Improving Accuracy of Wind Analysis with Multiple Sampling Rates of Wind Measurement

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Abstract. The sampling rate in wind measurement has influences on accuracy of wind analysis. Missing wind data problem can be prevented with high sampling rates. However, a lot of data are unnecessarily required in wind analysis. In this work, optimal sampling rates are determined in real time by the Nyquist sampling theorem according to varying wind conditions. It is found that all statistical results in wind analysis are obtained with percentage errors of less than 1% while the amount of wind data is decreased significantly from the benchmark at fixed sampling rate of 10 Hz.

1 Introduction

In wind measurement, high quality of wind data yields accurate statistical interpretation in wind analysis such as wind power density and annual energy production. During data acquisition in wind measurement, it is possible that a missing wind data problem might occur due to various causes. This makes degradation in completeness of the wind data. Currently, there are the number of studies solving missing wind data problems. It was reported that 10% of wind speed data, which were not recorded by a data acquisition system due to icing accretion, may cause 3.8% bias of determination on annual energy production where a seasonality model was proposed to eliminate the bias of wind data in winter [1]. Alternatively, an adaptive neuro-fuzzy inference system model was used to simulate dynamic changes of wind velocity for interpolating missing wind data [2], although it was efficiently implemented for fault detection and wind forecasting [3, 4]. With long term observation, spectral analysis was capable of forecasting wind speed data, consisting of missing values over long horizons [5]. However, there is still lack of study which realizes the missing wind data caused by unsuitable sampling rate in wind measurement under varying wind conditions.

In wind measurement, the sampling rate is the parameter that indicates how frequent the measured wind data is recorded. Theoretically, the sampling rate is high enough to capture dynamic behavior of wind. In case that the sampling rate is not sufficient, missing wind data can appear in aliasing where information of wind data is imperfectly reconstructed and fails to form its actual information. To prevent this problem, a high sampling rate of 10 Hz was recommended to measure the wind speed for accurate estimation of wind turbulence intensity and turbulence power spectral density in small wind turbine analysis [6]. However, using high sampling rate not only causes great amount of wind data but also increase computation time in wind analysis. The IEC 61400-12-1 standard recommends that a single sample of wind measurement is carried out per second [7]. The wind data is averaged every 10 min (0.0017 Hz) for recording so as to reduce the amount of wind data. This fixed sampling rate cannot be applied under various wind conditions. In this work, the sampling rate is adapted based on the wind condition in a given cycle period by utilizing the Nyquist sampling theorem where the proposed methodology prevents an excessive/missing wind data problem. With real-time implementation of multiple sampling rate to wind measurement, trade-off between accuracy and number of data can be determined where accurate information of wind data is essential for wind analysis.

2 Real time determination of sampling rate for wind measurement

As illustrated in Fig. 1, the Nyquist rate $f_s^{(N)}$ in a given cycle period T is determined based on the Nyquist sampling theorem [8]. The Fourier transformation is applied to time-series wind speed data in order to acknowledge its frequency component. The approach is to cut out all small amplitudes at high frequencies where the cut-out amplitude is defined as α at the maximum frequency component of $f_{\max}$ since those small amplitudes at high frequencies are insignificant in wind analysis.

At a given cycle period T, let define a set of wind speed data $v = \{v_0, \ldots, v_{i-1}, v_i, v_{i+1}, \ldots, v_{n-1}\}$ is respectively measured at time $t_0, \ldots, t_{i-1}, t_i, t_{i+1}, \ldots, t_n$ where n is the total number of wind speed data. At the given cycle period T_m in time sequence m, define the wind speed $v_{p,m}$, which is sampled from the set of wind speed data v with the Nyquist rate $f_{s,m}^{(N)}$,where $p = \{0, \Delta t_m, 2\Delta t_m, 3\Delta t_m, \ldots, \eta_m\}$ and $\eta_m = (n-1) - (n-1) \bmod \Delta t_m$ as shown in Fig. 2.

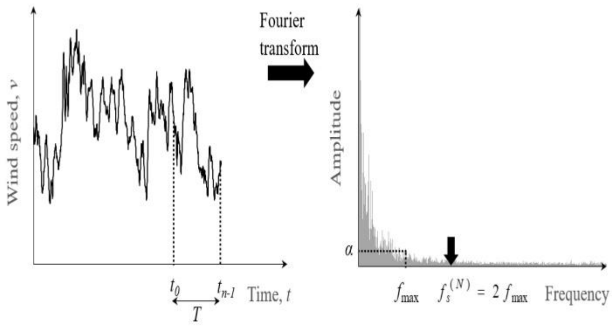

Fig. 1. Determination of cut-out amplitude.

