A Cross-European Efficiency Assessment of Offshore Wind Farms: a DEA Approach

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Abstract

Offshore wind energy is recognized as an important source of renewable energy and has experienced a rapid growth in recent years especially in north-western European countries. In this paper the efficiency of 71 offshore wind farms across five north-western European countries is assessed using the Data Envelopment Analysis (DEA) Method. The number of turbines, cost, distance to shore, and area of the wind farms are selected as the inputs and the connectivity to population centres, the produced electricity and the water depth are considered as the outputs. The results show that the average CCR efficiency score of all offshore wind farms considered in this study is 87%, and the relative median efficiency of offshore wind farms in different countries is not statistically different. This study offers a practical and holistic performance assessment to the offshore wind stakeholders and policy makers via including economic, environmental, technical and social inputs and outputs in the analysis.

Key words

Renewable Energy; Decision Making; Offshore Wind Farms; Data Envelopment Analysis; Efficiency Assessment

1 Introduction

The offshore wind industry has experienced remarkable growth in the past two decades, and has become a mainstream technology in many European countries while also expanding in Asia and North America. Countries such as the United Kingdom, Germany, Belgium, Denmark and the Netherlands are at the forefront of developing offshore wind farms, and by the end of 2018, Europe had a total installed offshore wind capacity of 18.4 GW [1]. Different factors including the accessibility from coastlines, lower visual impact, higher wind speed and the possibility to place large wind turbines to gain economies of scale and efficiency have increased the attractiveness of this type of renewable energy [2] . However, issues related to intermittency and unpredictability of the wind, harsh sea and weather conditions, and complex logistics are among the challenges faced by the industry[3]. In order to ensure that maximal efficiency gains are achieved in the countries in which offshore wind energy is being deployed in an industrial scale, the Data Envelopment Analysis method (DEA) is proposed in this paper. This analysis can provide a better understanding of the current state of the industry and provide a best practice frontier of the operational and in-construction wind farms across north-west Europe considering social, technical, economic and environmental factors.

In the seminal work of Charnes et al. [4] , DEA is introduced as a method for measuring the efficiency of a set of decision making units. The initial idea of DEA can be traced back in the economics literature through defining a simple measure for efficiency that could account for multiple inputs and outputs within the context of technical, allocative and productive efficiency [5]. Based on a survey by liu et al. [6], DEA has been used in traditional industries such as agriculture, manufacturing and health care, as well as modern industries such as software and e-business, and is particularly an accepted approach for efficiency evaluation and benchmarking in the energy and environment sector [7]. Within the context of benchmarking, DEA could be considered as a multiple criteria decision analysis method, however its main goal is to evaluate the relative efficiency of a set of comparable entities (decision making units) rather than choosing a specific alternative as it is usually the case in decision analysis methods [8]. Thus, DEA can be regarded as a descriptive analytical method, although an analysis of its results can lead to some prescriptive recommendations.

The contributions of this study are threefold including i) providing a benchmark study of the current efficiency status of the European offshore wind industry ii) determining the factors affecting the efficiency of offshore wind farms and iii) Providing a statistical analysis of the difference in efficiency scores of the countries by grouping the windfarms into three categories of UK, Germany-Denmark and Netherlands-Belgium. The remainder of this paper is as follows: In Section 2, the literature review is conducted and the gaps in the literature are highlighted. In Section 3, a DEA analysis is presented including a discussion of the results and the statistical and sensitivity analysis, and in Section 4 the conclusions and future research avenues are discussed.

2 Literature review

Data Envelopment Analysis is a non-parametric method that evaluates the relative efficiency of a set of Decision Making Units (DMUs) by a specific mathematical programming model. In contrast to parametric methods such as Stochastic Frontier Analysis (SFA), for which an explicit functional form for the technology and frequency for the distribution of the inefficiency term is imposed; in the DEA method no prior assumption on the underlying functional relationship between inputs and outputs is required [9] . The DEA method divides the DMUs into efficient and inefficient subsets, where efficient units receive value of 1 and inefficient DMUs receive values less than 1. Therefore, the method allows for the identification of DMUs exhibiting best practice and the formation of an efficient frontier [10].

