previous researchers. The first is the method of physical prediction (observation) and the second is using statistics. Meanwhile, [25] also voiced the same opinion. However, he suggested adding another method, namely the computer-based intelligence method. Therefore, for this study, the scope is only on statistical analysis methods.

The statistical method of obtaining parameters is a fundamental and critical component in evaluating wind speed data [25], [26]. At the same time, the parameter is the value that can provide information about a certain wind speed. So, it is imperative to use the best method to obtain the proper parameters. Moreover, this best method can predict the wind speed well too.

Therefore, the objective of this study is to optimise the method of obtaining Weibull parameters for low wind speeds in Malaysia. Consequently, there is a need for method optimisation to obtain parameters for wind speed [27]. The impact will lead to the reliability of the method, produce good information and at the same time will minimise the impact resulting from wind source uncertainty [25], [28], [29].

2. Materials and Methods

Statistical prediction methods include procedures for finding parameter values for a distribution. Weibull distribution has been used as a benchmark for wind research [8], [9], [30]. Therefore, this study only describes the statistical methods to obtain parameter values limited to Weibull distribution.

Based on previous studies, there are more than ten existing statistical methods used by previous researchers in determining the value of parameters and, at the same time, can determine the density of wind power in an area. The selection of methods is based on the findings of the literature review. A newly proposed method, Alternative Graphical Method (AGM) and selected method consisted of Maximum Likelihood Method (MLM), Empirical Method (EM), Graphical Method (GM) and Power Density Method (PDM).

Table 1. Types of the method according to the type of wind speed

Method	Type of wind speed	Sources
MLM	Medium, fast	[31]–[33]
EM	Medium	[11], [34], [35]
PDM	Medium	[24], [36], [37]
GM	Slow	[18], [30], [38]

The types of methods that correspond to the different wind speeds are shown in Table 1. Four methods correspond to the three types of wind speed: fast, medium, and slow. According to [11], slow winds are less than 3.5 m/s, moderate winds are between 3.5-8.5 m/s, and high winds are more significant than 8.5 m/s. As previously stated, in Malaysia, the majority of studies have focused on using existing methods to obtain wind speed parameters. At this point, a few researchers will then arrange the methods in the best possible order for a specific area of study. So the conclusion is that many studies are unable to make accurate estimates based on current methods.

The literature review revealed that one method could be used to predict high-speed wind speeds, which are listed in Table 1. These method is known as MLM and described in more detail in the following sections. Furthermore, the findings demonstrate that these two methods can produce encouraging results when predicting wind speeds at medium speeds too. Three methods can be used to predict medium-speed wind speed in total; the others are the EM and PDM methods. On the other hand, the GM method only predicts wind speeds in locations with low wind speeds.

According to Table 1, it can be concluded that the existing method is very suitable for making predictions for areas with high and medium winds, except for one method, which is the GM, which is suitable for areas with slow speed wind. Therefore it is necessary to investigate methods for predicting wind speed because the wind speed in Malaysia differs from other countries with different speeds. This is since Malaysia's winds are comparatively weak. Listed below are the upsides and downsides of each presently available method.

2.1 Maximum Likelihood Method (MLM)

The Maximum Likelihood Method (MLM) is the leading choice of researchers. This method is the most frequently used for the record based on the literature review. The high percentage of frequency of use indicates that the MLM method has several advantages. Among MLM advantages is accurately predicting parameter values [39], [40].

In addition, this method also has a place in the hearts of software developers. For example, "Easyfit" is among the software that uses built-in functions (built-in) for MLM methods. However, there is no denying that this MLM method also has some shortcomings. Among the shortcomings of this method involves the calculation of long iterations and it is necessary to ensure that the zero value of the data is removed first [8]. However, according to [32], the iteration can provide a minimum error value.

2.2 Empirical Method (EM)

The empirical method (EM) is a method that uses descriptive values , i.e., average values and standard deviations, to find the parameters for the Weibull distribution. Therefore, the empirical method is also known as the Standard Deviation Method (SDM). Empirical methods are arguably one of the easiest methods. The word "easy" definition here means that researchers only need two descriptive data values: average and standard deviation. However, this method has the disadvantage of predicting low speed wind data and has many zero data as in Malaysia. This disadvantage is due to the standard deviation that is easily biased if using data with a lot of zero value.

