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Framework for performance assessment of wind farms

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Abstract

This study develops a framework to provide insights regarding the performance of the farms of an energy player in the Portuguese wind sector. Firstly, the Data Envelopment Analysis is used to measure the efficiency of wind farms in producing electrical energy from the resources available and exogenous variables, during operating stage. This analysis enables the identification of the best practices of the efficient farms which can be emulated by inefficient ones. Secondly, Malmquist index is used to evaluate the changes in wind farms productivity. Bootstrap procedures are applied to obtain statistical inference on the efficiency estimates.

Keywords: Data Envelopment Analysis; Wind farm; Benchmarking; Bootstrap.

1 Introduction

This study proposes a framework based on Data Envelopment Analysis (DEA) to provide insights regarding the performance of the farms of an energy player in the Portuguese wind sector. DEA has been accepted as an important approach for performance assessment and benchmarking in several sectors. Zhou *et al.* [2008] presented a survey of DEA in energy and environmental modeling, from which benchmarking of electricity utilities accounts for the large number of studies although it does not include any application in wind energy sector.

In a Policies Scenario, taking into account both existing policies and declared intentions by countries, world primary energy demand is projected to increase by 1.2% per year, on average, between the current year and 2035. Electricity demand is projected to grow by a higher rate, 2.2% per year, given that it is expected that applications, formerly based on chemical energy, will be based on electrical energy in the following decades [IEA, 2010]. In this context, the share of world electricity generation from renewable sources is projected to tripling in the same period. Policies are being implemented to enhance the transition toward low-carbon technologies in the power sector, in which wind energy plays an essential role. According to Global Wind Energy Council, installed wind capacity has grown to accumulative worldwide installation level of 200 GW from which 38 GW had been installed in 2010. Europe is still the largest wind energy generator, despite the fact that other markets (*e.g.* USA, India, China) have also launched in recent years. Portugal accounts for about five percent of the wind energy installed capacity of the European Union, with approximately 4 GW of accumulated installed capacity in 2011 which is capable to generate about 15% of electricity consumed.

Several factors contributed to the development of the wind sector in Portugal. Since 2002, the implementation of a legal stable framework by the Portuguese government and several support schemes implemented by the European Commission have promoted the penetration of electricity produced from renewable energy sources [Martins *et al.*, 2011]. Despite technology's potential and investments in the clean energy market, the progress is too slow on attending outlined targets. The main reasons for the slow progress are related with a low share of energy-related investment in R&D activities, high investments when compared with thermal based electricity, uncertain time for the return of the capital invested, technical transmission system limitations and environmental impact.

There are ten main wind farm promoters acting in the wind energy sector in Portugal, with farms connected to the transmission or distribution grid system. Each promoter is concerned, among appropriate financial management, to ensure the maximum energy generation, with the highest availability rates and cost-effectiveness in terms of operation and maintenance. In this context, the development of performance assessment methodologies in the portfolio of a given promoter allows the identification of the best practices in operating stage in order to be emulated by inefficient farms. The use of DEA can contribute to enhance those methods through assessment of the potential for efficiency improvements and exploring their productivity change over time, as the emergent interest on productivity growth in electrical utilities. This is explored by using Malmquist index which can be decomposed in efficiency change and technological change. The efficiency change can be associated to internal operating practices observed in each farm, while the technological change can be related to specific conditions in which farms have to operate, for instance, the level of wind availability in each year.

In literature, the studies which use frontier methods to assess the performance of wind farms are scarce. Pestana Barros and Sequeira Antunes [2011] use Stochastic Frontier Analysis (SFA) to assess efficiency of Portuguese wind farms from different promoters. Outputs are measured by produced energy and capacity utilization, and the inputs are price for labor and capital invested proxied by the book value of physical assets. Findings of this study are that Portuguese wind farms' operational activity is affected by heterogeneous factors, farm size, managerial practices and ownership by energy companies, which have an impact on the efficiency. Iglesias *et al.* [2010] use DEA and SFA methodologies to measure the efficiency of a group of wind farms located in Spain. Models are output oriented concerning the produced energy, based on a relationship between capital, labor and fuel, similar to a conventional electricity generation technology. Capital factor is evaluated by the installed capacity in each farm and labor factor considers the number of fulltime employers responsible for operation, control and maintenance of the farms. Concerning fuel input, it is estimated based on the wind power incident per unit time on the interposed surface of the wind turbines of the farm and the annual average wind speed at each site. These two studies focus on the efficiency assessment of wind farms and argue the importance to model the non-discretionary factors regarding the wind in each farm.