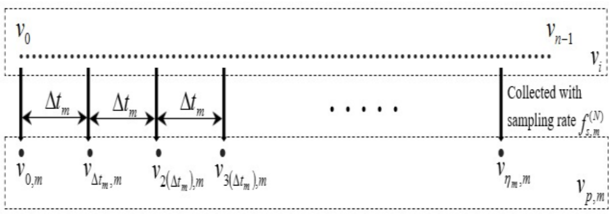

Fig. 2. Wind speed data sampled at Nyquist rate.

The Nyquist rate $f_{s,m}^{(N)}$ are different at each cycle period T_m. With the statistical wind analysis in [8,9], the mean wind speed $\bar{v}$, standard deviation σ, power density P, and annual energy production *AEP* are determined in Eq. (1), Eq. (2), Eq. (3), and Eq. (4), respectively, according to the weighing method [10].

$$\bar{v} = \frac{\sum_{m=0}^{M-1}\left(\sum_{p=0}^{\eta_m} \frac{v_{p,m}}{f_{s,m}^{(N)}}\right)}{MT_m} \tag{1}$$

$$\sigma = \left(\frac{\sum_{m=0}^{M-1}\left(\sum_{p=0}^{\eta_m} \frac{v_{p,m} - \bar{v}}{f_{s,m}^{(N)}}\right)}{MT_m}\right)^{\frac{1}{2}} \tag{2}$$

$$P = \frac{1}{2}\rho \frac{\sum_{m=0}^{M-1}\left(\sum_{p=0}^{\eta_m} \frac{v_{p,m}^3}{f_{s,m}^{(N)}}\right)}{MT_m} \tag{3}$$

$$AEP = \frac{\hat{M}}{M} \sum_{m=0}^{M-1}\left(\sum_{p=0}^{\eta_m} \frac{P_T\left(v_{p,m}\right)}{3600 \times f_{s,m}^{(N)}}\right) \tag{4}$$

where M is the total number of cycle periods T_m, ρ is the air density, $\hat{M}$ is the total number of cycle periods T_m in a year, and $P_T\left(v_{p,m}\right)$ is the power output of a given wind turbine at wind speed $v_{p,m}$.

3 Results and discussion

With a three-cup type anemometer, annual wind speed measurement is performed on a rooftop of laboratory building with a height of 20 m, as shown in Fig. 3(a). The sampling rate of the measurement is set to be 10 Hz. This sampling rate is assumed to be high enough to perceive dynamic behaviors of wind for this study. In Fig. 3(b), the wind speed data, sampled at the sampling rate of 10 Hz, can explicitly represent genuine continuity of wind speed data.

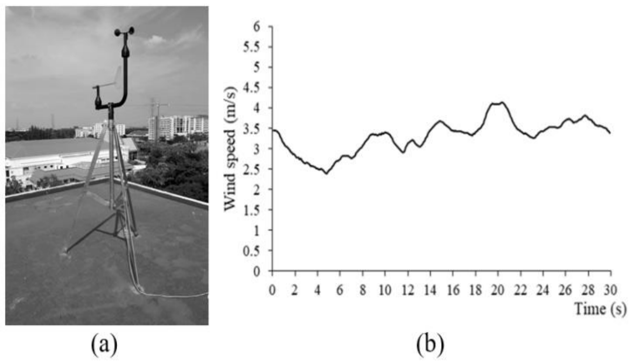

Fig. 3. Wind measurement: (a) Installation of three-cup type anemometer and (b) wind speeds sampled at rate of 10 Hz.

As reported in Fig. 4, the values of mean speed and standard devaiton of one-day wind speed data diverge from the values of benchmark at the sampling rate of 10 Hz as the sampling rates decrease. For the IEC 61400-12-1 standard with 0.0017 Hz, the standard deviation has the least accuracy, which is caused by using the averaged values of wind data for calculation. The sampling rate indicates how frequently the wind data is recorded; hence, high sampling rate results in big data that is recorded. It can be seen that the wind data at high sampling rates yield accurate analysis whereas they cause great amounts for computation and storage, as indicated in Fig. 5.

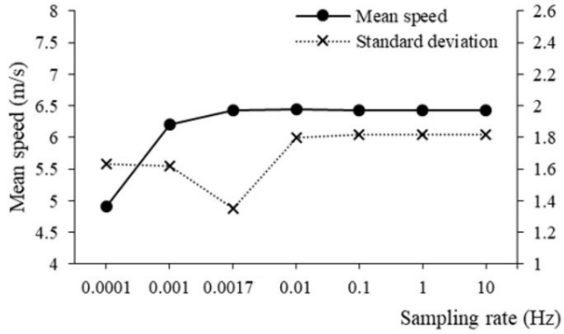

Fig. 4. Plots of mean speed and standard deviation against sampling rate.