2.3 Power Density Method (PDM)

This method is known by two acronym names, PDM or EPF. The abbreviation EPF refers to the Energy Pattern Factor produced in a location. The advantage of PDM is that it does not involve long calculations, it is accurate, and lastly good in terms of approximation [36], [37], [41], [42]. Nevertheless, it is not a problem because the same person creates both methods [40]. Furthermore, PDM uses the EPF approach to predict wind speeds in a location and it is one of the latest methods created.

2.4 Graphical Method (GM)

The Graphical Method (GM) is the most popular method among researchers. It is often used for research purposes related to wind energy. In addition, it is also known as the Least Square Method (LSM). The data must first be converted from a time series form to a frequency data form to use the graphical method. Next, the cumulative distribution function F(v) can be obtained easily. This cumulative distribution function is used to obtain a straight line. Thus, calm or zero wind data should be removed from the data [14], [30]. Finally, the best line can be determined using regression. However, now, this task is easier to do using a computer by doing linear regression analysis and this method does not require high skills to use it.

Furthermore, this graphical (GM) method can be the primary method for calculating Weibull parameters. In addition, this method has the same factors as the MLM method, which is to remove the zero value first before starting the analysis. Consequently, it becomes one of the most inappropriate methods for most studies [33], [41], [43], [44].

Wind speed data collected on a daily basis in 2009 is used to analyse, compare, and determine the most effective method. To obtain the parameter values for the Weibull distribution, use the formulas in Table 2 for the MLM, EM, PDM, and GM. These formulas are as follows:

Table 2. The formula for MLM, EM, PDM and GM

Method	Formula
MLM	$k = \left(\frac{\sum_{i=1}^{n} {v_i}^k \ln v_i}{\sum_{i=1}^{n} {v_i}^k} - \frac{\sum_{i=1}^{n} \ln v_i}{n} \right)^{-1}$ $c = \left(\frac{1}{n} \sum_{i=1}^{n} {v_i}^k \right)^{\frac{1}{k}}$
EM	$k = \left(\frac{\sigma}{\bar{v}} \right)^{-1.086}$ $c = \frac{\bar{v}}{\gamma\left(1 + \frac{1}{k}\right)}$
PDM	$\overline{v^3} = \frac{1}{n} \sum_{i=1}^{n} v_i^3$ $Epf = \frac{\overline{v^3}}{(\bar{v})^3} = \frac{\gamma\left(1 + \frac{3}{k}\right)}{\gamma\left(1 + \frac{1}{k}\right)^3}$ $k = 1 + \frac{3.69}{(Epf)^2}$ $c = \frac{\bar{v}}{\gamma\left(1 + \frac{1}{k}\right)}$
GM	$k =$ slope of straight line y-intercept $= -k \ \ln c$ $-\ln\{1 - (F(v)\} = k \ln v - k \ln c$

where k is the Weibull shape parameter, c is the Weibull scale parameter, v_i are the wind speed at term i and n is the total number of data, σ is the standard deviation, $\bar{v}$ is the average wind speed and γ is the Gamma function, Epf function refers to the energy pattern factor, m is the slope of the straight line, $F(v)$ is the cumulative distribution function.

2.5 Propose method - Alternative Graphical Method (AGM)

It is vital to obtain the best methods for modelling wind speeds [45], [46]. This study proposes this new method to predict wind speed using Weibull distribution. The wind speed at the site is said to be low because the descriptive analysis findings show that the average wind speed is less than 3.5 m/s [47].

Therefore, this propose method is an alternative for areas with low wind speeds. In addition, this method is built based on the disadvantages of other methods that do not consider the zero speed factor. In addition, the main strength of this method is to make full use of raw data without discarding any external or partial placement values. Thus it is not affected by the value of bias. First, the k parameter value can be found using Eq. (1). Next, the value of c can be obtained using the Eq. (2).