This paper intends to improve the existing methodologies in performance assessment of wind farms from a given promoter to provide insights concerning their efficiency and productivity growth over time. Findings of this study can support the decision maker in benchmarking wind farms during operating stage and in repowering or overpowering processes. In a first stage, DEA is used to measure the operating efficiency of the wind farms and establishing benchmarks, followed by a second stage, were changes in wind farms productivity are investigated using the Malmquist index over two years, in which the wind energy sector suffered a considerable decrease in electric energy produced. The robustness of the scores achieved by DEA models can be tested by using bootstrapping frameworks [Simar and Wilson, 1998, Simar and Wilson, 1999]. Finally, the proposed framework is applied to a case study, giving insights of the performance assessment of wind farms from Iberwind which has a market share of 18% on the Portuguese wind energy sector.

This study is organized as follows: next section presents the methodology for performance assessment of wind farms, section 3 presents context setting in the wind energy sector and applies the methodology to the case study, and section 4 presents main conclusions of this study.

2 Performance assessment methodology

The methodology proposed in this study intends to explore the productivity and the efficiency of wind farms. In a first stage, DEA is used to assess the farms efficiency by taking into account the resources and the non-discretionary variable, the wind, available in each farm to generate electric energy. This approach enables benchmarking among farms. The robustness of efficiency scores is tested by using bootstrap framework [Simar and Wilson, 1998]. In a second stage, we use panel data to assess the overall productivity change over time of the farms by using the Malmquist index and its components [Färe *et al.*, 1994], efficiency change and technological change. The efficiency change measures if the farm is moving closer or farther from the frontier while the technological change measures shifts in the frontier that can be characterized by progression, regression, or both. Finally, the robustness of these indexes is tested by using bootstrapping [Simar and Wilson, 1999] which allows the identification of significant aspects that may explain the performance of each farm over time. Following sections present the proposed methodology in detail.

2.1 DEA Model

DEA is a linear programming based technique to assess the relative efficiency of an homogeneous set of Decision Making Units (DMUs) in producing multiple outputs from multiple inputs. This allows to identify the "best practices DMUs" and their linear combination defines the frontier technology. By reference to this frontier, a single summary measure of efficiency is calculated for each DMU. In the original DEA model proposed by Charnes *et al.* [1978], the efficiency score of each DMU is estimated by using the frontier technology characterized by Constant Returns to Scale (CRS). For an output oriented analysis, we consider a technology involving n production units defined by j ($j = 1, \ldots, n$), which use the inputs x_{ij} $(x_{1j}, \ldots, x_{mj}) \in R^m_+$, to obtain the outputs y_{rj} $(y_{1j}, ..., y_{sj}) \in R^s_+$, *i.e.*, the production possibility set. In this model, the efficiency of each DMU j_o is given by the reciprocal of the factor (θ) by which the outputs of the DMU j_o can be expanded, according to the following linear model:

$$\max \Big\{ h_{j_o} = \theta |\ x_{ij_o} \geq \sum_{j=1}^{n} \lambda_j\ x_{ij}, \quad i = 1, \ldots, m \tag{2.1}$$

$$\theta\ y_{rj_o} \leq \sum_{j=1}^{n} \lambda_j\ y_{rj}, \quad r = 1, \ldots, s$$

$$\lambda_j, \ \geq 0, \quad \forall_{j,i,r} \Big\}$$

Model (2.1) assesses the relative efficiency of DMUs in the achievement of the output levels given the resources used. The measure of efficiency, given by $1/\theta^*$, equals to 100% when the unit under assessment is efficient, whereas lower scores indicate the existence of inefficiencies. For the inefficient units there is evidence that it is possible to obtain higher levels of outputs with the same or lower levels of the inputs currently used. For these units, it is also possible to obtain, as by-products of the DEA efficiency assessment, a set of targets for becoming efficient. The input and output targets for a DMU j_o under assessment are obtained as follows:

$$x^o_{ij_o} = x_{ij_o} - s^*_i = \sum_{j=1}^{n} \lambda^*_j\ x_{ij}$$

$$y^o_{rj_o} = \theta^*_o\ y_{rj_o} + s^*_r = \sum_{j=1}^{n} \lambda^*_j\ y_{rj} \tag{2.2}$$

where the variables s^*_i and s^*_r are the slacks corresponding to the input i and output r constraints, respectively, obtained at the optimal solution of model (2.1). The benchmarks for the inefficient DMUs j_o are the units with values of $\lambda^*_j > 0$ in the optimal solution of model (2.1). These are the Pareto-efficient DMUs.

