Demonstrating Measure-Correlate-Predict algorithms for Estimation of Wind Resources in Central Finland

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Preface

Renewable energy has been in use for several years and this use can reduce the greenhouse effect that is the main cause of global warming. Wind energy is a source of clean energy that can be used to generate electricity without air pollution. This is the main reason why we need to have more wind power plants. We do not know the long-term wind speed at every place which is why measure-correlate-predict algorithms are used to estimate wind speeds at sites that we are interested for construction of wind power plants but do not have long-term wind speed measurements for estimation of wind power potential.

I completed this work with the help of many people. Here I would like to thank Dr. Jussi Maunuksela. He led me through the whole work and instructed me about the research. With his great help, this study is finally done. I would also like to thank my family in Thailand and also in Finland especially Dr. Somjai Sangyuenyongpipat she is a great sister who has taken care of me all of the time when I have lived in Finland and Tero Isotalo my "big brother" who has always helped me when needed.

ความสำเร็จจากการจบการศึกษาปริญญาโทในครั้งนี้จะไม่เกิดขึ้น หากขาดกำลังที่สำคัญจากครอบครัวและเพื่อนๆทุกคน โดยเฉพาะอย่างยิ่งคุณพ่อ คุณแม่ที่คอยให้กำลังใจและอยู่เคียงข้างในยามที่ท้อแท้และเหนื่อยล้าให้กลับมามีกำลังในการสู้ต่อ ขอบคุณพี่สาวและพี่เขยที่คอยให้คำปรึกษาและอยู่เคียงข้าง ขอบคุณพี่น้องทุกคนที่คอยเป็นห่วงและเป็นกำลังใจให้ รวมไปถึงความห่วงใยจากเพื่อนๆทุกคนที่เป็นเสมือนหนึ่งพลังใจในการผลักดันให้ผมก้าวต่อไปตลอดช่วงเวลาที่ศึกษาอยู่ ณ ประเทศฟินแลนด์ และที่สำคัญต้องขอขอบคุณคณาจารย์ทุกท่านที่ได้เคยประสิทธิ์ประสาทวิชาทำให้ผมมีความรู้ความสามารถมาถึงจุดนี้ได้ จากโอกาศและความสำเร็จในครั้งนี้ทำให้ผมได้เรียนรู้ชีวิตและได้รับความก้าวหน้าทางวิชาการ ได้รับประสบการณ์หลายๆอย่างที่มิอาจหาซื้อได้โดยทั่วไป กระผมหวังเป็นอย่างยิ่งว่าคงได้นำความรู้ความสามารถกลับมาใช้พัฒนาประเทศและก่อประโยชน์ให้กับสังคม ครอบครัว และตนเองต่อไปในภายภาคหน้าได้อย่างดี

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Abstract

In this study, measure-correlate-predict (MCP) algorithms - Simple Linear Regression and Variance Ratio Methods - for predicting wind speed were studied. The MCP algorithms were successfully used to predict missing wind speeds at two sites in Jyväskylä and Viitasaari, respectively. These two algorithms used data from one of the site to predict missing wind speed data at the other site. The results obtained using the MCP methods were compared using metrics that showed the characteristics of the predicted data to be unbiased compared to measured data. From the data of this study, we also evaluated wind power density at both sites which categorized the local wind resources as poor since the determined wind power densities were less than 100 W/m^2.

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1. Introduction

Wind energy is a form of alternative clean energy for worldwide electricity production. Electricity production using wind power technology is more environmentally friendly compared to conventional electricity production because it can reduce air pollution and greenhouse gas emissions from fossil fuels. In 2008, the cumulative installed wind power capacity increased nearly 29% worldwide [1]. Since 1995 the wind power capacity in IEA wind member countries has increased from around 5 GW to nearly 92 GW in 2008 [2].

In 2009, the wind power capacity for example in Finland was 146 MW [14] and the environmental benefit of wind power production was estimated to be about 0.2 million tons of carbon dioxide savings [2]. The Finnish Government approved a new climate and energy strategy in 2008 where the target for the wind power capacity was set to 2,000 MW by 2020 which by then will be about 6 % of the total electricity consumption in Finland [2]. Therefore there will be a need for hundreds of new wind power plants in Finland between now and the 2020 target date.

The wind farm energy output, and hence the financial viability of the scheme, will be very sensitive to the wind speed seen by the turbines over the life of the project. Hence it is not generally considered acceptable in complex terrain to rely entirely on the short-term estimates of wind speed made during the initial site selection. To this end the measure-correlate-predict (MCP) techniques have been developed to obtain a prediction of the long term wind resource [8].

The purpose of a MCP method is to provide data for estimating the long term wind speed distribution and thus the annual energy capture of a wind farm at the given (target) site. We have several MCP methods that can be used to predict the wind resources [5]. These methods use data from a reference site to predict long term wind speed and direction distribution at the target site. This study demonstrates the capability of two MCP methods to predict the wind speeds for a target site: A method by Derrick [6, 7] that uses linear regression to characterize the relationship between the reference and target sites and a method by Rogers *et al*. [5] called Variance Ratio method. These methods are compared using a set of performance metrics that measure the consistence of the predicted data with data measured.

The wind speed data analysed in this study was measured in 2008 in Jyväskylä and Viitasaari in central Finland and was used to define the relationship between wind speeds at the two sites and some characteristics of the corresponding wind resource namely the mean wind speed, wind speed distribution and annual energy production [3].

2. Characterization of wind resources

Wind is caused by pressure and temperature differences in the earth's atmosphere which are a result of uneven heating by solar radiation. The variations in heat transfer to the earth's atmosphere create variations in the atmospheric pressure field that cause air move from high to low pressure [10]. In addition, this air circulation in the atmosphere is affected by the rotation of the earth as well as global and local effects resulting from orographic conditions [9, 10].

Wind speed varies continuously as a function of time and height measured from the ground. The variations in time can be divided into categories by time scales: Inter-annual, annual, diurnal and short-term (gust and turbulence). The inter-annual wind speed variations occur over time scales greater than one year and can have a huge effect on long term wind production. Estimation of the inter-annual variability at a given site can be almost as important as estimating the average long-term wind speed at site.

Meteorology generally concludes that determining the long term values of weather or climate data takes about 30 years and that it takes at least five years to arrive at a reliable estimate for the average annual wind speed at a given location. However data measured over shorter time periods can be useful. A statistically developed rule of thumb noted by Aspliden *et al.* was given in Ref [17] that states *"one year of recorded data is generally sufficient to predict long-term seasonal mean wind speeds within an accuracy of 10% with a confidence level of 90%."*

Annual variations in seasonal or monthly averaged wind speeds are common over most of the world because of the maximums wind speed occur at different seasons. Large wind variations can occur on a diurnal or daily time scale in both tropical and temperate latitudes. This wind speed variation is due to differential heating of the earth's surface during the daily radiation cycle. An increase in wind speed during the day is typically diurnal variation while the wind speeds are lowest during the hours from midnight to sunrise. Daily variations due to solar radiation are responsible for diurnal wind variations in temperature latitudes over relatively flat land areas.

The largest diurnal changes generally occur in spring and summer, and the smallest in winter. The location and altitude above sea level may cause the diurnal variation in wind speed. For example, at altitudes high above surrounding terrain, *e.g.,* mountains or ridges, the diurnal pattern may be very different. Mixing or transfer of momentum from the upper air to the lower air can be explained by this variation. Short-term wind speed variations including turbulence and gusts normally mean variations over time intervals of 10 minutes or less. They are typical given as ten-minute averages using a sampling rate of once every second.

The variations in wind speed during time periods from less than a second to 10 minutes are generally accepted having a stochastic character and are considered to represent turbulence. For wind energy applications, turbulence fluctuations in the flow are important for the turbine design considerations such as maximum load and fatigue prediction, structural excitations, control, system operation, and power quality. [10]

The two important factors which can be used to characterize the wind resource at a site are average wind speed and wind speed distribution such as the Weibull distribution that is defined by the scale and shape parameters. Next I will describe the statistical methods for estimating characteristics of wind resources.

