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Efficiency of wind power production and its determinants

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ABSTRACT

This article examines the efficiency of wind energy production. Using non-convex efficiency analysis, we quantify production losses for 19 wind turbines in four wind parks across Germany. In a second stage regression, we adapt the linear regression results of Kneip, Simar, and Wilson (2015) to explain electricity losses by means of a bias-corrected truncated regression analysis. The results show that electricity losses amount to 27% of the maximal producible electricity. Most of these losses are from changing wind conditions, while 6% are from turbine errors.

1. Introduction

Renewable energy production has experienced rapid growth over the last two decades and this growth is likely to continue. Wind energy production contributed a significant share to this expansion and has attracted institutional investors. The profitability of wind energy production is determined by generation costs, energy prices, and turbine productivity. In the past, investments in wind parks were able to attain comparably high returns on investments. In many countries, such as Germany and Spain, producers receive guaranteed prices for wind energy that are above market prices. Generation costs are also fairly stable since operating costs are relatively low and installation costs are rather transparent. Thus, productivity is the crucial driver for the profitability of wind energy production. Productivity, in turn, heavily depends on wind conditions, i.e., wind speed and its variability, at the production site. In fact, a careful assessment of wind conditions precedes any investment in wind parks. Given the importance of wind production, it is not surprising that a lot of effort has been devoted to developing models to predict how much of the installed capacity will actually be used during the investment period (e.g., Kusiak et al. [1]).

A second determinant of productivity, however, has received very little attention in the literature, namely, the efficiency of wind energy production, which is the distance between the actual energy and maximal energy output under a certain level of production factors. In the context of wind energy, the maximal producible power as a function of wind speed is depicted by a power curve. Power curves are usually calculated by turbine producers for a specific turbine type under ideal conditions.[1] In reality, wind production does not take place under ideal conditions and therefore actual energy production regularly deviates from the power curve. For example, shortfalls can be caused by rainfall, icing, suboptimal adjustment of the pitch angle and nacelle position under changing wind conditions, technical failures, and scheduled maintenance. Under marginal wind conditions or a scenario of declining subsidies, these production inefficiencies can diminish the profitability of wind power plants.

A few empirical papers analyze the productivity and efficiency of wind power generation. Homola et al. [3] analyze wind park data in Norway and suggest a correction for power curve estimation. Ilinca [4] estimates that power losses due to icing conditions amount to as much as 50% of total annual production. Hughes [5] and Staffell and Green [6] indicate declining turbine performance due to increasing age of turbines in Denmark and the UK. Some other papers apply nonparametric methods to estimate the wind energy production frontier. Kusiak et al. [7] use DEA (data

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[1] The industry standard for power curve estimation is IEC 61400-12-1 (Wächter et al. [2]; Homola et al. [3]).

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envelopment analysis) to assess the performance of wind turbines in the presence of faults. They identify turbine downtime as the major reason for power curtailment. Iribarren et al. [8] analyze the entire process of wind energy production and include further production factors, such as land and investment cost in their DEA model. To the best of our knowledge, Carvalho et al. [9] is the only study that applies DEA to estimate a power curve based on high frequency production data.

The objective of this paper is twofold. First, we estimate the wind energy production frontier based on production data and quantify production losses that occur relative to this benchmark. In contrast to most other wind energy efficiency studies, we base frontier estimations directly on high frequency production data and do not aggregate the data for a single turbine or wind park. This sheds light on the emergence of production losses over time and avoids information losses through data smoothing. Carvalho et al. [9] pursue a similar approach; however, they use a DEA model and thus estimate efficiency by assuming a convex production technology. This approach ignores the non-convex shape of a typical wind power curve and thus overestimates inefficiency along the whole range of wind speeds between cut-in wind speed and rated wind speed. To avoid this flaw of DEA, we resort to an FDH (free disposal hull) estimation of the frontier, which does not assume convexity.

The second objective of this paper is to explain the magnitude of the observed production losses and to trace them back to factors which may or may not be under the control of wind park operators. To this end, we apply a truncated regression model that accounts for biases in the regression of estimated efficiency scores in the first step of our analysis (Kneip et al. [10]). From an applied perspective, our findings help improve the assessment of wind energy production under real world conditions.

In the following section, we explain in greater detail how we estimate the wind energy production frontier and derive the corresponding production losses. Moreover, we present the bias correcting regression model. These methods are then applied to high frequency production data from four wind parks in Germany. Section 3 describes the data base and Section 4 presents results. The final section summarizes and draws conclusion for improving the productivity of wind energy generation.