The model (2.1) enables to assess the Technical Efficiency (TE) for each DMU which can be due to the ineffective operation of the production process in transforming inputs to outputs and also due to the divergence of the entity from the Most Productive Scale Size (MPSS). Banker *et al.* [1984] propose the DEA model that assesses the Pure Technical Efficiency (PTE) for each DMU by using the frontier technology characterized by Variable Returns to Scale (VRS). This model is achieved by including the constraint $\sum_{j=1}^{n} \lambda_j = 1$ in model (2.1). The divergence of the DMU from the MPSS is given by scale efficiency, which is determined by the ratio $\frac{TE}{PTE}$.

For Pareto-efficient DMUs it is possible to identify the local Returns to Scale (RTS) which enables to know if there are advantages in changing the scale of DMUs. In the study case under analysis, this information is very useful in repowering processes of wind farms. If increasing returns to scale hold at a Pareto-efficient DMU, then increasing its input levels by a given percentage will lead to expansion of its output levels by a larger percentage. This indicates that the DMU should increase its scale size. Similarly, a DMU operating at a point where decreasing returns to scale hold, it should decrease its scale. If a DMU operates at constant returns to scale point, its size is considered optimal. The Färe *et al.* [1985] approach is used to characterize the RTS of Pareto-efficient wind farms.

The DEA models enable to perform the benchmarking analysis of wind farms which can be used to support the decisions makers in management of the units observed. Although, these results should be explored with carefulness, since DEA assumes that the distance from each unit and the projected point in the frontier corresponds to inefficiency, which makes this method sensible to random noise in data. For this, we propose an integrative analysis in which the robustness of θ derived from model (2.1) is tested by using bootstrapping method proposed by Simar and Wilson [1998]. Thus, we derive for each DMU a confidence interval for θ, the bias and the bias-corrected score $\hat{\hat{\theta}}$. These scores are used to assess the wind farms performance.

2.2 Malmquist index on evaluation of overall productivity

In energy sectors, it is of great interest the investigation of the productivity change over time. The Malmquist productivity index was introduced by Caves *et al.* [1982] and developed further in the context of performance assessments by Färe *et al.* [1994] for conducting performance comparisons of DMUs over time. The high popularity of this method is related with several factors. Firstly, the index is applied to the measurement of productivity change over time, and can be decomposed into an efficiency change index and a technological change index. Secondly, it is not necessary to use price data, assumptions of cost minimization or revenue maximization. Thirdly, it can be used in case of oriented and non-oriented analysis. Fourthly, it enables the determination of the total factor productivity in the generic case where production technology uses multiple inputs to produce multiple outputs by deriving efficiency scores in DEA models.

The Malmquist index, as proposed by Färe *et al.* [1994], is used to derive the overall productivity of each DMU. It is based on radial measures which are defined by distance functions. In output-oriented analysis, the output distance function is equal to the efficiency score estimated by model (2.1), given by $1/\theta^*$ for each DMU for a given period. Considering n DMUs in period t, which use the inputs $x^t \in R_+^m$ to obtain the outputs $y^t \in R_+^s$, and the same n DMUs in period $t+1$, which use the inputs $x^{t+1} \in R_+^m$ to obtain the outputs $y^{t+1} \in R_+^s$. To simplify the notation, the efficiency score estimated for each DMU_{j_o} in period t is given by $E_o^t(t)$ while the efficiency score estimated for each DMU in period $t+1$ is given by $E_o^{t+1}(t+1)$. Thus, the score in parenthesis represents the period in each DMU is assessed while the superscript denotes the frontier technology used as reference. The Malmquist index derived for each DMU_{j_o} is calculated as follows:

$$I_o^{t+1,t} = \left(\frac{E_o^t(t+1)}{E_o^t(t)} \frac{E_o^{t+1}(t+1)}{E_o^{t+1}(t)} \right)^{\frac{1}{2}} \tag{2.3}$$

In terms of interpretation, a score of $I_o^{t+1,t}$ greater than one indicates better performance in period $t+1$ than in period t.

The mixed-period distance functions, $E_o^t(t+1)$ and $E_o^{t+1}(t)$, can be greater, equal or lower than 1. For example, the distance function derived to the period $t+1$ for a DMU observed in period t can be lower or equal to 1 if the input-output vector of this DMU belongs to the Production Possibility Set (PPS) of period $t+1$. This occurs for $E_o^t(t)$ and $E_o^{t+1}(t+1)$ cases. In opposite, the distance function derived to the period $t+1$ for a DMU observed in period t is higher than 1, if the input-output vector of this DMU is outside the PPS of the period $t+1$.

