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Assessing the effect of wind power uncertainty on profitability

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ABSTRACT

Wind energy has been the fastest growing and most promising renewable energy source in terms of profitability in recent years. The annual installed capacity in the European Union (EU) has risen from 814 MW in 1996 to 10,163 MW in 2009. However, one major drawback of wind energy is the variability in production due to the stochastic nature of wind. Integrating the risk of wind energy uncertainty into profitability assessments is important for investors in wind energy. The article presents statistical simulation methods to incorporate risks from stochastic wind speeds into profitability calculations. We apply the Measure-Correlate-Predict (MCP) Method within the Variance Ratio Method to generate long-term wind velocity estimates for a potential wind energy site in Austria. The bootstrapping method is applied to generate wind velocities for the economic life-time of a wind turbine. The Internal Rate of Return is used as profitability indicator. We use the Conditional Value at Risk (CVaR) approach to derive probability levels for certain internal rate of returns, as the CVaR is a reliable risk measure even if return distributions are not normal. Our approach closes the gap in the scientific literature on statistical simulation methods for the economic evaluation of wind energy sites. In contrast to other scientific publications, our methodology can be generally applied, because we do not rely on estimated distributions for wind speed predictions, but on measured wind speed distributions, which are usually readily available. In addition, the CVaR has not been applied as a measure of risk for wind site evaluation before and it does not rely on any specific function regarding the profitability distribution. The approach has been developed in collaboration with a leading Austrian utility company and has been applied to a wind park in Austria.

Contents

1. Introduction

Wind energy was the fastest growing renewable energy resource in the European Union (EU) in the last decade. The annual installed capacity has risen from 814 MW in 1996 to 10,163 MW in 2009 [1]. In 2009, approx. EUR 13 billion, including EUR 1.5 billion offshore were invested in wind energy in the EU [1]. In this respect, the wind power capacity shall reach approx. 80 GW by 2010 becoming the renewable energy technology with the highest installed capacity in the EU, second only to hydro power [1]. In 2009, approx. 5.4% of the electricity consumption was produced with wind energy in the EU. It is projected that the contribution of wind energy to total electricity consumption within the EU will increase to approx. 15.5% in 2020 [2].

The stochastic nature of wind leads to fluctuations in wind energy production. The literature concerning wind speed uncer-

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tainty can be divided, for instance, into literature focusing on uncertainty in wind energy output and on economic profitability. With respect to uncertainty in wind energy output, Kwon [3] has elaborated a numerical procedure for evaluating the uncertainty caused by wind variability and power performance using probability models in order to assess the risk of power output deviations. He conducted a case study analysis to show that the standard deviation of the annual energy output normalized by the average value of power output is approx. 11%, which can cause investments to be unprofitable. Tindal et al. [4] have compared the predicted annual power production with the actual power production. Their dataset included 510 wind farms across Europe and the US. They showed that the actual wind power output is 93.3% of the predicted wind power output. According to the authors, a major reason for this deviation is the rather poor quality of wind speed measurements which have been conducted before the installation of wind turbines.

A number of articles have statistically analysed wind speed data by assessing the wind energy potential in a certain region (e.g. [5–11]). Thereby, the economic potential and profitability have been identified by applying traditional methods of financial analysis such as the Net Present Value approach, the Internal Rate of Return approach, or the Life Cycle Cost Analysis approach.

Morthorst [12], for example, analysed whether there is a relationship between the expected profitability of a wind turbine and the annual increase in installed capacity in Denmark. He used the net Internal Rate of Return approach (after tax) as a measure for profitability. Kaldellis and Gavras [13] conducted a sensitivity analysis in order to show the impact of different parameters on the economic viability and attractiveness of a wind energy plant. However, Montes and Martin [14] argue that statistical simulation methods should be used to account for and assess the economic risk resulting from the variability in wind speed.

Some authors analyse the wind energy potential of a specific site by using either Monte Carlo simulations for predicting wind speeds or by using the wind speed measurement data directly if sufficient measurement data are available [3,9,15–17]. However, Monte Carlo simulations require assumptions with respect to the distribution of the wind speeds. Consequently, Carta et al. [18] concluded that not every wind regime can be accurately described with known probability distributions.