$$k = \sum_{i=3}^{1+3.3\log n} p\left(\widehat{x_i}\right) \tag{1}$$

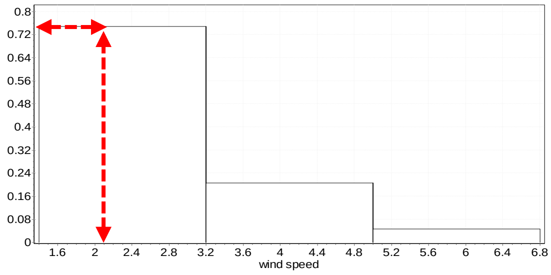
$$c = \frac{\bar{v}}{\gamma\left(1+\frac{1}{k}\right)} \tag{2}$$

where k is the Weibull shape parameter, c is the Weibull scale parameter, n is the number of data, i is the number of bin generated, p is a probability, $\widehat{x_i}$ is the mode at bin i, $\bar{v}$ is the average wind speed and γ is the Gamma function.

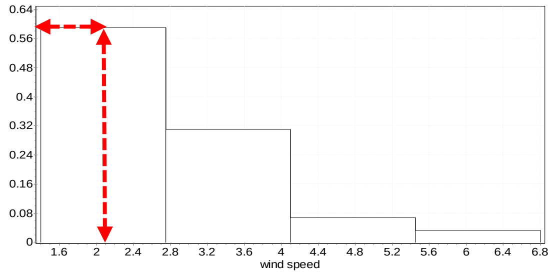
The reason for using a "bin" is to get a "mode" value for each "bin" value. This is because this newly proposed method is based on the fact that the value of k is the peak of the Weibull distribution's probability density function (pdf). Since the mode is the highest value in each histogram, the value of k is found by adding all the probabilities of the mode.

Figure 1 refers to each histogram with a different number of bins smallest to the largest number of bins (relationship $1 + 3.3\log n$). The bins will be optimal based on the Sturge law. Once the histogram is run, the subsequent attention is given to the mode value. For the year 2009, the mode value is equivalent to 2.1 m/s (red line on the x axis). Next, the probability of a mode value (red line on the y axis) for each histogram of a different bin is needed. Thus, the sum of each probability value is the value of k.