According to Färe *et al.* [1994], this index can be decomposed in two components: $IE_o^{t+1,t}$ and $IF_o^{t+1,t}$. The sub-index $IE_o^{t+1,t}$ corresponds to efficiency change and compares the efficiency spread between the periods observed for each DMU_{j_o}. The sub-index $IF_o^{t+1,t}$ corresponds to technological change and compares the relative position of the frontiers associated to periods t and $t+1$ for the input-output mix of each DMU_{j_o} observed. This decomposition implies that the sources of better performance can be associated with two factors: less dispersion in the efficiency score of DMU in each period and/or better productivity associated to the period frontier.

The efficiency change derived for each DMU_{j_o} is calculated according to:

$$IE_o^{t+1,t} = \frac{E_o^{t+1}(t+1)}{E_o^t(t)} \tag{2.4}$$

A value of index $IE_o^{t+1,t}$ greater than 1 means that efficiency spread is smaller in DMU_{j_o} observed in period $t+1$ than that observed in period t, measuring how much the DMU_{j_o} is getting closer (catch up) or farther from the frontier.

Concerning the technological change derived for each DMU_{j_o}, it is given by:

$$IF_o^{t+1,t} = \left(\frac{E_o^t(t)}{E_o^{t+1}(t)} \frac{E_o^t(t+1)}{E_o^{t+1}(t+1)} \right)^{\frac{1}{2}} \tag{2.5}$$

When $IF_o^{t+1,t}$ is higher than 1, this means that the productivity of frontier $t+1$ is better than the productivity of frontier t, which implies that the frontier has progressed. This index can be seen as an average aggregated change in technology of a DMU_{j_o} since it is obtained as the geometric mean of two components. The first component $(\frac{E_o^t(t)}{E_o^{t+1}(t)})$ corresponds to the distances between the frontiers t and $t+1$ when assessed for the DMU_{j_o} observed in period t. The second component $(\frac{E_o^t(t+1)}{E_o^{t+1}(t+1)})$ is calculated in a similar way for the same DMU observed in period $t+1$.

It is possible to analyze globally the relative position of the two frontiers, which enables to identify if the frontiers have regressed, progressed or crossed over. To do so, it is necessary to analyze each component of $IF_o^{t+1,t}$ for all DMUs observed in the periods under analysis. Some typical situations may occur: for instance, if the component is always higher than 1, this means that there has been a progression in the technology; on the other hand, if the component is always lower than 1, this means that there has been a regression in the technology; in the case when there are at least one component higher than 1 and one component lower than 1, this indicates that frontiers are crossed over, signifying that for some input-output mix the frontier progressed and for others, the frontier regressed.

The bootstrapping framework proposed by Simar and Wilson [1999] is used to evaluate the robustness of the estimates of $I_o^{t+1,t}$, $IE_o^{t+1,t}$ and $IF_o^{t+1,t}$ (hereafter *I*, *IE* and *IF*, respectively) obtained for each DMU_{j_o}, which allows the computation of confidences intervals for each index. If the interval contains the value 1, we cannot infer that significant changes occurred in the DMU_{j_o}. On the other hand, if the lower and upper bounds are smaller (or higher) than 1, this implies that there was a decline (or progress) in the DMU_{j_o}. This approach is currently used in several studies [Gilbert and Wilson, 1998, Tortosaausina *et al.* 2008, Odeck, 2009, Horta *et al.*, 2012]. This analysis is extended to the components of IF for all DMUs observed to find out the relative position of the frontiers.

3 Performance assessment of wind farms

This section applies the methodology proposed in previous section to evaluate the performance of wind farms owned by Iberwind in Portugal. This study focus in the wind farms efficiency analysis during operating stage, for a given distribution of wind speed in the location of the farms, installed capacity and number of wind turbines, oriented to the maximization of the output electric energy produced.

3.1 Contextual setting

Relevant decisions and factors that affect the productivity of wind farms are prior to start-up, including for instance wind farm location and engineering design process such as the installed capacity, type of generator and turbine layout. The focus of wind farms performance assessment is during operating phase, when wind farms perform the energy conversion and it is delivered to the grid. Even though, the performance of a wind farm is closely linked to prior start-up phase, the operating stage is relevant throughout estimated lifetime of the assets from the point of view of maximizing the energy production, ensuring the highest availability rates and cost-effective operation and maintenance.

