2014 4th International Conference on Future Environment and Energy
IPCBEE vol.61 (2014) © (2014) IACSIT Press, Singapore
DOI: 10.7763/IPCBEE. 2014. V61. 10

Analytical Method for Evaluating Output Fluctuation in Distributed Wind Farms

Pradeepa Lakmal WEVITA[1+], Ryuji MATSUHASHI [2] and Tsuyoshi YOSHIOKA [3]

[1,2]Dep. of Electrical and Information Systems, Graduate School of Engineering, The University of Tokyo
[3]Center for Low Carbon Society and Strategy, Japan Science and Technology Agency, Tokyo, Japan

Abstract. In this study we examine output power of 12 geographically distributed wind farms in Tohoku area in east Japan to understand the nature of wind power fluctuations. The main objectives of this study are to suggest an analytical method to evaluate the output fluctuations of distributed wind power generation and estimate the impacts on the power systems in the event of high penetration levels of wind energy. We analyzed measured wind power data for period of 1 year with the sampling period of 10 seconds, which is converted to frequency domain and correlation characteristics are calculated using frequency components of Power Spectral Diagrams (PSD). The results show that the fluctuations with a time period less than 40 minutes are non-correlated. We were also able to observe seasonal and regional patterns of correlation coefficients. Furthermore, our examination of data shows clearly that the smoothing effect of distributed wind farms can contribute largely to its output fluctuation. We also discuss the expected impacts on power system stability, in the event of high level wind power penetration and we recommend the correlation analysis of wind power is essential to utilize the maximum wind power resources into power systems.

Keywords: Wind power, output fluctuation, correlation coefficients, power system stability, Frequency domain analysis.

1. Introduction

Wind Energy is a source of renewable power which converts kinetic energy in to electricity. Today, wind power is one of the fastest growing markets in the world due to its advantages such as environmental friendliness, fuel diversity and cost stability [1]. In the year 2010, the wind capacity reached worldwide 196 630 Megawatt, after 159 050 MW in 2009, 120 903 MW in 2008, and 93 930 MW in 2007[2]. Energy policies in most countries tend to increase the penetration level of renewable energy. As a result, system operators attempt to take whatever the wind resources are available. In Japan, wind capacity reached 2,500 MW in 2011[3] which is less than 5% of Japan's power demand. According to the Ministry of Environment, it is expected to increase the wind capacity up to 50GW by 2050 to supply more than 10% of total power consumption [4].

Wind power introduces additional uncertainty into the operation of the power system due to its specific characteristics including variability, geographical and seasonal distribution patterns. To meet these challenges, there is a great importance of knowing the behaviour of wind itself, how much extra flexibility is required and how much flexibility already exists in the power system. The output variation is one of the major challenges into the operations of power systems. As a highly variable output, wind power is far more similar to load than to conventional generation resource. Because of spatial variations of wind from turbine to turbine in a wind farm and to a greater degree from wind farm to wind farm. A sudden loss of all wind power on a system simultaneously due to a loss of wind is not a credible event, and sudden loss of large amounts of wind power cause to voltage dips and frequency instability in the grid [5], [6].

[+] Corresponding author. Fax: +81-3-5841-8565 .
E-mail address: pradeepa@enesys.t.u-tokyo.ac.jp

Although there are many studies published in recent years [7],[8] regarding output fluctuation, lack of understanding about the phenomena leads to extra costs to ensure the stability in the power system and eventually results in less penetrations levels of wind power.

In this study, we discuss the output variation of distributed wind power generation from the perspective of system control. The proposed numerical technique uses frequency domain analysis and allows evaluating expected output variations in Load Frequency Control (LFC) and Economical Load Dispatch (ELD) regions. It can also estimate the expected variation in the event of future installations.

2. Measurement Outline and Site Description

In this study, we collected the power generation data of 12 wind farms in Tohoku Japan, over a period of one year from April 2005 to March 2006. Fig.1 shows the distribution of wind farms. The wind farms were grouped as A, B, C, and D by considering their geographical distribution. As it is shown in Fig.4, group A is a dense wind power area, where 5 wind farms with 92 wind turbines located closer to each other. Group B stands along the coast line of Japanese sea. This group consists of 4 wind farms with 79 wind turbines. Group C consists of 2 wind farms with 55 wind turbines located in a mountain region in both sides of Ou Mountains. The details of measurements are shown in Table 1.