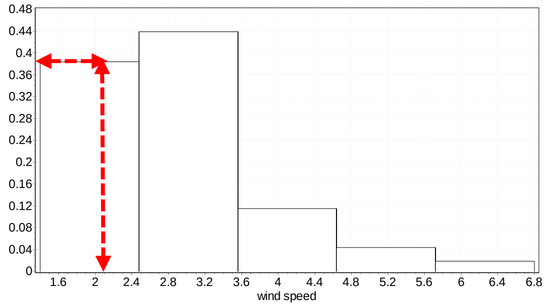
a) Histogram with three bins



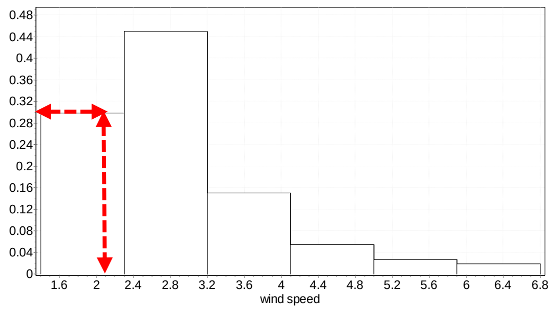
b) Histogram with four bins



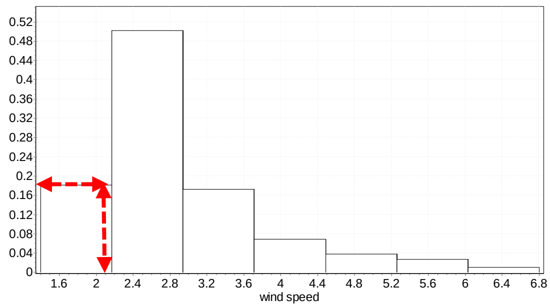
c) Histogram with five bins



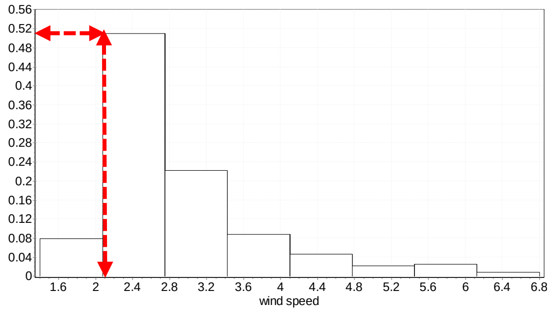
d) Histogram with six bins



e) Histogram with seven bins



f) Histogram with eight bins



g) Histogram with nine bins

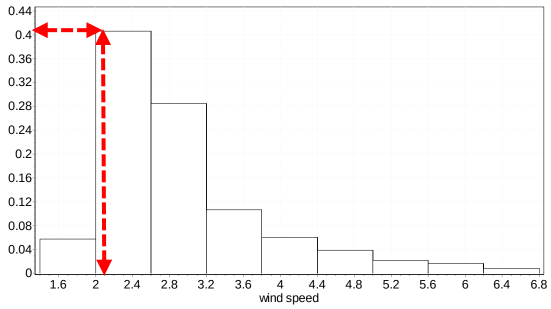


Fig. 1. Histogram according to the number of bins (a-g).

The probability of the mode value can be summarised in Table 3. Based on the table, the mode probability values for each different histogram of bin are 0.75, 0.59, 0.385, 0.30, 0.18, 0.51 and 0.409.

Table 3. Probability value according to the number of bins

Number of bins	Probability Value
Three bins	0.75
Four bins	0.59
Five bins	0.385
Six bins	0.30
Seven bins	0.18
Eight bins	0.51
Nine bins	0.409

Table 3 presents a summary of the probability of the mode value occurring. According to the table, the mode probability values for each different bin histogram are 0.75, 0.59, 0.385, 0.30, 0.18, 0.51, and 0.409, with 0.75 being the highest and 0.59 being the lowest. The basis of the production of this method is based on facts, where the value of k is the peak for pdf distribution Weibull. Since the mode is the highest value of each histogram, then all the probability values of the mode are added to get the value of k. Thus, the AGM technique gives a value of shape parameter (k) equals 3.124 while using formula 2 generates a value of 3.2241 for scale parameter (c).

3. Analysis and Discussion

3.1 Comparison of Methods

This study aims to determine the most effective method for optimising Weibull distribution parameters while also improving the accuracy of wind speed predictions. Following that, once the parameter values are known, the comparative analysis of the probability density function Weibull distribution will be carried out in greater depth. This investigation is required in order to make a performance comparison between the five methods used in conjunction with the AGM method.

Table 4. Comparative analysis of scale (c) and shape (k) parameters based on the types of method

	Method				
	MLM	EM	PDM	GM	AGM
k	4.094	3.429	2.983	3.097	3.124
c	3.170	3.209	3.231	2.851	3.224

Table 4 shows the parameter values of the Weibull distribution, which has two main parameters, namely the shape parameter (k) and the scale parameter (c). These parameters are obtained using six different methods. The main differences between the methods can be seen based on the formula used to obtain the parameter values of the form parameters (k) as well as the scale parameters (c).

The higher the value of the shape parameter (k) gives the impression that an area has a stable (constant) wind speed [48] and no unit for the value of k [21].The highest value parameter of the form (k) is obtained using the MLM method, 4.094, followed by the EM method with almost the value of 3.429. Next is the AGM method with a value of 3.124, while GM is equivalent to 3.097 and the lowest is PDM of 2.983.

While the scale parameter (c) value provides information on whether an area has the appropriate wind potential, this is because the scale parameter (c) has to do with the descriptive value, i.e., the average wind speed and the unit are the same. The wind speed unit is according to the common practice of meters per second (m/s). The higher the scale parameter value (c) means, the higher the wind potential in the area. By referring to Table 2, the highest value of scale parameter (c) is obtained by using the PDM method, which is 3.231 and in second place, the AGM method has a value of 3.224. Next, the EM methods where the value is the 3.209. While the MLM method and the lowest GM method with 3.170 and 2.851, respectively.