Wind is a variable source of power: output rises and falls as wind strength fluctuates in a hourly or 10 minutes time scale although it is consistent from year to year. This variability poses a challenge when integrating wind power into grids, especially when wind becomes a major component of the total system. Wind speeds suitable for electricity generation range from 5 m/s (cut in) to 25 m/s (cut out). The frequency of wind speeds usually fits a Weibull distribution function and an average value does not relate to the amount of energy a wind farm can produce. Installed capacity and the number of wind turbines in a farm, along with the variability of wind, relate to the capacity factor of a wind farm, i.e., the ratio of actual productivity in a year to its theoretical maximum. The rated power of a unit of the wind farm (given by the ratio of the installed capacity and the number of wind turbines) if small, could lead to an higher capacity factor but the farm may not be able to produce energy at higher wind speeds, which translates in less profit. On the other hand, if the rated power of units is high, the turbine may stall at low wind speeds and the extra power at high wind speeds may not compensate the higher costs of the turbine. Therefore, these resources are important to assess efficiency and productivity analysis during operating phase and may provide useful information in repowering or overpowering processes. Concerning the output, it should be point out that electric energy produced from wind is not constrained by load demand or other market players, as currently regulated.

3.2 DEA model

The DMU is formed by a group of wind turbines connected to the transmission or distribution grid utility. The number of DMUs under analysis is 31, spread out in North and Center of Portugal. The final data set considers 30 wind farms since one of them was eliminated due to a repowering process that began in 2010. Total capacity installed ascends to 683.75 MW through 319 wind turbines, from 15 different models, provided by five manufacturers (Vestas, Nordex, Enercon, GE and Winwind). We consider a panel data set regarding 2010 and 2011 years collected from Annual Reports and Accounts1[1]. The 30 farms under analysis are located in six wind typical locations in Portugal (Bragança, Vila Real, Viseu, Coimbra, Leiria, Lisboa).

The wind farms can be considered homogenous as they result from similar set-up stages and use a similar generation process. The strong disposability of inputs and output is adopted and the convexity of the frontier is valid, as any input combination inside the PPS determined by the wind farms sample is feasible. The output-oriented perspective is used, as the objective of the farms is to produce maximum electric energy, taking into account the non-discretionary variable, the wind, and the resources available in each farm, during the period under analysis. We use the constant returns to scale to assess the technical efficiency of wind farms observed. In order to model the farm activity, the input-output set should cover the full range of resources used and the outputs that are relevant for the objectives of the analysis [Dyson *et al.*, 2001]. The output corresponds to the amount of electric energy delivered to the grid. Concerning the inputs, we consider installed power, number of turbines and wind availability. The descriptive measures concerning inputs and output under analysis are summarized in Table 1. Installed power capacity of the farms is determined by the number of wind turbines multiplied by the rated power of each one. The number of turbines relates with the area occupied by the farm. To capture the effect of the wind variability into the model, we consider the number of hours per year that wind speed is within the range defined by cut in and cut out speeds (hereafter named wind hours). For each wind farm location, the wind data is collected from a meteorological data base throughout identification of the station which represents its wind profile, defined by the nearest meteorological station. The inclusion of this non-controllable input assures that a farm with unfavorable conditions regarding wind resource is not penalized in the performance assessment. This is an internal non-discretionary input because it is used for the definition of the PPS, according to Camanho *et al.* [2009]. Data concerning maintenance and operation costs are confidential and, for this reason, they are not included in the model.

Table 1: Mean and standard deviation values for inputs and output of wind farms

	2010		2011	
	Mean	Stand. Deviat.	Mean	Stand. Deviat.
Inputs				
Installed power (MW)	22.4	30.4	22.4	30.4
No of wind turbines	10.4	10.7	10.4	10.7
Wind hours	3773.6	1082.4	3280.5	980.4
Output				
Electric Energy (GWh)	56.5	81.5	51.1	75.8

The standard deviation of observed variables is quite high relative to the mean, indicating a considerable amount of diversity in the wind farms.

The summary of the technical efficiency estimates, using the formulation in model (2.1) is presented in Table 2. The robustness of these estimates is tested by calculating the bias corrected efficiency scores (as the inverse of $\hat{\hat{\theta}}$) [Simar and Wilson, 1998] which summary results are presented in Table 2.

Table 2: Summary results of original and bootstrapped efficiency scores

	Year 2010			Year 2011		
	Bias corrected eff.	Bias	Efficiency estimated	Bias corrected eff.	Bias	Efficiency estimated
Mean	72.92%	-8.00%	77.73%	66.33%	-10.54%	73.97%
Stand. Deviat.	10.13%	4.30%	12.33%	10.86%	4.92%	13.44%

The efficiency scores estimated are relative, since the farms in a given year are only compared with all farms in the sample operating in the same year. We may observe that the wind farms analyzed are more homogenous in 2010 than in 2011 which is confirmed by bootstrapping analysis. The absolute value of bias is slightly higher in 2011 due to the differences between bias-corrected efficiency scores, and efficiency estimates are higher in 2011 year. Globally, this indicates that farms moved farther from the frontier. This effect is captured by the analysis of efficiency change index (IE) for each farm, which is explored in productivity analysis. Figure 1 presents the average of bias corrected efficiency of the farms located in the same region for both years. We confirm that the level of efficiency spread increased in 2011 for all regions but we observe some differences among them.