2.1 Direct use of data

The long term mean wind speed, $\overline{U}$, over the total period of data collection is given by

$$\overline{U} = \frac{1}{N}\sum_{i=1}^{N} U_i \quad , \qquad (1)$$

where U_i is measured wind speed at each hours. The standard deviation of the individual mean wind speed, σ_U, is then given by

$$\sigma_U = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(U_i - \overline{U})^2} \ . \qquad (2)$$

2.2 Method of bins

The method of bins provides a way to summarize wind data and help determine expected turbine productivity. The data must be separated into the wind speed intervals or bins in which it occurs. It is most convenient to use the bins of equal size. Suppose that the data are separated into N_B bins of width w_j , midpoints m_j and with f_j, the number of occurrences in each bin or frequency, is so that:

$$N = \sum_{j=1}^{N_B} f_j \qquad (3)$$

$$\overline{U} = \frac{1}{N} \sum_{j=1}^{N_B} m_j f_j \qquad (4)$$

$$\sigma_U = \sqrt{\frac{1}{N-1}\left\{\sum_{j=1}^{N_B} m_j^2 f_j - N\left(\overline{U}\right)^2\right\}} \qquad (5)$$

A histogram showing the number of occurrences of wind speed is usually plotted when using this method. Fig. 1 shows a histogram of the wind speed data of Jyväskylä and Viitasaari sites where the blue colour denotes Jyväskylä site and the red colour Viitasaari site.

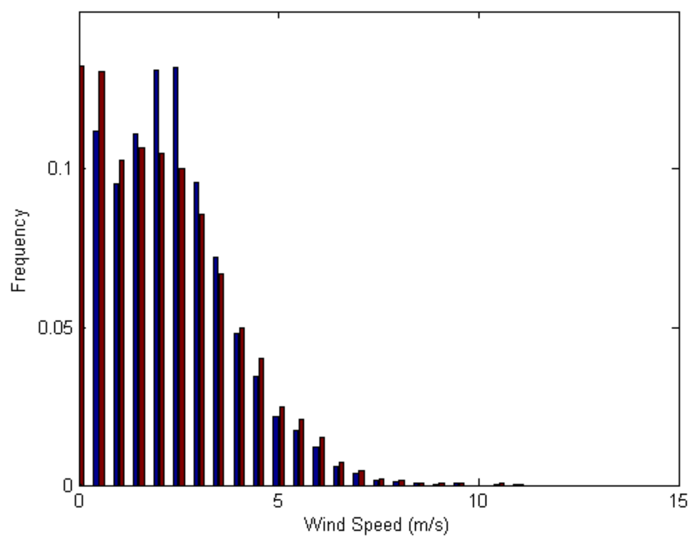

Figure 1 Wind histogram for Jyväskylä and Viitasaari sites.

2.3 Weibull and Rayleigh Distributions

In wind data analysis Weibull or Rayleigh probability density functions are used for characterization of the wind speed distribution. The Weibull distribution is given by a function of two parameters that can be determined from measured wind speed frequency distribution. This function called the Weibull probability density function is as follows:

$$p(U) = \left(\frac{k}{c}\right)\left(\frac{U}{c}\right)^{k-1} \exp\left[-\left(\frac{U}{c}\right)^{k}\right] \quad \text{Weibull p.d.f.} \qquad (6)$$

where k is called the shape parameter and c is called the scale parameter. The Weibull function equals the Rayleigh function when the shape parameter is equal to 2. The Rayleigh probability density function is given below:

$$p(U) = \frac{\pi}{2}\left(\frac{U}{\overline{U}^{2}}\right)\exp\left[-\frac{\pi}{4}\left(\frac{U}{\overline{U}}\right)^{2}\right] \quad \text{Rayleigh p.d.f.} \qquad (7)$$

Here $\overline{U}$ is the average wind speed at the site given either by Eq. (1) or (4) [5].

2.4 Cumulative distribution function

The cumulative distribution function represents the time fraction or probability that the wind speed is smaller than or equal to a given wind speed. By integrating Eq. (6) we get the cumulative distribution function for the Weibull distribution:

$$P(U_i) = P(U \le U_i) = 1 - \exp\left[-\left(\frac{U_i}{c}\right)^{k}\right] \qquad (8)$$

where $P(U < U_i)$ is the probability that the wind speed is less than U_i [11].

2.5 Wind Power Density

An important parameter of wind power conversion is wind power per unit area or wind power density which is proportional to the density of air at standard conditions and cube of the wind velocity [10]:

$$WPD = \frac{1}{2}\rho\overline{U}^{3} \quad (9)$$

where $\overline{U}$ is the average wind velocity (m/s) and ρ is the air density at sea level at a temperature of 15 ^{o}C and a pressure of 1 atm (1.225 kg/m^3). [4, 5]

3. Estimation of Weibull parameters

There are a number of methods that can be used to get the parameters c and k in Eqs. (6) and (8).

3.1 Regression Method

The Regression method is a graphical method based on logarithmic transformation of the cumulative distribution function in Eq. (8):

$$\ln\{-\ln[1-P(U<U_i)]\} = k\ln U_i - k\ln c \qquad (10)$$

Using this method, a straight line $y = mx + b$ where $y = \ln\{-\ln[1-P(U<U_i)]\}$ and $x = \ln U_i$ is fitted. The slope of the straight line m gives k and the intersection gives c so that $c = \exp(-b/m)$.

3.2 Chi-Square method

Another method that can be used to get the parameters c and k are called the Chi-Square method. This method uses the cumulative distribution $P(U_i)$ obtained from the measured wind data. The parameters c and k are estimated such that

$$\sum\left(P(U_i) - 1 + \exp\left[-\left(\frac{U_i}{c}\right)^k\right]\right)^2 \qquad (11)$$

is minimized [13]. The estimates obtained from the Regression method were used as initial values for the minimization. A Matlab® function fminsearch [15] for function minimization was used for computing the parameter values.

4. Measure-Correlate-Predict (MCP) Methodology

The MCP is a statistical technique used for predicting the local long-term wind resource based on series of short term measurements of wind speed at a site planned for wind power plant and correlating them with simultaneous wind speed measurements made at a meteorological station [8, 16]. Wind speed and direction data are measured simultaneously at both wind sites at least 6 months [8]. The MCP algorithms use models to predict wind speed at the target site from wind speed and possibly other conditions at the reference site [5].

4.1 Simple Linear Regression Method

Simple linear regression is a method for analyzing the relationship between two sets of data. In this study the method was used to estimate missing wind speed data by defining a relationship between the wind speeds measured at target and reference sites [6, 7]. The relationship was characterized using the following linear equation:

$$\hat{y} = mx + b, \qquad (12)$$

where x is the wind speed at the reference site, $\hat{y}$ is the wind speed at the target site, m and b are the slope and offset determined from linear regression.

To predict missing wind speed data at Jyväskylä site, I first used wind speed data available from both Viitasaari and Jyväskylä sites to estimate the linear relationship i.e. to estimate the slope and offset values. The same method can be used when estimating wind data missing from Viitasaari site. When simple linear regression is used the mean of the predicted and observed wind speed at the target site should be close to the mean of the observed wind speed [5].

4.2 Variance Ratio Method

Variance ratio was developed from simple linear regression by Rogers *et al.* [5] where it is assumed that the variance of the predicted wind speed at the target site is expected to have the same overall variance as observed at the target site. The variance ratio method uses the following equation:

$$\hat{y} = \left(\overline{U}_y - \frac{\sigma_y}{\sigma_x} \overline{U}_x \right) + \left(\frac{\sigma_y}{\sigma_x} \right) x \qquad (13)$$

where x is the wind speed at the reference site, $\hat{y}$ is the wind speed at the target site, $\overline{U}_x$ and $\overline{U}_y$ are the sample mean wind speeds at the reference and target sites, respectively, and σ_x and σ_y are the corresponding sample standard deviations.