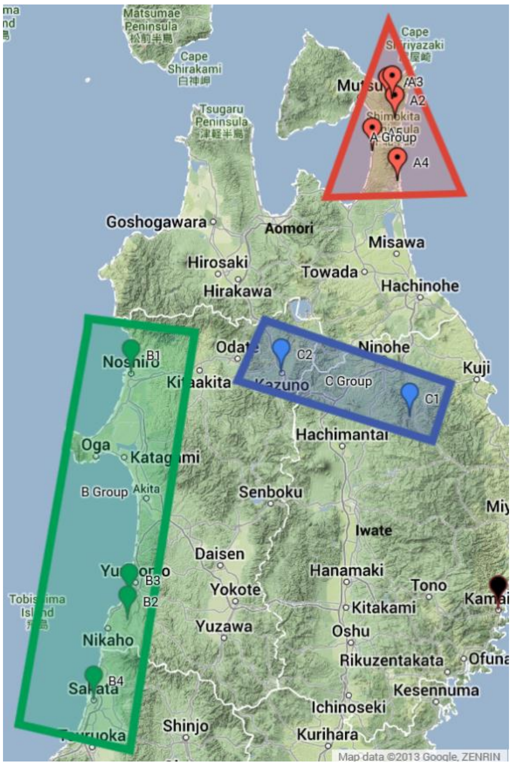

Fig. 1: Distribution of wind farm

Table 1: Measurement outline

Wind turbines	201
Total Capacity	192 MW
Sampling period	10s
Data resolution	100 kW

Geographically Tohoku is 66,889 square kilometers, which makes up 18% of Japan. The land is mountainous and volcanic. The Ou Mountains divide Tohoku into east and west with sporadic plains and valleys where most of the cities are found. Climate is just like any other part of Japan; Tohoku has a rainy season in addition to the four seasons, is hit by typhoons, and suffers occasional earthquakes due to its location in an area where plate boundaries meet. The Sea of Japan side is one of the snowiest regions in the world. However, in the summer, a foehn wind causes extremely hot temperatures.

3. Analytical Process

The basic analytical process is shown in Fig.2. Main objectives of this analysis are to evaluate the output fluctuations by its variation length and the effect when it is aggregated as a system. By using Power Spectral Analysis (PSA) method [9], we were able to examine the fluctuations with different time periods. As frequency components of PSA revels the characteristics of fluctuations of each wind farm, we employed this information to calculate correlation coefficients among wind farms.

The power spectrum reveals the existence or the absence of repetitive patterns and correlation structures in a signal process. These structural patterns are important in a wide range of applications such as data forecasting, for many applications, FFT-based methods produce sufficiently good results. The main statistical measure in this study is correlation coefficient between the frequency components of i, and j wind farms. If the correlation coefficients relevant to all frequency domains are 1, then the data series are perfectly correlated. This means that the generation patterns are same and the aggregated output variation contains 2 times of output variation in that frequency domain. When the correlation coefficient is -1, there is a perfectly negative correlation. A zero value corresponds to a complete non-correlation. The coefficient is used to determine both the interdependence between wind farms [10].

For analytical purposes, the collected wind power data is standardized as power generation for 1MW wind power installation.

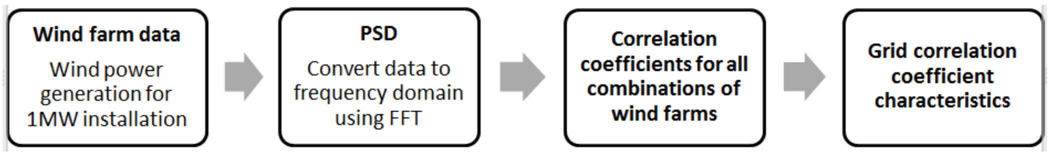

Fig. 2: Analytical process

Power generation of i^{th} wind farm wind is denoted as $x_i(k)$ (k=1~N-1), where total number of wind farms is N. The power generations from wind farms are converted to frequency domain using Fast Fourier Transform (FFT). $X_i(j\omega)$ Represents the Fourier Transform of $x_i(k)$ while"a" and "b" represent the real and complex components of Fourier Transform. $S_i(f)$ Power Spectral Density (PSD) for i^{th} wind farm can be calculated using following method [8].

$$X_i(j\omega) = \sum_{k=o}^{N-1} x_i(k) e^{-j\omega kT} \tag{1}$$

$$X_i = a + jb \tag{2}$$

$$S_i = X_i X_i^* = \sqrt{a^2 + b^2} \tag{3}$$

The star denotes complex conjugation and for compactness the frequency argument of X_i has been suppressed. Frequency components of PSD revels the contribution to the output power generation. The magnitudes of frequency components are used to calculate correlation coefficients.