[1]The constraint of the panel data is limited to 2010 and 2011, because there is missing wind data in former years from meteorological stations.

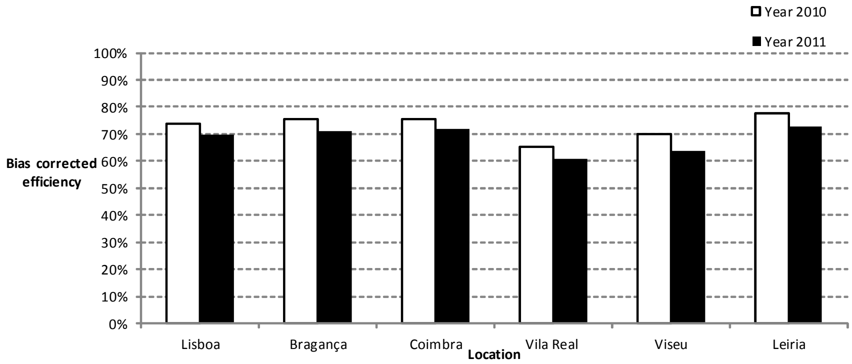

Figure 1: Comparison of the average of bias corrected efficiency of the farms located in the same region for 2010 and 2011 years

3.3 Benchmarking analysis

The benchmarks farms and their best practices should be identified in order to be emulated by inefficient units. These practices may be related to the use of more efficient wind turbines, enhanced wind farm design and layout, better operation and maintenance schemes, which may be used to support the inefficient farms to achieve the appropriate targets. It is also important to identify the nature of returns to scale of the Pareto-efficient farms to explore changes in their size.

From the sample used, there are only 3 efficient farms: Achada, Candeeiros and Pampilhosa. These farms maintain the efficiency status in both years. In 2011, Achada and Candeeiros are the benchmarks which are used as reference 27 and 22 times, respectively. There are no units which are compared with Pampilhosa, since this farm is the largest unit in terms of number of wind turbines and installed power. In the following, we explore the profile of the benchmarks in terms of location and type of wind turbines used.

Benchmarks are located in areas with high wind potential (Lisboa, Leiria and Coimbra) and their energy conversion system is based on asynchronous generators. The wind turbines of Achada are produced by Nordex while the wind turbines of Candeeiros and Pampilhosa are produced by Vestas. These farms are the largest ones while Achada is a smaller farm. Figure 2 compares the age, inputs and output of benchmarks with those observed in inefficient farms, in 2011 (the some profile occurs in 2010). In this graph the scores were normalized by the average scores observed in benchmarks to simplify the comparison. The installed power of inefficient units is, in average, 80% less of that observed in benchmarks and the electric energy produced follows a decrement of the same magnitude. The inefficient units have, in average, 67% less number of wind turbines of those observed in benchmarks. Given that wind hours in geographical areas where inefficient units are located have a small reduction (about 14%), this suggests inefficient farms are prone to a repowering process, in order to increase their electric energy, as they are not exploring all wind energy potential. The fact that inefficient farms are, in average, 15% older than benchmarks can explain some inefficiency in some farms.

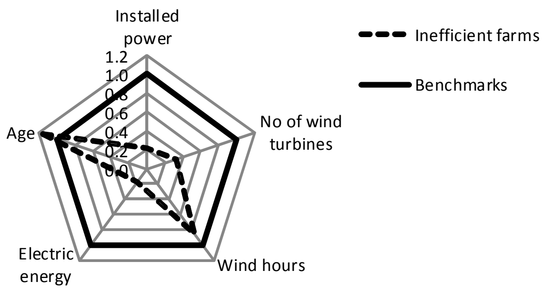

Figure 2: Comparison between benchmarks and inefficient farms in 2011

In both years, the most inefficient unit is the same farm: the Lomba Seixa I with scores equal to 56.7%, in 2010, and 49.4%, in 2011. The lowest score can be due to age of technology of the conversion system installed in this farm, as it is 11 years old. This farm has 11 wind turbines which were produced by Nordex.

The results also indicate that all inefficient farms have slack in the constraint relative to number of wind turbines. Conversely, there is no farm with slack in installed power. Thus, the inefficient farms would increase the energy produced by using a lower number of wind turbines and the actual installed power. This upshot is important in repowering processes. Although, it is important to use a relevant number of turbines to catch the wind potential in a given location, these results suggest that wind farm design could be enhanced and used to decrease the environment impact of future wind farms projects. There are only four farms which have slack relative to available wind hours in both years (Borninhos, Jarmeleira, Rabaçal and Serra Escusa). This may be related with inefficient scheduling of maintenance operations, in times with high wind potential.