5. Metrics

In this study I used metrics to compare the mean wind speeds and wind speed distributions estimated with MCP methods and to analyze if the result of each method was biased or unbiased. The result is biased when the value of metrics is not equal to one and otherwise the value is close to or equal to one. [5]

The first metric used is m_1 which can be used to analyze mean wind speed by dividing the predicted mean wind speed at target site with the mean observed wind speed from the target site. The mean wind speed is a important factor to characterize a potential wind station site where y_i and $\hat{y}_i$ are the measured and predicted hourly averaged wind speeds at the target site and N is the total number of paired data points used in the analysis [5]:

$$m_1 = \frac{\frac{1}{N}\sum_{i=1}^{N}\hat{y}_i}{\frac{1}{N}\sum_{i=1}^{N}y_i} \qquad (14)$$

The wind speed distributions are also factors that can be utilized to determine the wind farm energy capture and fatigue loading. The Weibull parameters can be used to define m_2 that is a ratio of scale parameter (c) and m_3 that is a ratio of shape parameter (k) as follows [5]:

$$m_2 = \frac{c_{\hat{y}}}{c_y} \qquad (15)$$

$$m_3 = \frac{k_{\hat{y}}}{k_y} \qquad (16)$$

The Chi-Square goodness of fit measure is a metric m_4 that uses characteristic wind speed distributions to provide a measure of how well two distributions agree with each others' binned data. For estimated wind speed distribution we start by dividing the wind data into bins from $i=1$ to M. For the predicted and observed target site wind speeds, the number of observations and predictions in each bin are counted and used to estimate the Chi-Square statistic [5]:

$$m_4 = \sum_{i=1}^{M} \frac{\left(n_{y,i} - n_{\hat{y},i}\right)^2}{n_{y,i} N} \qquad (17)$$

Normally the Chi-Square statistics are used only as a relative goodness of the fit. The magnitude of Chi-Square in this study depends on the number of bins which remained the same for all data sets.

6. Wind Speed Measurements

In this study the wind data studied was collected using two Davis Vantage Pro weather stations located in Jyväskylä and Viitasaari, respectively. The Viitasaari weather station is located in Kokkosalmentie 7, Viitasaari at map coordinates 63° 4'N, 25° 52'E [12]. The weather station measured wind velocity using a cup anemometer at the height of 34 meter from the ground.

The weather station in Jyväskylä is located on the roof of the University of Jyväskylä, Chemistry department building at map coordinates 62° 13'N, 25° 44'E [12]. Here the cup anemometer shown in Fig. 2 is installed at the height of 4 meter above the roof of the building. The distance between two stations is 96 km. [12]

The range of wind speed measure using cup anemometer is from 1 to 67 m/s and the accuracy is $\pm$ 1 m/s. The wind speed data of cup anemometer was saved every 1 minute and in this study we used hourly averages calculated from this data.

Figure 2 Wind station at Jyväskylä site.

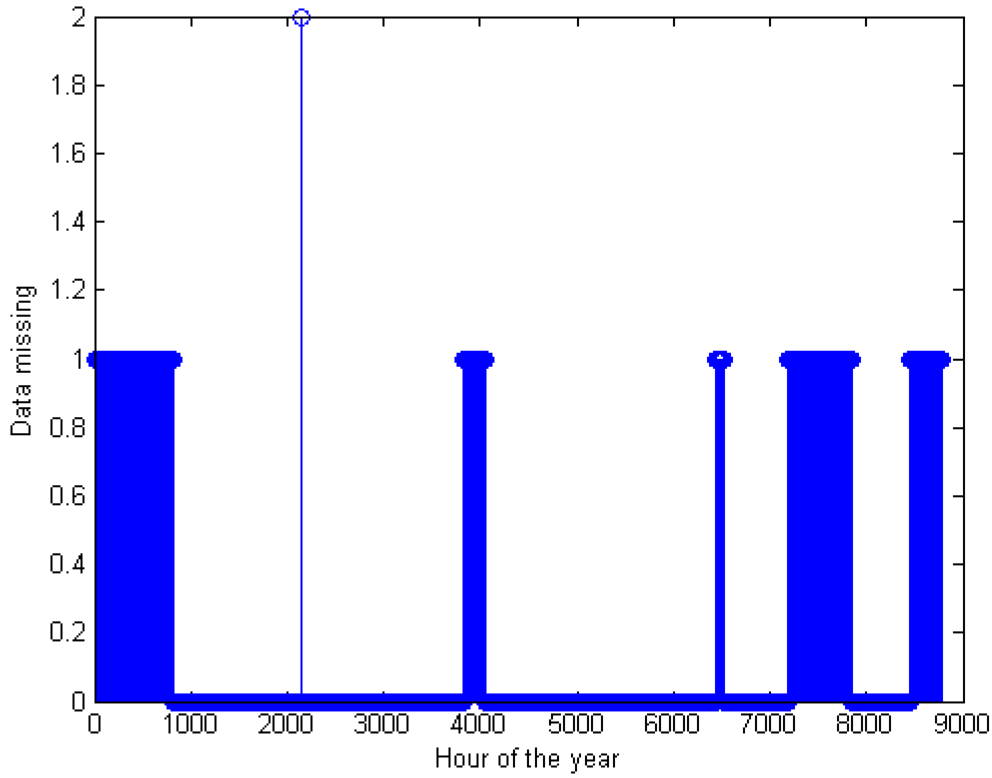

Figure 3 Number of missing wind speed data by hour of the year at Jyväskylä and Viitasaari sites.

The wind speed data analyzed in this study was measured in 2008. Fig. 3 shows the number of missing wind speed data by hour of the year. Here, the values "1" indicate that the data is missing from either Jyväskylä or Viitasaari site and values "2" indicate that data is missing from both sites. Figs. 4 and 5 show the hourly averages of measured wind speeds at Jyväskylä and Viitasaari sites.

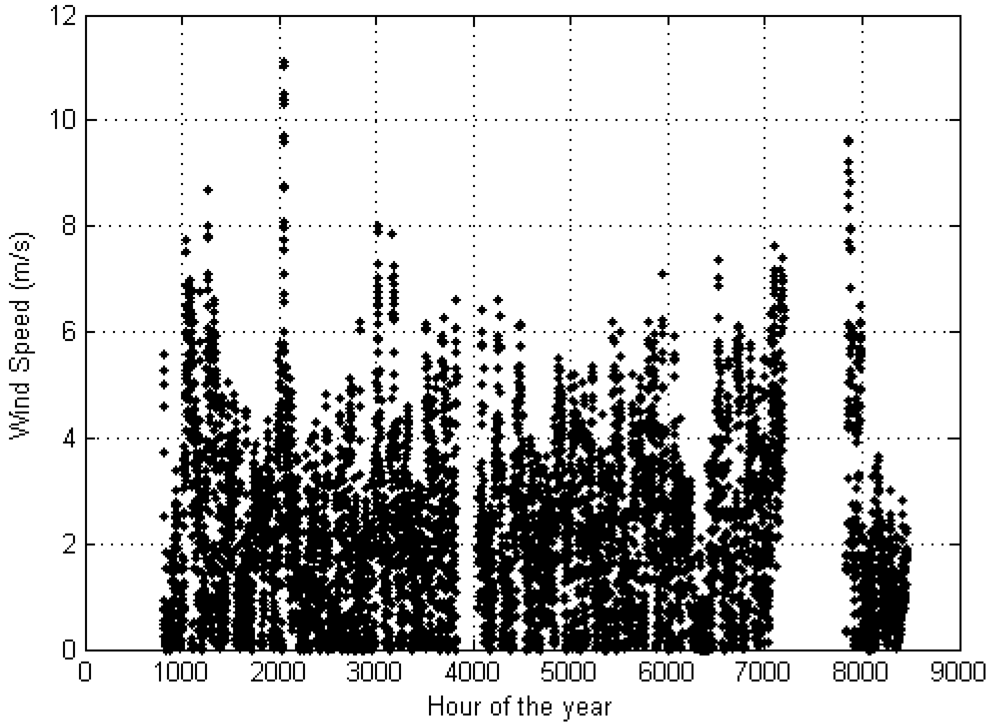

Figure 4 Measured wind speed by hour of the year at Jyväskylä site.