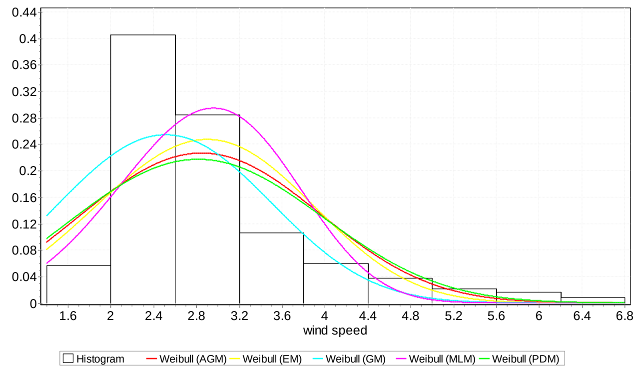


Fig. 2. Histogram and probability density function (pdf) wind speed for MLM, EM, PDM, GM and AGM methods.

Next, by using the parameter values obtained through various methods, Fig. 2 was constructed. The diagram shows a histogram and the probability density function of 2009 was plotted. A histogram refers to the frequency of actual wind speed data collected. Several significant values can be obtained from this histogram. The minimum and maximum data values can also be easily obtained from Figure 3. The minimum data is 1.4 m/s, while the maximum value is 6.8 m/s. In addition, the most common wind speed information (mode) can also be identified. Wind speed mode is in the range of 2.0-2.6 m/s. This value is equivalent to the input separator value for some wind turbines, 2.5 m/s. It is a good sign and at the same time, this location can generate electricity from wind energy.

The probability density function (pdf) is a forecast plot for wind speed data. For this study, the focus is only on pdf distribution Weibull. There are six methods used to find the value of a parameter that can provide the optimum value (pdf). MLM, EM, PDM, GM, and AGM are among the methods used.

Based on Fig. 2, the best method selection is based on the predicted results according to the actual data. The best predictions are graphs that can provide similar graphs to the actual data [24]. The method used is seen to give almost identical predictions to each other. In conclusion (Fig. 2), it is difficult to determine which method is best for this finding. In order to obtain certainty and explanation, there is a need to use a more scientific and systematic way to determine the best method [24] a statistical instrument, Goodness of Fit (GOF), is used due to this factor.

Table 5. Comparative analysis based on Goodness of Fit (GOF) for 2009

GOF	Method				
	MLM	EM	PDM	GM	AGM
KS	0.185	0.176	0.167	0.242	0.170
AD	22.03	18.31	19.35	28.48	18.67
χ^2	6622	307.8	179.0	871.8	191.6

Table 5 displays the results of the analysis of the adaptive goodness method among the methods that have been used. For this study, the method of adaptive goodness (GOF) is a type of statistical instrument used to determine the position of a method. The position of the method can be arranged according to the best method up to the poor method. Among the GOFs used for this study were Kolmogorov-Smirnov (KS), Anderson-Darling (AD), and Chi-Squared (χ^2). The results for all these customisation methods are selected based on the method that obtains the lowest value.

Based on Table 5, the results are different for the AD adapting as the goodness of fit. This significant difference in results may be due to the fact that the pdf graph curve is being focused on at the edges. The analysis results show that EM are the most effective method, i.e., 18.31. The AGM method occupies the second position with a value of 18.67, while the PDM method occupies the third position with 19.35. MLM comes in fourth with a value of 22.03, and the GM comes with 28.48, putting it in last place overall. These significant values also demonstrate numerous errors in making predictions on both sides of the graph curve in the GM.

On the other hand, KS has demonstrated that the PDM method is the best method by obtaining the lowest value of 0.167, while the second is followed by the AGM method with only a value difference of 0.003 between the two methods. Following that, the EM methods produce results, i.e., 0.176. Furthermore, the MLM method obtained a value of 0.185, whereas the GM method obtained an enormous value of 0.242, making it the most inaccurate method. In light of this enormous value, the GM method has a significantly higher prediction error in the middle portion of the graph curve than other methods. As a result of this finding, no best method is claimed to be capable of predicting wind speed data; as a result of this factor, it is necessary to use another GOF, which is χ^2. Moreover, it is consistent with the recommendations derived from the literature finding [49].

Findings χ^2 (Table 5), show that the PDM method is the best. This best method is due to providing the lowest value of 179. Next, the second best method is AGM with a value of 191.6, while the third and fourth places are owned by EM and GM methods with 307.8, and 871.8, respectively. The low value indicates a minimum difference between the data collected and the predicted data. However, there are times when the value of χ^2 can reach up to thousands. For example, the MLM method ranked last, with its value equal to 6622. These figures illustrate a significant difference between the predicted and collected data.