The following article presents an approach that accounts for the uncertainty of wind speed in profitability assessments. The approach can easily be applied for any actual and potential wind energy site without specifying the distributions of wind speed. The article is structured as follows: Section 2 presents the methodology. Section 3 presents a case study analysis in which the methodology has been applied to and Section 4 discusses the results and draws major conclusions from the methodology and analysis.

2. Methodology

Our approach consists of generating long-term wind speed data for a potential wind energy site ('target site') where only short time series of wind measurement data are available using the Measure-Correlate-Predict (MCP) algorithm with wind speed data from a reference site (Fig. 1). A bootstrapping procedure is applied to compute wind speed data for the economic life-time of the wind turbine. The Internal Rate of Return approach is used as profitability index. The bootstrapping procedure allows more accurately reflecting the distribution of the wind regime in the predicted wind speeds than methods currently applied in the scientific literature on wind energy production. Furthermore, the bootstrapping procedure can be applied to any wind regime. As a measure of risk we use the Conditional Value at Risk ('CVaR') approach. The CVaR can be uniformly applied and is not only appropriate if returns are normally distributed [19]. The CVaR also provides information at which probability level a certain Internal Rate of Return can be expected.

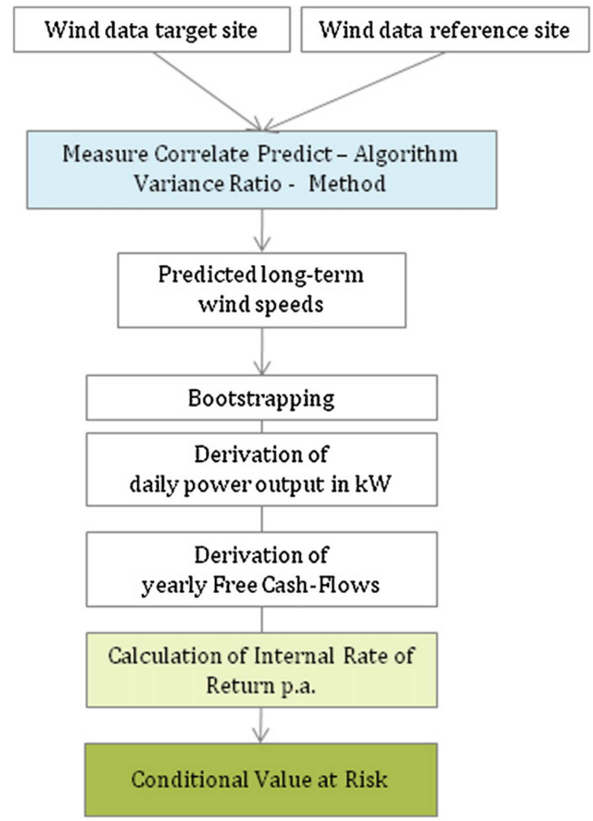

Fig. 1. Overview of the methodology.

2.1. Assessment of the wind energy potential at a specific site

Wind speed measurement data are usually collected at a specific site (target site) through a period of one year or less. Wind speed frequency distributions are computed from the data in order to estimate a probability density function. Several probability density functions have been used in the literature, but the two-parametric Weibull and the one-parametric Rayleigh distribution, which is a special case of the Weibull distribution, are usually used to predict wind speeds [3,13,15,16]. The two-parametric Weibull probability density function is given by the following equation [9]:

$$f(V) = \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} \exp\left\{-\left(\frac{V}{c}\right)^{k}\right\}, \quad 0 < V < \infty \tag{1}$$

where c and k are the scale and shape parameters and V the wind speed. The shape parameter k is usually between 1.5 and 3.0. If the value of the shape parameter is 2.0, the distribution is called Rayleigh distribution. The probability density function of the Rayleigh distribution is shown in Eq. (2) [9]:

$$f(V) = \frac{2V}{c^2} \exp\left\{-\left(\frac{V}{c}\right)^{k}\right\} \tag{2}$$

The review by Carta et al. [18] shows that the two-parametric Weibull distribution has several advantages compared to other probability density functions proposed in the scientific literature. However, not every wind speed regime can be described by a probability distribution. Therefore, the bootstrapping procedure does not require any assumptions on the distribution of the wind speed [18,20]. However, long-term wind measurement data are needed