Two main varieties of DEA are developed in the literature, the CCR (Charnes, Cooper and Rhodes) model, which is based on the hypotheses of constant returns to scale (CRS) and it measures the overall efficiency; and BCC (Banker, Charnes and Cooper) model, which is based on the hypotheses of variable returns to scale (VRS) measuring the pure technical efficiency. The scale efficiency is estimated through the ratio of overall efficiency score to pure efficiency score. The CRS model has been applied for this analysis since constant return to scale is assumed.

2.1 Applications of DEA in the renewable energy sector

In this section, some of the applications of DEA in the onshore wind, offshore wind and wave sector are presented in order to review the inputs and outputs that have been used in the literature. Ederer [10] has applied the DEA methodology for assessing the efficiency of 22 offshore wind farms in Europe in terms of capital cost efficiency and operating cost efficiency. For the assessment of capital cost efficiency, the capital cost is considered as the input and installed capacity, distance to shore and water depth as the outputs. For the operating cost efficiency, the operating cost is the input and the installed capacity, distance to operating port, energy performance and availability are the outputs. Using both BCC and CCR methods, the scale efficiency of the wind farms is determined. The learning-by-doing rate for capital cost efficiency shows that the efficiency has increased with accumulated experience. Furthermore, the Tobit regression applied in their study shows increasing capital cost efficiency as a function of time, and a decreasing operating cost efficiency as a function of operating year.

Saglam [11]uses a two stage DEA model for efficiency assessment of onshore wind energy in 39 states in the United States. In the first stage of the model, a BCC and CCR model is developed that takes the installed wind capacity, number of wind turbines, total project investment and annual land lease payment as inputs; and the net generation, percentage of in-state energy production, number of US homes powered, wind industry employment, annual water savings and CO2 emissions avoided as the outputs. Sensitivity analysis is also conducted for assessing the robustness of the model and shows that electricity generation related output variables and capital and technology related inputs are critical factors affecting the efficiency scores. Furthermore, Tobit regression models investigate the effectiveness of the invested money and the productivity of the wind turbine technologies and shows that early installed wind power was more expensive and less productive than the current installed wind power.

Wu et al. [12] apply a two stage DEA for efficiency assessment of 42 onshore wind farms in China. They use the installed capacity, electricity consumption and wind power density as the inputs and the generated electricity and availability as the outputs. The Tobit regression analysis is used to assess the relationship score of the CCR model with the uncontrollable variables (age, wind curtailment rate, dummy variable for ownership effect). The regression findings suggest that age and wind curtailment rate have a negative effect on the productive efficiency while the ownership effect does not have a significant impact.

Iglesias et al. [13] use DEA and SFA to measure the efficiency of 57 Spanish onshore wind farms using the capital, labour and fuel (wind) as inputs and the electrical energy produced by the wind farm. Their result show that the DEA BCC model has the highest efficiency score, followed by SFA and CCR model. High average technical efficiency (exceeding 75 %) is reported and they show correlation of the average size of the standard wind turbine with the year of installation.

Halkos and Tzeremes [14], apply a bootstrapped DEA model for evaluation of financial performance of 78 firms operating in the Greek renewable energy sector and concluded that firms operating in the wind power energy sector had higher financial efficiency compared to firms in the hydroelectric power sector. They have considered debt/equity ratio, current ratio and asset turnover ratio as input variables and return on equity, return on asset gross profit margin and operating profit margin as output variables. San Cristobal [15] uses DEA to assess the efficiency of thirteen different renewable energy technologies related to wind power, hydroelectric, solar, biomass and biofuel using the investment ratio, implement period and operating and maintenance cost as inputs and power generation, operating hours, useful life and CO_2 avoided as outputs. Kim et al. [16] apply DEA to assess the investment efficiency of photovoltaic, onshore wind power and fuel cells in South Korea considering policy objectives of public investment, technological development and wider dissemination of new and renewable energy in South Korea. Based on their analysis, wind power turns out to be the most efficient technology from a government investment perspective. Stallard et al. [17] use the DEA method to compare the efficiency of a set of three hypothetical and one prototype wave energy conversion technologies at eight distinct UK wave climates considering 7 inputs and one output. It is suggested that the DEA provides straight forward means of selecting the technology, which maximises aggregate electricity generation with minimum inputs and without recourse to conducting a cost study for each site.