Overall, the best methods for 2009 are ranked as follows. PDM was granted the first place. The newly developed method (AGM) came in second, with EM in third. Meanwhile, the MLM method ranks higher than the GM method, fourth and fifth.

3.2 Validation by Experimental Data

This step must be done to ensure the new method (AGM) is reliable. Besides that, it can ensure that the AGM method is the best and can accurately predict wind speeds. However, in order to make sure that the predictions made are correct, some steps need to be taken first. One of the steps is to predict what will happen in the next few years, such as in 2010, 2011, 2012, 2013, 2014, 2015, 2016 and 2018. This forecast can be made by using parameter values based on data from 2009. However, due to space constraints, the figures in the results and discussion section only present analysis for 2010 and 2011, namely Table 6 and 7.

Table 6. Comparative analysis based on Goodness of Fit (GOF) for 2010

GOF	Method				
	MLM	EM	PDM	GM	AGM
KS	0.322	0.301	0.283	0.156	0.289
AD	52.50	42.19	37.67	16.12	38.78
χ^2	237.1	164.5	171.4	128.9	166.7

Table 7. Comparative analysis based on Goodness of Fit (GOF) for 2011

GOF	Method				
	MLM	EM	PDM	GM	AGM
KS	0.154	0.148	0.140	0.185	0.142
AD	19.27	14.75	15.34	23.80	14.80
χ^2	2900	1013	161.7	4369	241.2

In general, based on Tables 6 and 7, the best methods are ranked as follows. PDM was awarded the top spot. The newly developed method (AGM) was ranked second, followed by EM. Meanwhile, the MLM method ranks higher than the GM method, fourth and fifth, but sometimes swap positions between these two methods. Therefore, the newly developed method (AGM) methods demonstrate that the parameter values obtained are consistent and accurately predict wind speed. This can be understood from the following graphic, Fig. 3.

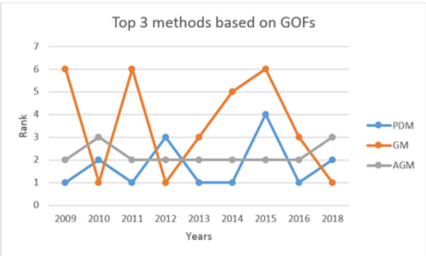


Fig. 3. Position of top 3 methods based on GOFs (2009-2018).

Based on the forecast values, the diagram (Fig. 3) illustrates the position of the three best methods for 2009-2018. The three methods are GM, PDM, and the newly developed AGM. When compared to the AGM and PDM, it can be seen that GM is very fragile and ineffective. This is because the GM can be in the first or last position at any given time.

Despite the fact that the PDM approach has been proved to be inconsistent. As evidence, 2012 and 2015 show that the AGM method outperforms PDM. Moreover, PDM is also viewed as unreliable, as it ranks first, second, third, and fourth in multiple years, compared to the AGM technique, which appears to be relatively constant, as it consistently ranks second and third throughout the period 2009-2018. This diagram also reveals that the AGM method has good durability and consistency.

3.3 Uncertainty Analysis of The Proposed Method

The new method (AGM) has been subjected to several uncertainty analyses. AGM's ultimate goal is to enhance precision and evaluate the method's rigidity.

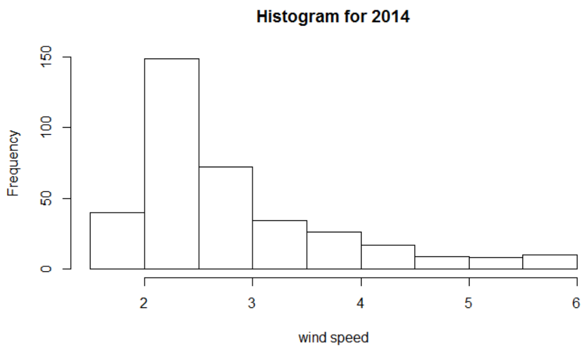


Fig. 4. Histogram of wind speed (a-c).