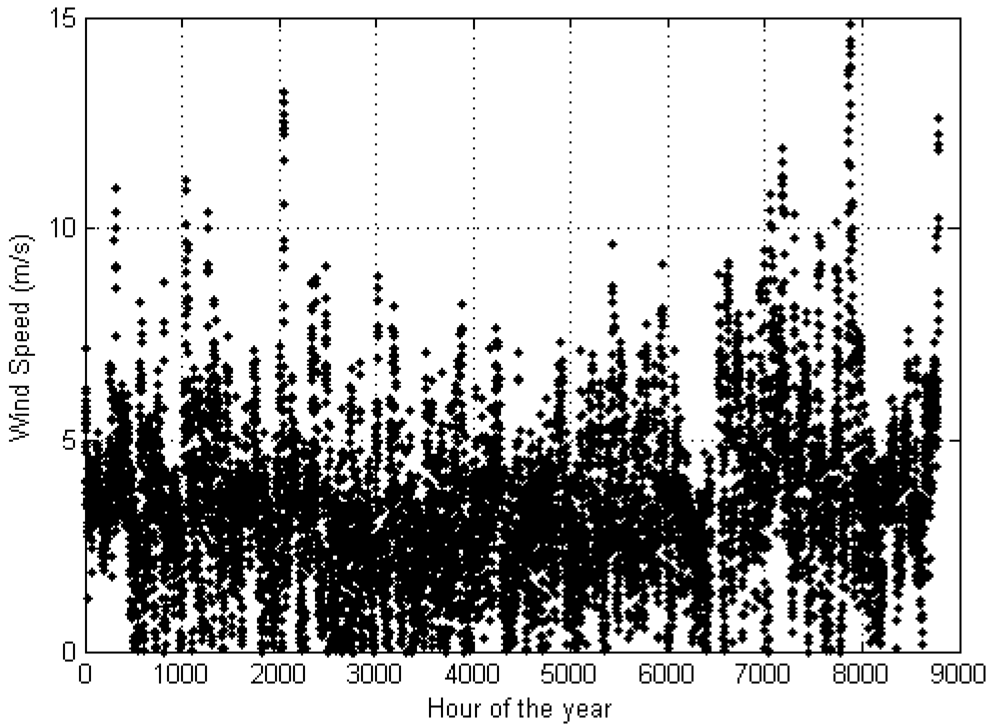

Figure 5 Measured wind speed by hour of the year at Viitasaari site.

7. Results

The statistics for the wind data are shown in Table 1. They present the mean wind speed and standard deviation of the data measured at Jyväskylä and Viitasaari sites calculated using frequency distribution and probability density functions. The wind data used in these calculations was measured during year 2008 which had 366 days. In this study the data consisted of hourly averages – total of 8784 hours.

Figs. 6 and 7 show the frequency distribution and Weibull p.d.f.'s determined using Weibull-Fit, Regression and Chi-Square methods, respectively, for the wind speed data measured at the Jyväskylä and Viitasaari sites. At Jyväskylä site the Weibull-Fit and Chi-Square methods give the best fit of wind speed data. The Chi-Square method is the best fit with wind speed data for Viitasaari site.

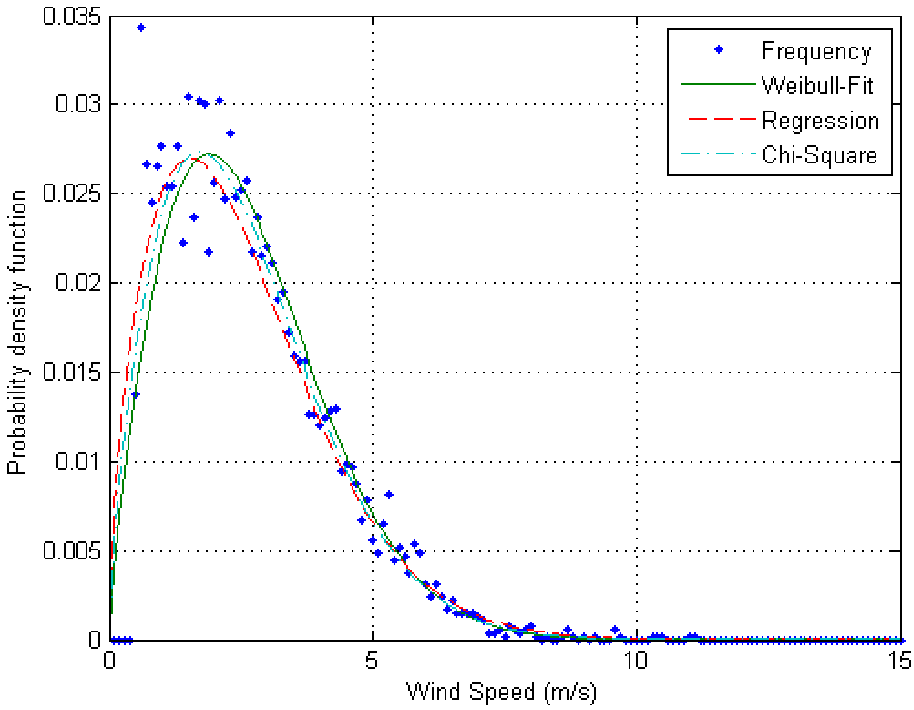

Figure 6 Frequency distribution and Weibull p.d.f.'s determined using Weibull-Fit, Regression and Chi-Square methods, respectively, and the wind speed data measured at the Jyväskylä site.

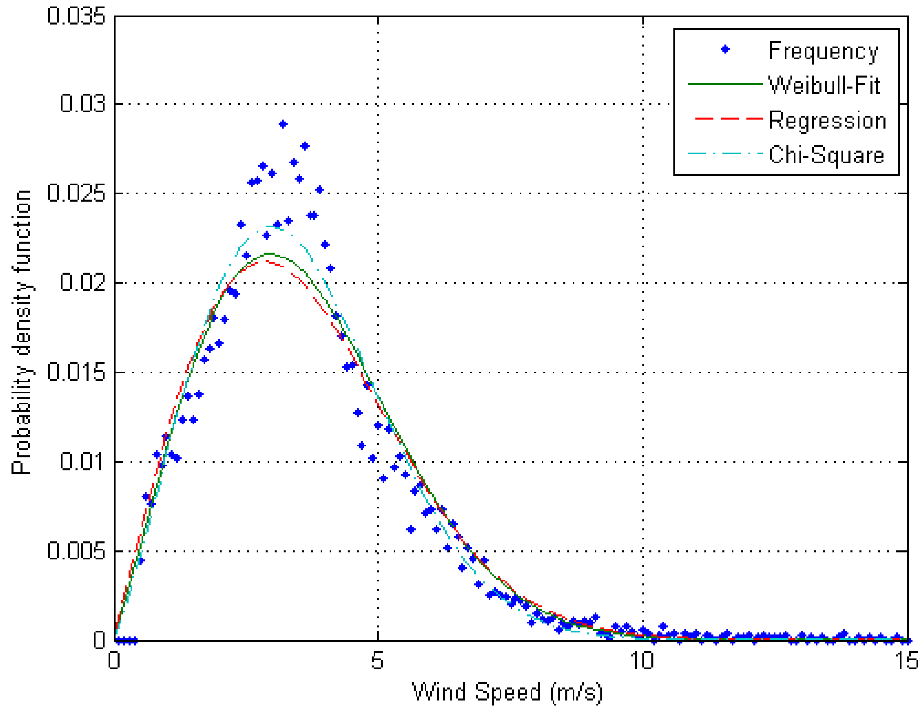

Figure 7 Frequency distribution and Weibull p.d.f.'s determined using Weibull-Fit, Regression and Chi-Square methods, respectively, and the wind speed data measured at the Viitasaari site.

At Jyväskylä site the mean wind speed obtained using Regression method got a result more close to the measured mean wind speed (Table 2). It was followed by the values obtained from Chi-Square Weibull distribution and Frequency distribution, respectively. The values of standard deviation indicate the best method could be Chi-Square method because the mean wind speed value is not too different from the one for measured data. Also, the standard deviation is smallest for the Regression method. At Viitasaari site the mean wind speed and standard deviation of Chi-Square method are close with the measured data.

Table 2 shows the summary of average and standard deviation values calculated directly from the wind data measured and then complemented using different MCP methods. The missing wind speeds in Jyväskylä site were replaced by Linear Regression and Variance Ratio methods correlated to measured wind data from Viitasaari site. The Linear Regression method predicted mean wind speed and standard deviation are closer with measured data than the data predicted with Variance Ratio method. The data missing at Viitasaari site was predicted using wind data from Jyväskylä site. The results shown are in excellent agreement with the measured data.