These findings should be explored and discussed with the promoter, in order to enhance performance of the wind farms. For inefficient units, it is possible to specify appropriate targets based on internal benchmarking, as proposed in the next section.

3.3.1 Target setting

For each inefficient farm, we can define targets for performance improvement. These targets are determined by linear combination of the benchmarks for each inefficient unit. For example, the technical efficiency of Farm 17 (Lousã I) is about 67%. The scores for 2011 period, regarding inputs and output of farm 17, DEA targets (determined by (2.2)) and peers, are presented in Table 3.

Table 3: Target setting of Farm 17

			Benchmarks	
			Farm 1	**Farm 7**
	Observed	Target	$\lambda = 0.213$	$\lambda = 0.302$
Installed Power (MW)	35	35	6.9	111
No of wind turbines	14	11.8	3	37
Wind hours	2598	2598	5397	4787
Electric Energy produced (GWh)	71.7	107.1	22.4	338.9

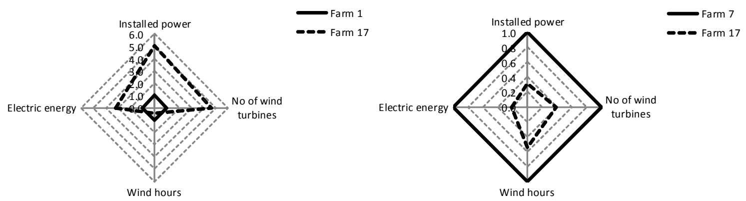

Figure 3: Comparison between actual values of Farm 17 with benchmarks 1 and 7

The target for a given variable (input or output) of farm 17 is defined by the linear combination of 21.3% of the score observed in farm 1 (Achada) and 30.2% of the score observed in farm 7 (Candeeiros). Farm 17 is larger than farm 1 and smaller than farm 7. Targets indicate that it is possible to increase the electric energy to 107.1 GWh by using the actual installed power with the same wind hours available in 2011, with a slack roughly equal to 2 turbines. In theory, the ratio between the total installed power and the number of turbines should be increased, via increment of the rated power of each turbine. We can compare the actual inputs and output observed in farm 17 with each benchmark by using the radar graphs in Figure 3, where the scores were normalized by those observed in benchmarks to simplify the comparison. Farm 17 has an installed power and a number of wind turbines which are almost 5 times higher, but 48% less wind hours than those observed in benchmark 1. Taking into consideration the exogenous characteristic of the input wind hours, thus non-controllable, it is not evident a possible increase in electric energy production. On the other hand, farm 17 has a installed power and a number of wind turbines about 70% and 60%, respectively, less than those are observed in benchmark 7 while the reduction in the wind hours is about 50%. We can conclude that inputs of farm 17 are, in average, 60% lower than those observed in benchmark 7 and a similar percentage of reduction in electric energy would be expected and not a decrease of 80%, as observed. From the comparison with peers, namely wind farm 7, the farm 17 could produce higher level of electric energy from the resources observed. Hence, it is necessary to identify the best practices observed in benchmarks 1 and 7 which should be emulated by inefficient farm 17.

As the production technology of wind farms is characterized by constant returns to scale, the farm efficiency score, $1/\theta^*$, includes sources related with resources under-utilization and scale size. Next, we explore the scale of the farms based on internal benchmarking.

3.3.2 Exploring changes in wind farms size

As the scale size affects the productivity of a DMU, it is important to calculate the scale efficiency to measure the distance between CRS and VRS frontier technologies at the scale size of the assessed unit. So, the larger the difference between TE and PTE efficiency scores, the lower the value of scale efficiency is, and the adverse impact of scale size on productivity is more significative. The average scale efficiency score is, in average, 95.38%, and 93.31%, in 2010 and 2011, respectively. This means that scale size only affects the productivity of a small proportion of units observed (Jarmeleira, Borninhos, Rabaçal, Chiqueiro, Malhadizes, Degracias, Lousã I, Lousã II, Malhadas), where the scale efficiency has the lowest scores, with a range between 73.4% and 88.9%. This strengthens using constant returns to scale frontier technology to assess the wind farms efficiency.

The analysis of local returns to scale according to Färe *et al.* [1985] shows that Achada, Candeeiros and Pampilhosa are characterized by an optimum size. Jarmeleira, Lousã II, Malhadas and Rabaçal have increasing returns to scale, which indicates that the size of these units could be increased with a repowering process which enables increasing their productivity. There is no unit where we observe decreasing returns to scale, which indicate that there is no one with higher size than the required, taken into account the level of electric energy produced.