Firstly, the uncertainty analysis for the proposed new method remains valid even if the wind data form input is altered. The findings for 2015 further support this claim (Fig. 4). In 2015, the AGM method again achieved good results, remaining in second place overall, compared to the best PDM method, which was in fourth place (Figure 3). Following an investigation, wind speed data in 2015 was in a slightly different format than in previous years. This difference can be seen at wind speeds of around 2-3 m/s. In 2014 and 2016, the value was nearly identical, but there was a difference in 2015. This difference is very observable, implying that it almost has two mode values. This difference is also due to a lack of slow-speed winds this year, as evidenced by the histogram for 2015. Furthermore, this leads to the discovery that one of the AGM method's strengths and consistency is its ability to predict different data form especially when meet with the two modes.

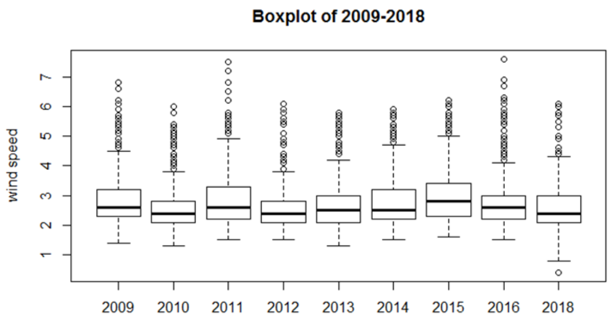


Fig. 5. Boxplot of data (2009-2018).

The second is connected to the value of the range. In other words, if there are outlier values, then this newly developed method (AGM) is not affected. A boxplot (Figure 5) is a way to show the entire data set. The minimum, maximum, median, first quartile, third quartile and outlier values are among the summaries that can be obtained. According to Fig. 5, outlier values can be noticed in 2011, 2016, and 2018. However, based on the position (Fig. 3), these external values do not affect the AGM approach.

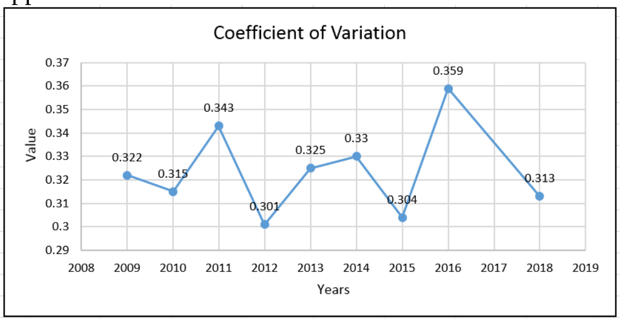


Fig. 6. Coefficient of variation (COV) for 2009-2018.

Consequently, the third step in analysing uncertainty is to use the coefficient of variation (COV) value. The coefficient of variation indicates the ratio of the standard deviation to the mean, and it is a valuable statistic for comparing the degree of variation between data series, even if the means are vastly different. A low value implies a low degree of variation, and vice versa.

The lowest COV values were in 2012 and 2015 (Fig. 6). Low values indicate that the data is in good condition and an acceptable state. The AGM method overcame the PDM's decisions once again these two years. This finding immediately demonstrates the effectiveness of the AGM method. Furthermore, it was discovered that the proposed method was most accurate when used in regions where the entire data stream was the data in the most optimal condition.

4. Conclusion

This study aims to determine the most effective method for predicting low-speed wind speeds. Based on Table 4, we can conclude that the newly developed AGM is comparable to the methods used by previous researchers in their investigations. It is capable of accurately predicting wind speed. These results are based on its ability to produce good results for all three goodness of fit (GOF) measures, namely KS, χ^2 and AD. In the findings of χ^2, it ranks second behind the PDM method with a difference of 7 per cent, demonstrating that it is a viable alternative. However, when it comes to the use of KS, the AGM method again comes in second place behind PDM, however this time by a more significant margin of 1.8 per cent. After all, AGM is also ranked second in terms of AD as well, but this time with a forecast performance that is 3.7% higher than that of the PDM method. In this case, it appears that AGM has the potential to be used as one of the methods for predicting wind speed, mainly when dealing with low wind speeds. Finally, it is suggested that the next step in realising this potential is to conduct tests and validate the AGM method using as much data as possible over the next several years. The approach used in this research can be replicated to assess wind resources in other parts of the world, which is a significant benefit.

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