DEA is also used for the analysis of energy efficiency on country level. DEA has been applied to assess the efficiency of BRIC countries and Mediterranean countries respectively, both using energy consumption, labor force and gross fixed capital formation as inputs and the GDP as an output by [18] and [19]. Location optimization of wind plants in Iran has been conducted using fuzzy DEA in which in addition to wind speed, local and social criteria such as population of the region, geological and geographical consideration and cost have been considered by [20].

It is noted that, whilst the above papers conducted successful and informative DEA analyses, they concentrate on onshore rather than offshore wind farms in their assessment of wind energy. Furthermore, there is often, but not exclusively, an emphasis on financial efficiency factors rather than technical/ logistical factors. This paper presents an efficiency analysis for a offshore wind farms across five European considering social, technical, environmental and economic factors and fills the gap in the current literature in the application of the DEA method to the offshore wind energy sector.

3 A DEA analysis of the offshore wind industry

DEA was extended by Charnes et al. [4] and Banker et al. [21] to propose the Charnes-Cooper-Rhodes model (CCR) with constant returns to scale (CRS) and Banker-Charnes-Cooper (BCC) with variable returns to scale (VRS). The CCR model is formulated below by (1)-(3) assuming that there are j DMUs to be evaluated $(j = 1, \dots, n)$, r is the output index $(r = 1, \dots, s)$; i is the input index $(i = 1, \dots, m)$; x_{ij} the value of the i_{th} input of the j_{th} DMU; and y_{rj} the value of the r_{th} output; u_r is the weight assigned by the DEA model to the r_{th} output; v_i is the weight assigned by the DEA model the i_{th} input; and θ the relative efficiency of DMU_j in the following manner:

$$Max\ \theta = \sum_{r=1}^{s} u_r y_{rj}$$

s.t.

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$\sum_{i=1}^{m} v_i x_{ij} = 1$$

$$u_r, v_i \geq 0 \quad \forall\, r, i$$

Although the DEA methodology has its roots in economics and production theory, it has been used extensively within the realm of operations management for benchmarking the performance of decision making units. In this domain, instead of forming a production frontier, the efficient DMUs form a best practice frontier [18]. In the remainder of this section the rationalization behind the selection of the inputs and outputs of the DEA model developed in this paper is presented.

3.1 Selection of Inputs and outputs

For the classification of inputs and outputs, it is suggested that if the underlying problem represents a form of production process, then the selected inputs are usually the resources used or required, and the outputs are the outcome of the process. However, if the problem refers to a benchmarking problem, then the inputs may be selected based on the assumption of "the less the better" and the outputs may be selected based on the assumption of "the more the better" [22]. For this analysis, DEA is employed as a multiple criteria decision making tool where the DMUs are alternatives and the inputs and outputs are two sets of performance criteria where the input is to be minimized and the output to be maximized [22]. The problem of efficiency assessment of offshore wind farms can therefore be classified as a benchmarking problem as it does not only consider the production of electricity given a number of resources, but it assesses the offshore wind farms including other factors including the social impact, cost, and the connectivity to population centres. While it can never be guaranteed that the chosen set of inputs and outputs that perfectly reflect the process under study are included in the DEA analysis, every attempt should be made to insure that the selected measures reflect the process under study in as detailed a way as possible. In the next section, a description and justification for selection is provided for each of the inputs and outputs used in this study. The main categories of the inputs and outputs are defined as: i) the *Economic* criteria including the cost, and the amount of produced electricity, ii) the *Technical* criteria including the number of turbines, and water depth, iii) the *Social* criteria including the distance to shore and connectivity to population centres and iv) the *Environmental* criteria including the area of the offshore wind farm. A detailed description of all the inputs and output is provided in Sections 3.1.1 and 3.1.2.