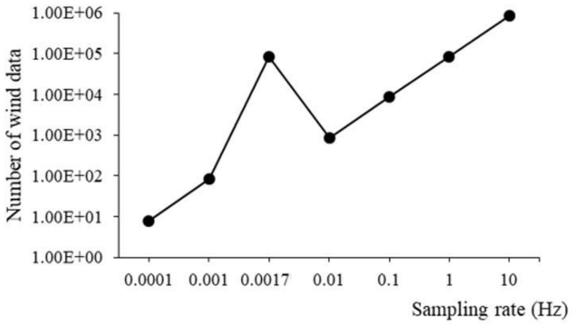

Fig. 5. Plots of number of data against sampling rate.

To provide trade-off between accuracy and the number of wind data, the wind measurement with multiple sampling rate is performed in a given cycle period according to wind conditions. Without loss of generality, the power curve of a wind turbine in Fig. 6 is applied for AEP calculation in Eq. (4). In wind analysis, the statistical results from the annual wind speed data at 10-Hz sampling rate, listed in Table 1, are determined form Eq. (1) to Eq. (4) as the benchmark. The cut-out amplitude α of 0.1 m/s is chosen since it yields one of the most accurate results according to observation. The cycle period T_m is varied by 10 min, hour, day, week, and month.

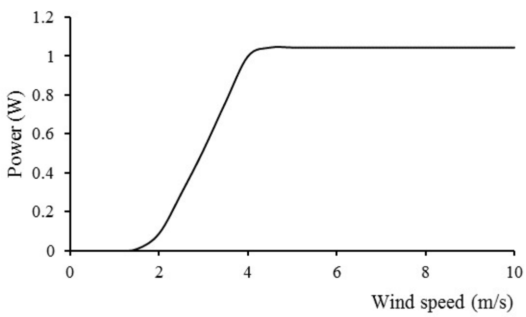

Fig. 6. Power curve of a wind turbine [11].

Table 1. Wind analysis from annual wind speed data sampled at rate of 10 Hz

Mean speed (m/s)	Standard deviation (m/s)	Power density (W/m^2)	Annual energy production (Wh)
2.32	1.84	32.50	2460.0

Fig. 7 shows absolute relative error of wind analysis from the wind speed data. It is found that most statistical results at the sampling rate of IEC 61400-12-1 standard yields significantly high absolute relative error compared to the others. It can be interpreted that 10-min averaged values of IEC 61400-12-1 standard cause flaws of wind information. In turn, the multiple sampling rate approach provides better accuracy of wind analysis, especially when the short cycle periods T_m are implemented. However, the value of cycle period T_m should be carefully selected since the low value of T_m tends to yield high numbers of wind data as shown in Fig. 8. In a cycle period of day, the percentages of absolute relative errors are less than 1% of all statistical results at the sampling rate of 10 Hz. The number of wind data can be decreased significantly.

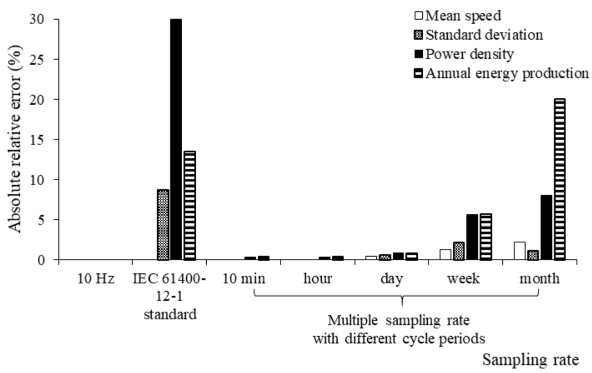

Fig. 7. Absolute relative errors of statistical results against different sampling rates.

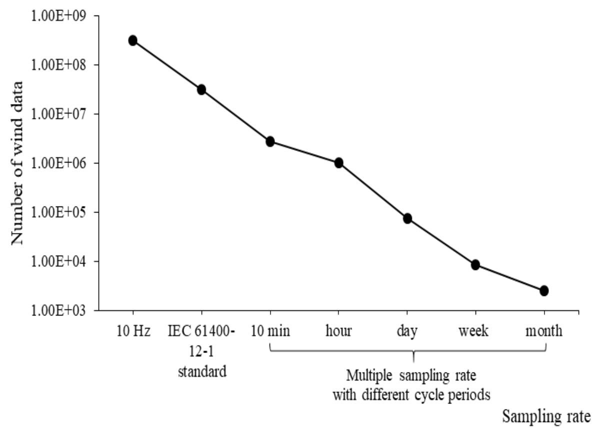

Fig. 8. Plots of number of wind data against different sampling rates.

4 Conclusion

In wind measurement under varying wind conditions, the adaptation of sampling rate should be implemented in order to prevent informaiton loss in wind data analysis and energy assessment. Wind measurement with a fixed sampling rate causes significant excessive or missing wind data problems due to varying wind conditions. With multiple sampling rate approach, optimal trade-off between accuracy and numbers of wind data can be obtained. In the cycle period of day, the statistical results of wind analysis have percentages of absolute relative error of less than 1% while the amounts of wind data are decreased significantly from the benchmark at sampling rate of 10 Hz.

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