Table 1. Average and standard deviation of the wind speed at a given site. The average and the standard deviation values were calculated directly from the data measured and from the Weibull probability density function (p.d.f.) with the shape (k) and scale (c) factors determined from the measured data using the Regression and the Chi-Square methods.

	Jyväskylä (N=6776)		Viitasaari (N=8707)	
	$\overline{U}$ [m/s]	σ_U [m/s]	$\overline{U}$ [m/s]	σ_U [m/s]
Frequency distribution	2.62(2)	1.53(6)	3.59(2)	1.82(7)
Regression Method Weibull p.d.f.	2.53(2)	1.61(0)	3.58(1)	1.87(6)
Chi-Square Method Weibull p.d.f.	2.55(6)	1.53(4)	3.48(3)	1.68(3)

Table 2. Average and standard deviation of the wind speed at a given target site. The average and the standard deviation values were calculated directly from the data measured and the data complemented using the Linear Regression and Variance Ratio MCP methods with the target/reference sites as follows: Jyväskylä/Viitasaari and Viitasaari /Jyväskylä.

Values estimated from the given resource	Jyväskylä.			Viitasaari		
	$\overline{U}$ [m/s]	σ_U [m/s]	N [-]	$\overline{U}$ [m/s]	σ_U [m/s]	N [-]
Measured data	2.12(7)	1.68(4)	6776	3.45(5)	1.90(8)	8707
Data complemented with Linear Regression	2.18(3)	1.55(6)	8784	3.45(8)	1.90(4)	8784
Data complemented with Variance Ratio	2.19(8)	1.67(0)	8784	3.46(1)	1.91(2)	8784

Figs. 8 and 9 show the cumulative distribution function for measured wind speed and for Weibull statistics with parameter calculated from the measured data using the Regression and Chi-Square methods. In Jyväskylä site, both cumulative distribution functions obtained by these method are close with the cumulative frequency distribution function but in Viitasaari site there is a difference between the line for Chi-Square method and Regression method.

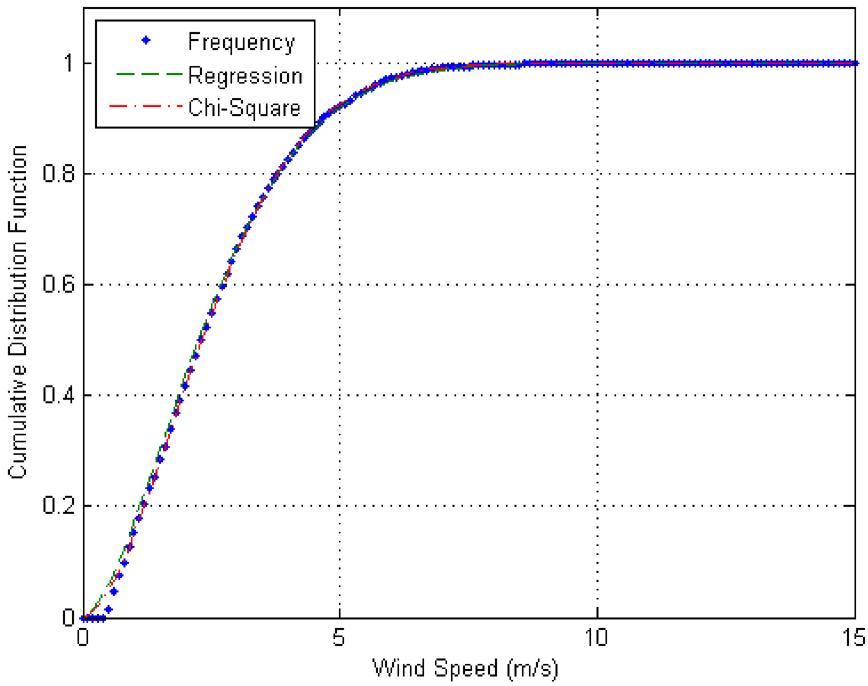

Figure 8 Cumulative distribution function for measured wind speed and for Weibull statistics with parameter calculated from the measured data using the Regression and Chi-Square methods. The wind speed data measured at Jyväskylä site.

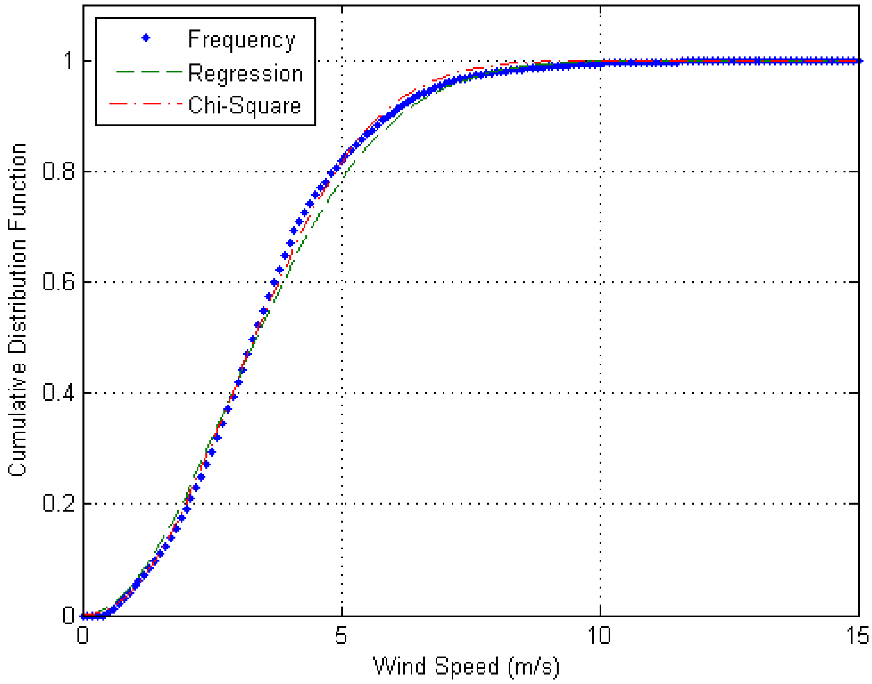

Figure 9 Cumulative distribution function for measured wind speed and for Weibull statistics with parameter calculated from the measured data using the Regression and Chi-Square methods. The wind speed data measured at Viitasaari site.

Table 3 shows the results of Weibull parameters determined using Weibull Fit-function, Regression and Chi-Square methods and calculated from the data measured at Jyväskylä and Viitasaari sites. The Regression method provided values of scale and shape parameters close to values for measured data at Jyväskylä site. The Chi-Square method provided values of scale and shape parameters close to values for measured data at Viitasaari site.

Table 3. Weibull p.d.f. parameters (c, k) determined for the given sites. The shape factor c and the scale factor k were calculated from the data measured at the given site using MATLAB's Weibull Fit (wblfit)-function, Regression and Chi-Square methods.

Parameters' Estimation Method	Jyväskylä		Viitasaari	
	c [m/s]	k [-]	c [m/s]	k [-]
Weibull Fit-function	2.96(1)	1.80(8)	4.06(3)	2.07(4)
Regression Method	2.82(6)	1.60(8)	4.04(0)	1.99(4)
Chi-Square Method	2.86(7)	1.71(5)	3.93(3)	2.18(3)

The measured data was complemented with the MCP methods. The linear regression method was used to estimate the relationship between two wind speed data sets. Figs. 10 and 11 show graphs of the two wind speed data sets plotted as a function of each other. The linear relationship between these two data sets was determined by fitting a linear function to the plot giving the slope and offset values that were then used to predict the missing wind speed data.

Figs. 12 and 13 show the predicted wind speed data of Jyväskylä and Viitasaari sites, respectively, calculated using Linear Regression method. In Fig. 12 the measured values are denoted by blue marker and predicted by green marker. In Fig. 13 the measured values are denoted by green marker and predicted by blue marker.