3.4 Productivity analysis

In a second stage, we investigate the productivity of wind farms by disentangling the efficiency change and technological change effects observed in wind farms in 2010 and 2011 years. An aggregate analysis is performed by identifying the global effects which had occurred in the period under analysis. Changes in efficiency (IE), technology (IF) and productivity (I) indexes of farms are explored through identification of scores higher, lower or equal to 1 which correspond to improvement, deterioration or stagnation, respectively. This analysis is complemented with bootstrapping framework, as proposed by Simar and Wilson [1999], to identify if those changes, for each farm, are significant. Table 4 aggregates the results in terms of number of wind farms which improve, decline or maintain the performance for each index.

Table 4: Significant scores for I, IE and IF

	I	IE	IF
Improvement	1 (in 1)	1 (in 3)	-
Deterioration	27 (in 29)	19 (in 24)	17 (in 30)
Stagnation	2	10(3)	13

We observed that 27 farms decreased overall productivity levels in year 2011, as indicated by significant scores of I index. This effect is mainly due to deterioration in the productivity levels of the frontier for some inputs-output mix and decreasing efficiency levels in some farms. Only Serra Escusa improves overall productivity level due to improvement on its efficiency in 2011. Pampilhosa and Candeeiros maintain overall productivity levels in 2011.

There are 19 farms that moved farther from the frontier in 2011, as indicated by significant scores of IE index. These farms had the worst performance in 2011, so the reasons for that should be investigated. Only Serra Escusa moved closer to the best practices. It is recommended to identify how this farm carried out its operations and maintenance services in order to be emulated by the inefficient farms. The remaining farms maintained the efficiency spread levels observed in 2010.

Globally, the productivity of the best-practices frontier decreased considerably in 2011 for the input-output combinations of 17 farms, although for the remaining input-output mix, the productivity of the frontier maintained the level of productivity observed in 2010. This is connected with the decrease of produced electric energy observed in wind energy sector in 2011. Next, we explore the relative position of frontiers for the farms observed in each period. To do so, we analyze if the ratios of IF ($\frac{D^{2010}(2011)}{D^{2011}(2011)}$, $\frac{D^{2010}(2010)}{D^{2011}(2010)}$) are statistical significant throughout bootstrap framework [Simar and Wilson, 1999]. Table 5 aggregates the results in terms of number of wind farms which improve, decline or maintain the performance for each ratio.

Table 5: Significant scores for ratios of IF

	$E^{2010}(2010)/E^{2011}(2010)$	$E^{2010}(2011)/E^{2011}(2011)$
Improvement	0	0 (in 2)
Deterioration	14 (in 30)	18 (in 28)
Stagnation	16	12

The input-output combinations of 14 farms observed in 2010 are located in areas of the production possibility set where the productivity of the frontier declined. The remaining farms are located in areas of the PPS where the frontier maintained the productivity. During 2011, there are 18 input-output combinations of wind farms located in areas of the PPS where the frontier regressed, while the other remaining farms are located in areas where the frontier maintained the productivity. There is no statistical evidence of crossed frontiers for all input-output combinations.

4 Conclusions

This study proposes a methodology to assess the efficiency and productivity change of wind farms, which can support decision makers during operating phase of wind farms, and also in location and project design phases of new farms and in repowering processes. In first stage, the efficiency assessment of wind farms enables to identify benchmark profiles, set targets for inefficient units and explore the scale size of existing farms. These results can be useful in project design and layout of new farms and also in repowering processes. The second stage explores the efficiency and productivity over time of wind farms by identifying the global effects which occurred in terms of changes in internal practices observed and productivity of the frontier, during the established time frame.

Regarding the operating stage of the farms analyzed, 3 farms are the benchmarks, whose best practices can be related with well-performing operations and maintenance programs. Between 2010 and 2011, different profiles of wind farms were identified in terms of overall productivity change, efficiency change and technological change. Almost all farms decreased overall productivity levels, mainly due to the decline in the productivity levels of the frontier, which is in accordance with decrease in wind availability, measured in wind hours, observed in 2011. The productivity of the frontier declined for some input-output combinations observed in 2011 and for the other combinations, the frontier maintained its productivity. In this case, there is one farm that improved its overall productivity due to the improvement of its efficiency in 2011 and two farms which maintained overall productivity as they kept the efficiency levels. We observed also that 19 farms had the worst performance in 2011 which requires further investigation to reveal the reasons.

Further research should be conducted using a large panel data set in order to analyze the impact of wind availability on the productivity of wind farms. The inclusion of variables concerning the operation and maintenance schemes should also be explored in future performance assessments of wind farms.

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