3.1. Correlation coefficients

Table 2: Description of parameters

$\sigma_i(f_0)$	Standard deviation of i^{th} wind farm output at frequency f_0
$\sigma_T(f_0)$	Standard deviation of aggregated wind farms output at frequency f_0
$S_i(f_0)$	Frequency component of i^{th} wind farm output at frequency f_0
$S_T(f_0)$	Frequency component of aggregated wind farms output at frequency f_0
$\rho(f_0)$	Total correlation coefficient of aggregated wind farms at the frequency f_0

Frequency components $S_i(f)$ of PSD are used to calculate the correlation coefficients among the wind farms. The total number of correlation coefficients "K" between wind farms can be expressed in eq. 4.

$$K = {}_N C_2 \tag{4}$$

For 12 wind farms, K =66 and 66 correlation coefficients were analyzed. Eq. (5) and (6) is used to evaluate correlation coefficient between “i” and “j” wind farms [11].

$$\sigma_i(f) = S_i(f)\ ,\quad \sigma_j(f) = S_j(f)\quad \sigma_T(f) = S_T(f) \tag{5}$$

$$\sigma_T^2(f_0) = \sum_{i=1}^{12}\sigma_i^2(f_0) + 2\sum_{i=1}^{12}\sum_{j>i}^{12}\rho_{ij}(f_0)\sigma_i(f_0)\sigma_j(f_0) \qquad (i<j) \tag{6}$$

In order to apply the concept of correlations in to wind farm distribution, we defined total correlation coefficient ρ as shown in Eq. (7).This relationship merges all 66 correlation coefficients that can be evaluated using Eq. (6).

$$\rho(f_0) = \frac{\sigma_T^2(f_0) - \sum_{i=1}^{12}\sigma_i^2(f_0)}{2\sum_{i=1}^{12}\sum_{j>i}^{12}\sigma_i(f_0)\sigma_j(f_0)} \tag{7}$$

This method is used to calculate the combinations of 66 correlation coefficients between 12 wind farms. The correlation coefficient $\rho(f_0)$ for N number of aggregated wind power output can be evaluated by Eq. (7). Frequency characteristics of correlation coefficient can be evaluated by performing the above calculation for each frequency and plotted on the wave length axis.

4. Results, Observations and Discussion

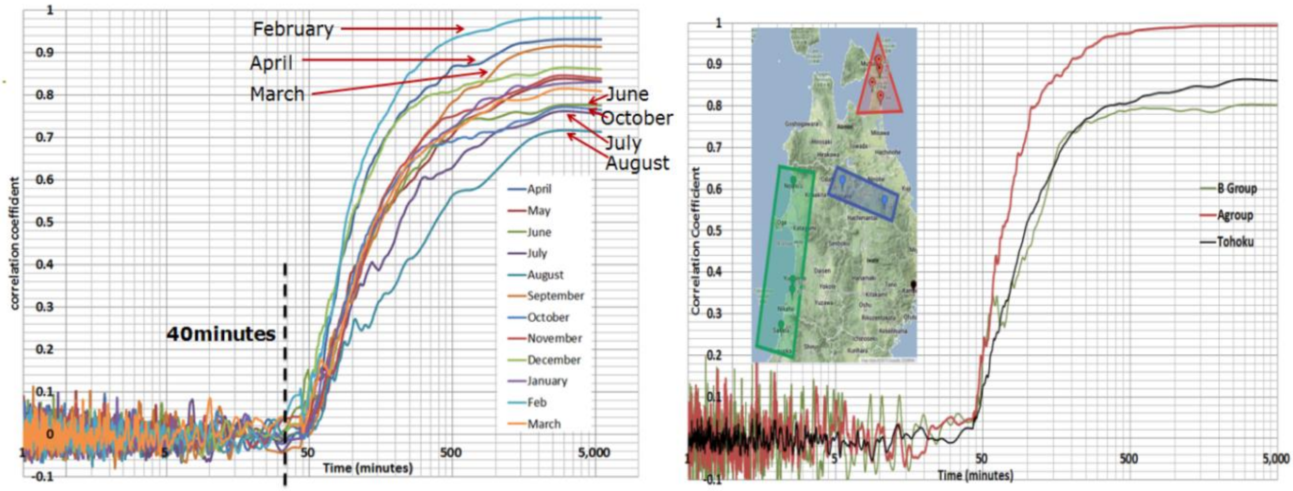

Fig. 3 (a): Correlation coefficients of wind farms in Tohoku; (b): correlation coefficient characteristics by groups