The Weibull parameters were determined for both data sets complemented using the linear regression method. The parameters were obtained using the Weibull Fit-function, Regression and Chi-Square methods and are shown in Tables 4 and 5 for Jyväskylä and Viitasaari sites, respectively. These tables also show the parameters obtained using Variance Ratio method and we can see that the scale and shape parameters for Linear Regression and Variance Ratio using Chi-Square method are closest to the values for measured data.

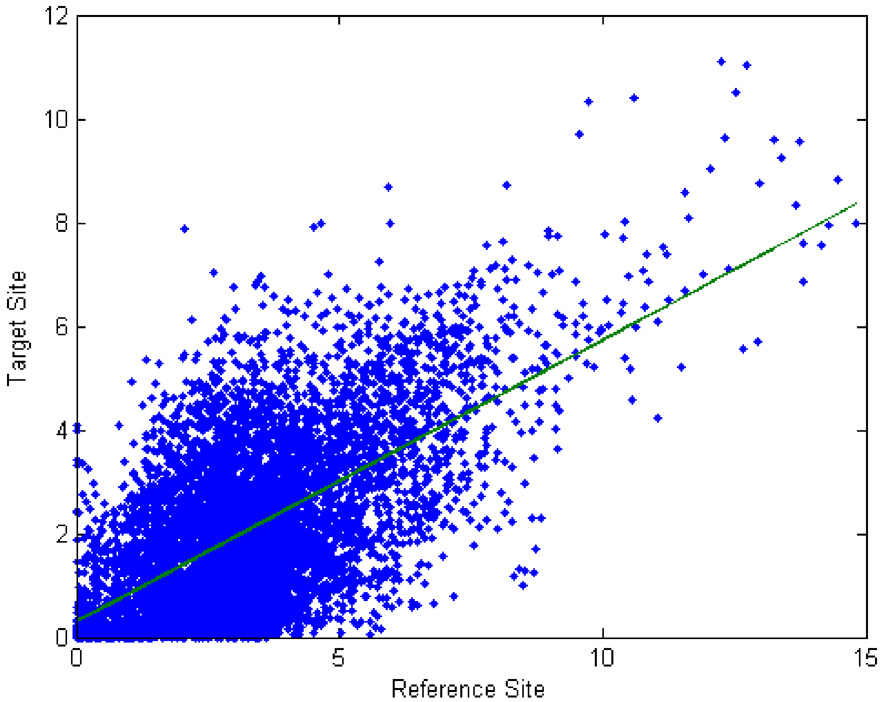

Figure 10 Wind speed at the target site (Jyväskylä) versus wind speed at the reference site (Viitasaari). The linear regression line $y = mx + b$ where $m = 0.54$ and $b = 0.3$.

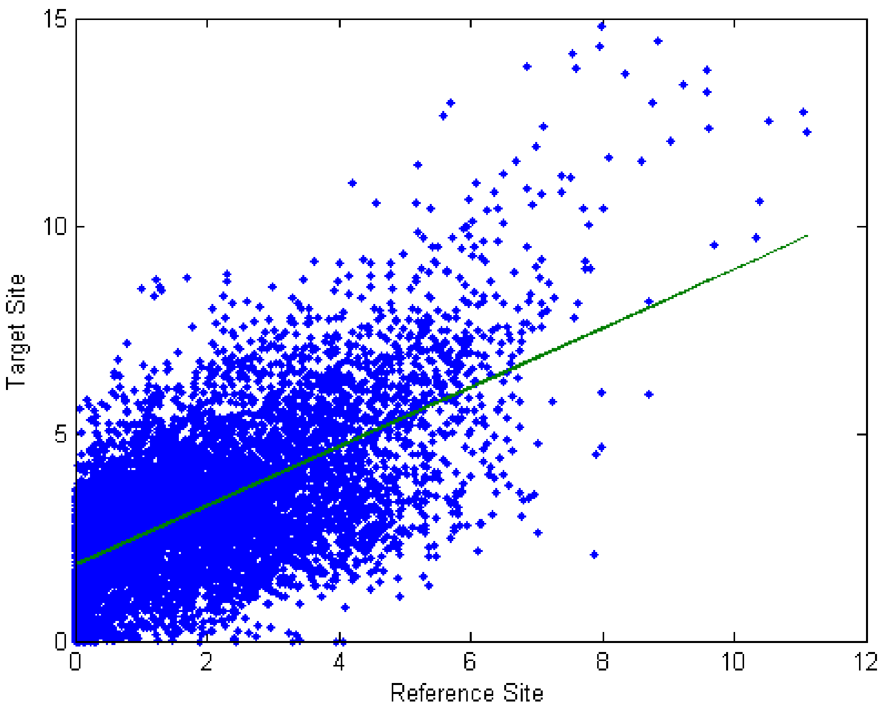

Figure 11 Wind speed at the target site (Viitasaari) versus wind speed at the reference site (Jyväskylä). The linear regression line $y = mx + b$ where $m = 0.71$ and $b = 1.8$.

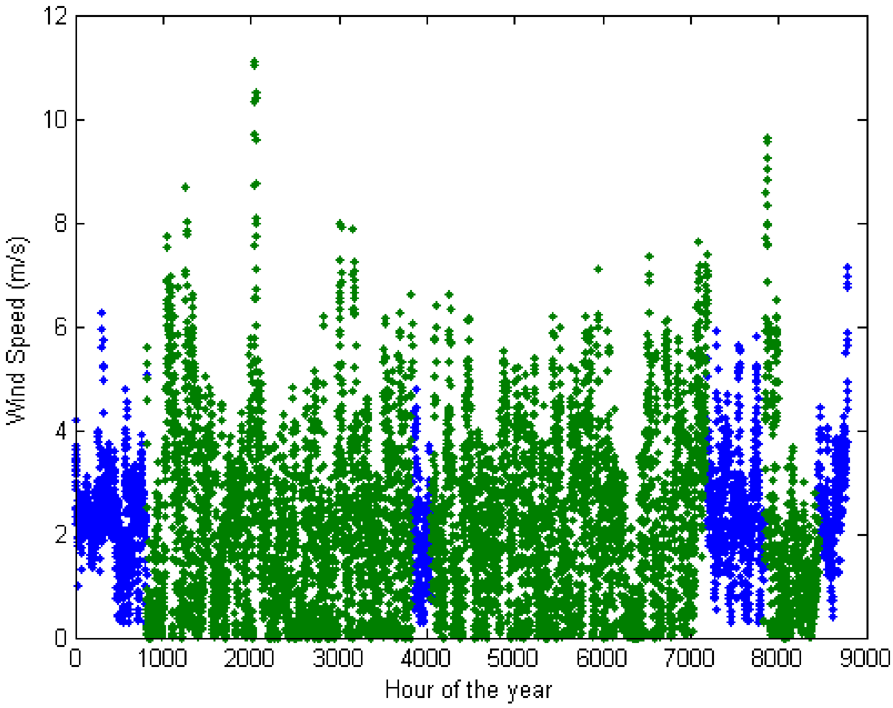

Figure 12 Predicted wind speed data of Jyväskylä site calculated using Linear Regression method. The measured values are denoted by blue marker and predicted by green marker.