2. Methodology

The amount of wind's kinetic energy (E_k) available to be converted into electricity can be described by the following function (Hennessey [11]; Gunturu and Schlosser [12]):

$$E_k = 0.5\pi r^2 d w^3, \tag{1}$$

where r is the rotor size, so that the rotor swept area is πr^2, d is the air density, and w denotes wind speed. Air density is directly proportional to air pressure and inversely proportional to air temperature. Kinetic wind energy increases with wind speed and air density. It is important to note that according to Eq. (1), kinetic wind energy is a cubic function of wind speed. This characteristic results in a non-convex technology for wind speeds lower than the rated wind speed and has implications for the estimation of the production frontier. Air density is directly proportional to air pressure and inversely proportional to air temperature. Density is higher in the winter when the temperature is colder and is lower in the summer when the temperature is warmer. Air pressure causes variability in this general trend: High air pressure increases air density and low air pressure decreases density. However, only a portion of the wind's kinetic energy can be transformed into electricity. The efficiency of this transformation process depends on various technical and managerial factors and is the subject of this study.

In general terms, the production process is characterized by a production technology, which is defined as the set of all inputs (in our case: wind speed and air density) that are feasible to produce electric power:

$$T = \{w, d, e : (w, d) \ \ can \ \ produce \ \ e\}, \tag{2}$$

where w is wind speed, d is air density, and e is wind electricity.

As mentioned above, wind speed is monotonically related to the amount of electrical power produced, but the rate of transformation is non-constant and increasing up to the rated wind speed. However, to preserve the machine equipment from destructive centrifugal forces, the rotational speed and thus power production are limited for wind speeds greater than the rated wind speed. These features of the production technology process can be captured by a non-convex FDH for a sample of n observation points $\{w_i, d_i, e_i\}_{i=1}^{n}$:

$$\widehat{T}_{FDH} = \{w, d, e : w \geq w_i, \ \ d \geq d_i, \ \ e \leq e_i, \ \ \forall i = 1, \ldots, n\}. \tag{3}$$

The FDH technology set creates an outer envelope of the data points included in technology T without assuming convexity. As a measure of the efficiency of the turbines in exploiting wind and air density conditions, we measure the nonparametric distance between each point and the frontier envelope. Since inputs cannot be controlled by producers and instead are determined by nature, it is reasonable to measure distance in the direction of the outputs. We define this efficiency measure for unit (w_0, d_0, e_0) as follows:

$$\widehat{\lambda}_{FDH}(w_0, d_0, e_0) = \sup\left\{\lambda : (w_0, d_0, \lambda e_0) \in \widehat{T}_{FDH}\right\}. \tag{4}$$

In Fig. 1, these equations are illustrated for a one input–one output (w, e) technology. The technology set $\widehat{T}_{FDH}$ in Eq. (3) is the area below the production frontier (marked in gray). Calculating the efficiency of unit (w_0, e_0) implies searching for all units that "dominate" unit (w_0, e_0). The dominating units of (w_0, e_0) are all units that produce more or the same output with less or equal input. Among those dominating units, the one with highest output is used as a benchmark (point (w_i, e_i) in Fig. 1). The measure of the distance function $\widehat{\lambda}_{FDH}$ in Eq. (4) is then calculated

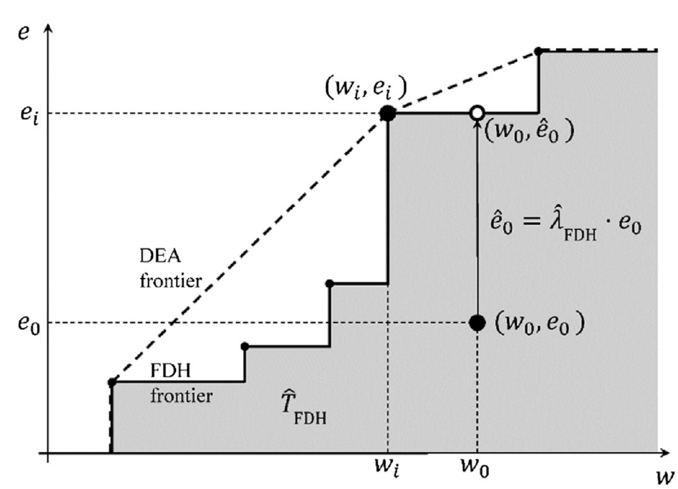

Fig. 1. Illustration of the FDH approach.