Correlation coefficients evaluated using the method in section 3, is shown in Fig.3 (a). The 12 graphs are corresponds to 12 months of the year. We can observe 0 correlation coefficients in the fluctuation less than 40 minutes. In other words the fluctuations in this region are totally non-correlated and independent. This revels that aggregation can smoothen the signal into $1/\sqrt{N}$ times compared to fluctuations in correlated regions. Correlation coefficients are form one to few hours are significantly high and the maximum values depends on the season. Generally months in winter shows higher correlation coefficients while relatively low in summer. Physically, higher correlation coefficients revels the likelihood of moving into same directions. In wind farms, it means simultaneous increasing or decreasing which may cause to a sudden large power loss in the large system. The back resource must be employee to maintain the stability of the system.

The regional characteristics are shown in Fig.3 (b).It is clear that the regional characteristics are appear in fluctuations with longer time periods. Group B which has a less density of wind farms revel a significantly lower correlation coefficient compared to whole Tohoku area and group A. This result well provide a impotent clue that we can adjust the correlations by optimizing the wind farm in a system which can be employees to ensure the lower fluctuation levels of the aggregated system.

5. Conclusion

In this study we proposed numerical process for evaluating output fluctuation of a distributed wind farms in power system. The method discussed in the paper gives an better outlook for fluctuation levels for aggregated wind power in grid. Considering the results of this study, we came to the following conclusions.

Although the geographical characteristics of an area have a greater influence in correlation, it is clear that the variations less than 40 minutes remain “0” at correlation level. We expect a greater degree of smoothing effect in this non-correlated region. Aggregated wind power output can contributes to stability in LFC region. Mathematically, smoothing effect can reduce the output fluctuation to $1/\sqrt{N}$ times compared to its correlated case.

In contrast, fluctuations greater than 40 minutes are highly correlated and they consist of geographical and seasonal characteristics. This highly correlated fluctuation from 40 minutes to few hours are the key constrains which system operators must consider about. Smoothing effect is not been seen in this region. They mean the risk of losing most of wind power simultaneously within a period of few hours. ELD resources must be kept in the schedule to overcome the challenge.

The correlation phenomenon is highly related to geographical location of wind farms. The behavior of correlation coefficient shows that there is a significant difference of correlation characteristics with their distribution. Dense wind farms in wind rich areas can result to higher output fluctuations in the region of one to several hours.

Even though there are good wind sites, it is important to consider the correlations between other wind sites to avoid large output fluctuations in the domain from tens of minutes to several hours. On the other hand, it is possible to reduce the output flatiron of wind power by installing wind farms in to areas where the less potential of correlation. It is recommended to examine the correlations of wind as well as wind conditions in the event of wind installation in the future.

6. References

[1] New Energy and Industrial Technology Development Organization. Japan .Wind power capacity and installation report 2012, 2012

[2] World Wind Energy Association. World Wind Energy Report 2010, 2011

[3] **N**ew **E**nergy and Industrial Technology **D**evelopment **O**rganization. Current scenario of wind energy in Japan, 2011.

[4] Ministry of Environment. Report for Power System Integration Potential of Renewable Energy 2009, 2009

[5] Richard Piwko, Peter Meibom, Hannele Holttinen, Baozhuang Shi, Nicholas Miller, Yongning Chi and Weisheng Wang. Penetrating Insights- Lessons Learned from Large-Scale Wind Power Integration, IEEE Power & Energy magazine, 2012.

[6] RED ELECTRICA DE ESPANA. Challenges to TSO with large with large integrated renewable energy, 2011

[7] T. Nanahara , T. Maejima, K. Yamaguchi, T. Sato, M. Asari. A Study on Smoothing Effect on Output Fluctuation of Distributed Wind Power Generation ,2002

[8] Kasuhiro Hata .Research on Power long term planning in the event of high penetration level of solar power, The University of Tokyo, Faculty of System Innovation,2012.

[9] M. Hino. Spectrum Analysis,1977

[10] Saeed V. Vaseghi, POWER SPECTRUM AND CORRELATION, Advanced Digital Signal Processing and Noise Reduction, Second Edition. 2000, 264-296.

[11] Siaw-Peng Wan, Modern Portfolio Theory, chapter 5-5.