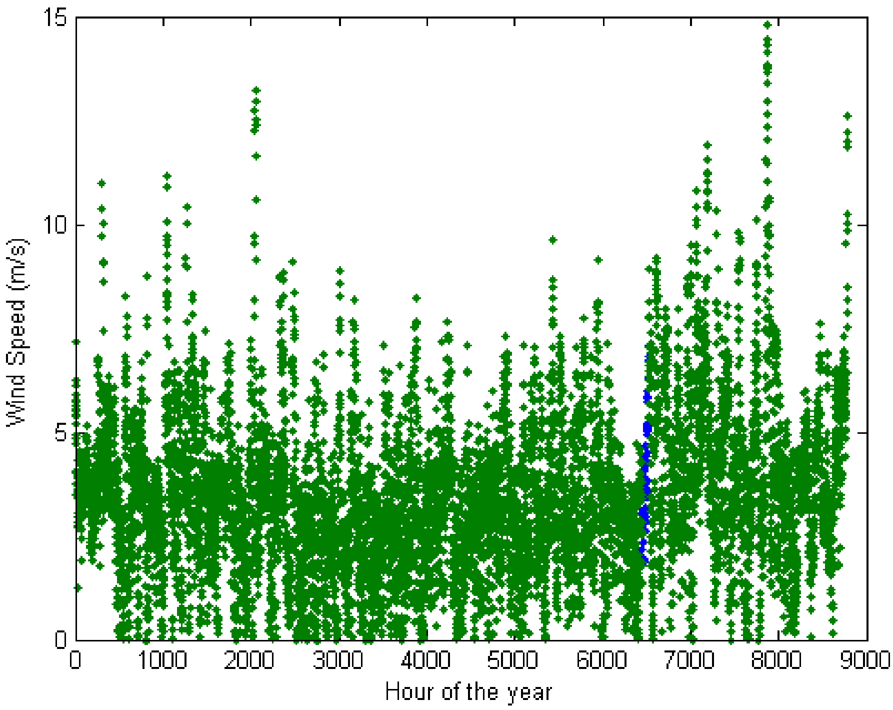

Figure 13 Predicted wind speed data of Viitasaari site calculated using Linear Regression method. The measured values are denoted by green marker and predicted by blue marker.

Table 4. Weibull p.d.f. parameters calculated using MATLAB's Weibull Fit (wblfit)-function, Regression and Chi-Square methods from the data measured at the Jyväskylä site and complemented using either Linear Regression or Variance Ratio MCP methods.

Parameters' Estimation Method	Linear Regression		Variance Ratio	
	c [m/s]	k [-]	c [m/s]	k [-]
Weibull Fit-function	2.90(4)	1.93(5)	2.99(9)	1.87(2)
Regression Method	2.48(9)	1.58(1)	2.52(3)	1.47(1)
Chi-Square Method	2.41(4)	1.40(7)	2.42(3)	1.29(7)

Table 5. Weibull p.d.f. parameters calculated using MATLAB's Weibull Fit (wblfit)-function, Regression and Chi-Square methods from the data measured at the Viitasaari site and complemented using either Linear Regression or Variance Ratio MCP methods.

Parameters' Estimation Method	Linear Regression		Variance Ratio	
	c [m/s]	k [-]	c [m/s]	k [-]
Weibull Fit-function	4.06(4)	2.07(9)	4.06(8)	2.07(3)
Regression Method	3.90(8)	1.88(9)	3.91(0)	1.88(5)
Chi-Square Method	3.83(4)	2.02(2)	3.83(7)	2.01(3)

Figs. 14 and 15 show the frequency distribution and Weibull p.d.f. functions with scale and shape factors determined using Weibull Fit -function, Regression and Chi-Square methods and calculated from the wind speed data measured and complemented using Linear Regression MCP method at the Jyväskylä and Viitasaari sites, respectively. It can be seen from the figures that the Weibull-fit function gives the best fit for wind speed data from Jyväskylä and the Chi-Square method for the wind speed data from Viitasaari.

Figs. 16 and 17 show the frequency distribution and Weibull p.d.f. functions with scale and shape factors determined using Weibull Fit -function, Regression and Chi-Square methods and calculated from the wind speed data measured and complemented using Variance Ratio MCP method at the Jyväskylä and Viitasaari sites, respectively. It can be seen from the figures that the Weibull-fit function gives the best fit for wind speed data from Jyväskylä and the Chi-Square method for the wind speed data from Viitasaari.

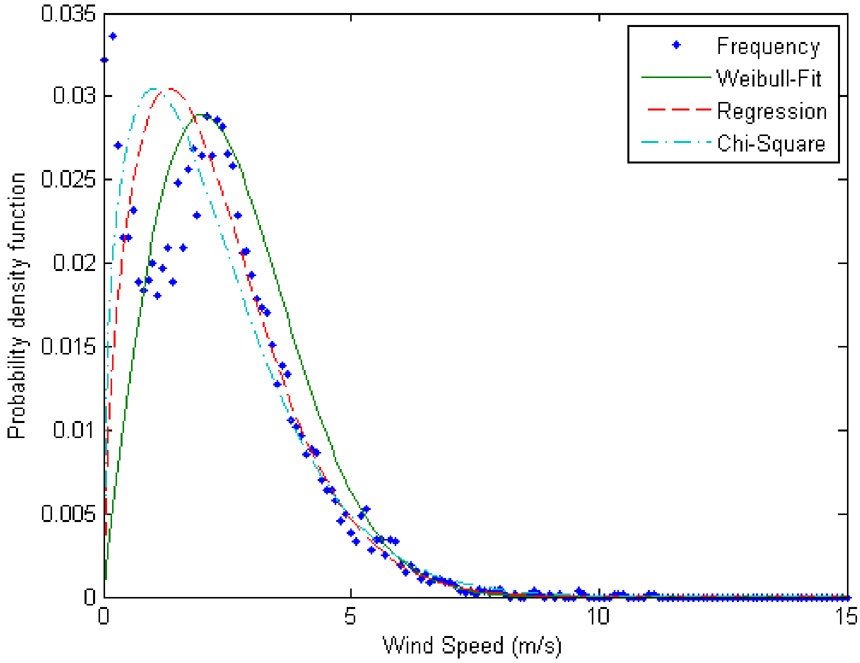

Figure 14 Frequency distribution and Weibull p.d.f. functions with scale and shape factors determined using Weibull Fit -function, Regression and Chi-Square methods and calculated from the wind speed data measured and complemented using Linear Regression MCP method at the Jyväskylä site.

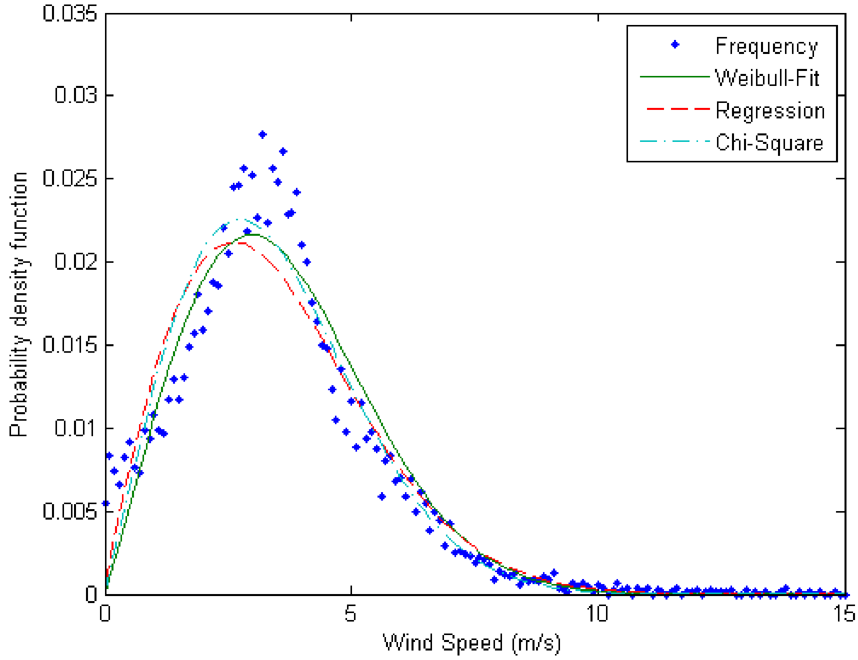

Figure 15 Frequency distribution and Weibull p.d.f. functions with scale and shape factors determined using Weibull Fit -function, Regression and Chi-Square methods and calculated from the wind speed data measured and complemented using Linear Regression MCP method at the Viitasaari site.

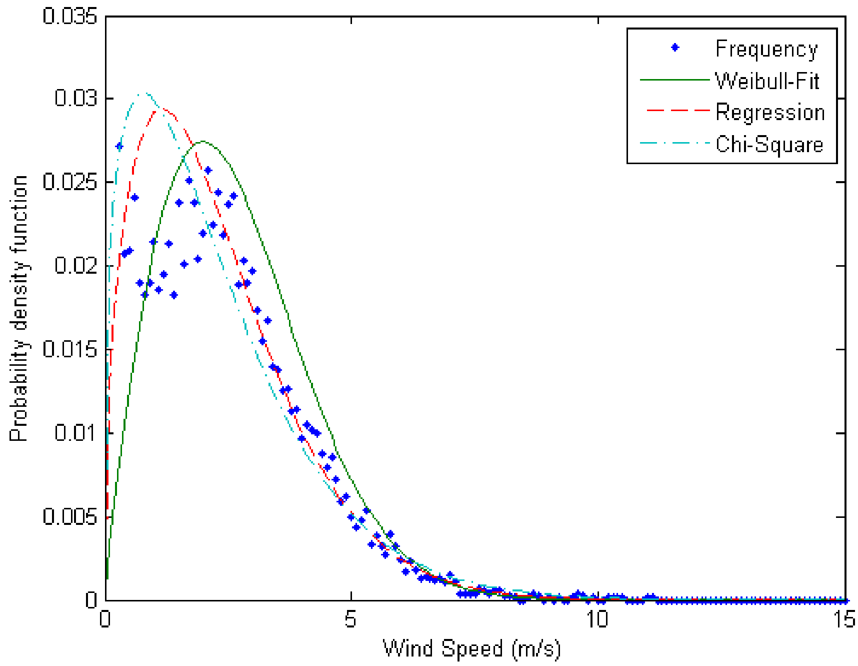

Figure 16 Frequency distribution and Weibull p.d.f. functions with scale and shape factors determined using Weibull Fit -function, Regression and Chi-Square methods and calculated from the wind speed data measured and complemented using Variance Ratio MCP method at the Jyväskylä site.

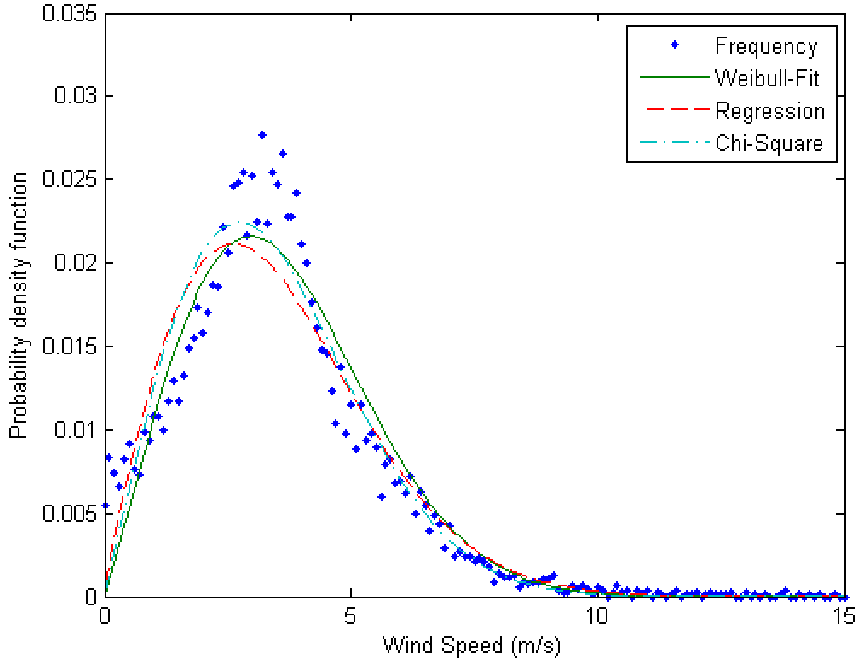

Figure 17 Frequency distribution and Weibull p.d.f. functions with scale and shape factors determined using Weibull Fit -function, Regression and Chi-Square methods and calculated from the wind speed data measured and complemented using Variance Ratio MCP method at the Viitasaari site.

The results for metrics given by the ratios of mean wind speed, scale parameter, shape parameter and speed distribution obtained using Chi-Square method are shown in Tables 6 and 7 for Jyväskylä and Viitasaari sites, respectively.

At Jyväskylä site all methods provided biased estimates of the mean wind speed. The results of scale parameter for Linear Regression and Variance Ratio by using Weibull Fit-function provide unbiased estimates of scale parameter. For the results of shape parameter the Linear Regression MCP method using Regression method provides unbiased estimates of shape parameter. Finally, speed distribution metric Variance Ratio method results in the lowest values of this metric.

The results of all metrics at Viitasaari site are listed in Table 7 and display unbiased values. Results of scale and shape parameters calculated using Weibull Fit-function show unbiased estimates and thus the best values of both parameters also the other methods provided results very close to unbiased. For the wind speed distribution of Chi-Square both methods provided a very small values for the metric.

Table 6. Comparison of values and parameters with different metrics for predicted and observed wind speed at the Jyväskylä site.

Compared values and parameters	MCP algorithm	
	Linear Regression	Variance Ratio
Mean wind speed	1.02(6)	1.03(4)
Weibull p.d.f. parameters calculated using Weibull Fit-function		
Scale factor, c	0.98(1)	1.01(3)
Shape factor, k	1.07(0)	1.03(5)
Weibull p.d.f. parameters calculated using Regression method		
Scale factor, c	0.88(1)	0.89(3)
Shape factor, k	0.98(3)	0.91(5)
Weibull p.d.f. parameters calculated using Chi-Square method		
Scale factor, c	0.84(2)	0.84(5)
Shape factor, k	0.82(0)	0.73(3)
Speed distribution (Chi-Square method)	0.14(5)	0.13(5)

Table 7. Comparison of values and parameters with different metrics for predicted and observed wind speed at the Viitasaari site.

Compared values and parameters	MCP algorithm	
	Linear Regression	Variance Ratio
Mean wind speed	1.00(1)	1.00(2)
Weibull p.d.f. parameters calculated using Weibull Fit-function		
Scale factor, c	1.00(0)	1.00(1)
Shape factor, k	1.00(2)	1.00(0)
Weibull p.d.f. parameters calculated using Regression method		
Scale factor, c	0.96(7)	0.96(8)
Shape factor, k	0.94(7)	0.94(5)
Weibull p.d.f. parameters calculated using Chi-Square method		
Scale factor, c	0.97(5)	0.97(6)
Shape factor, k	0.92(6)	0.92(2)
Speed distribution (Chi-Square method)	$1.74(0)\times10^{-4}$	$3.80(3)\times10^{-4}$

I also calculated the average wind power density for both wind sites using both measured data and data complemented with MCP methods. Table 8 displays the calculated average wind power densities and we can see that the wind resources can be categorized as poor since wind power densities are less than 100 W/m^2 [10]. When comparing the wind power densities obtained for wind data measured at Jyväskylä site and complemented with MCP methods we can see that the Variance Ratio method gives a result that is closer to the result for measured data. In Viitasaari site both methods gave results very close to the result for measured wind data.

Table 8. The annual wind power density for the given site calculated from the measured wind speed data and the measured data complemented using either the Linear Regression or the Variance Ratio MCP methods.

Wind data	Wind Power Density [W/m^2]	
	Jyväskylä	Viitasaari
Data measured	19.5(6)	52.3(5)
Data complemented with Linear Regression	18.0(0)	52.2(9)
Data complemented with Variance Ratio	20.0(8)	52.5(7)

8. Conclusion

The wind speed data measured at Jyväskylä and Viitasaari sites was used successfully for characterization of the wind resources and for demonstrating prediction of missing wind speed data using two MCP methods. The average wind speed, standard deviation of the wind speed, wind speed distributions and wind power density were studied.

From the data at Jyväskylä and Viitasaari sites, we can reasonably deduce that both MCP methods work well. The biggest difference in the results using the two methods can be seen in the shape parameter of the Weibull distribution for Jyväskylä site. Of the two methods Linear Regression method is better than Variance Ratio because the results of metrics were less biased.

Wind power density results are also affected by the missing data. From the comparison of measured and complemented data, we can see that the Variance Ratio method gives good results at both sites. But the Linear Regression method shows different value only for Jyväskylä site. The quality of data decrease could be caused by large sections of missing data.

Since the wind power densities measured in this study were so low, we can say that the Jyväskylä and Viitasaari sites are not suitable for large-scale power production. However they can be used for small scale wind power production. But to get a better picture of the real potential at both sites, new measurements should be done at a higher altitude. This could be one idea for future research at these sites.

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