3.1.1 Inputs

The description of the four inputs including the number of turbines, cost, distance to shore and the area of the wind farm is provided below:

1) Number of turbines: the number of turbines has been selected as an input since it corresponds to the capacity of the wind farm and also affects the construction, operation and maintenance of the wind farm. The number of turbines has a direct impact on the cost of the wind farm, particularly the operation and maintenance cost, and also the amount of area that the wind farm occupies in the sea, which is a factor which affects its

environmental impact. Therefore, this parameter has been chosen as an input since the best output performance from as few a number of turbines is desirable.

2) Cost: amongst the most important parameters with which offshore wind projects are assessed is the cost of the project. Distance from the shore, water depth, the technology used and many other factors can have an impact on the cost of the wind farm. For this analysis the cost component comprises of the construction and operation and maintenance costs (CAPEX plus OPEX) of the wind farm throughout its entire life cycle. Similar to the study by [23] in which the CAPEX value is retrieved from online sources, the authors relied on the publically available sources, and the available literature. The CAPEX data is taken from [24] as the primary source, with [25] used as a secondary source if the wind farm's CAPEX is not found in [24], and the estimated OPEX is taken from [26]. The cost data for the wind farms has been inflation adjusted based on their year of commissioning up to the end of year 2018 [27] . The cost parameter has been chosen as an input since a best output performance at a lower cost is desirable.

3) Distance to shore: the distance to shore is included as it relates to the sea scape, landscape and visual impact of the wind farm. While offshore wind farms are subjected to the NIMBY effect (not in my back yard) less than that of onshore wind turbines, there are still issues associated with their visual impact, and the impact they could have on the local industries of the region such as tourism. An example of this case is the rejected Navitus Bay wind farm that was planned to be built in the South of England. Amongst the important reasons for the rejection of this project was that the scale and location of the project would affect areas of outstanding beauty over a widespread area of coastline. The wind farm would be visible from vantage points along a 30 km section of the eastern edge of the World Heritage site with the closest point lying on the shore approximately 15 km from the edge of the wind turbine layout [28]. It is therefore desired that the wind farms are built at a distance from the shore to lower their negative social impact, which is better. Certainly this can lead to a trade-off between the cost and social impact inputs that forms part of the intrinsic reasoning of the DEA analysis. Table 1 presents the figures used for calculating the impact of the distance to shore of the windfarms.

4) Offshore wind farm area: this input is related to the marine footprint of the offshore wind farm. Although offshore wind farms are under less space restriction compared to on-land wind farms, they are still in competition with other sea-users in terms of the space that can be allocated to them. However, some studies suggest the positive effect of the construction of offshore wind farms for the marine environment. This is due to the fact

that the construction of the offshore wind farms have contributed to the recovery of vulnerable species due to those areas being closed to beam trawl fisheries [29].

However, the overall impact of the offshore wind farm area is such that it can be considered as an input, since best output performance from a smaller area is desirable for the wind farms. This is particularly true of the crowded maritime spaces in European waters where the wind farms considered in this study are located. Hence, in this study the negative impacts of the offshore wind farm area have been considered and this parameter is used as an input (i.e. the lower the better). The area that the offshore wind occupies in the sea is important due to the following reasons [30]:

- The larger the area, the larger the marine footprint which may lead to marine life interruptions, fishing industry prohibitions, and leisure industry limitations.
- The larger area of the wind farms could lead to marine transportation disruptions, since the offshore wind industry competes with other industries such as container shipping, bulk shipping, defence vessel movements, and passenger ferry line alterations.
- The larger area of wind farm may be due to greater number of turbines employed or larger spacing between turbines which could lead to higher installation, O&M and decommissioning costs. Therefore, it may be desirable to increase the capacity of the wind turbines rather than the number of turbines.

Distance from shore (km)	Impact score
1-10	5
10- 20	4
20-30	3
30-40	2
Distance>40	1

Table 1: distance from shore impact score

3.1.2 Outputs

Three outputs, namely the connectivity to population centres, produced electricity and the water depth have been selected for the DEA model as described below:

1) Connectivity to population centres: the connectivity and proximity of the wind farm to the population centres is an important parameter since this will allow a lower strain in terms of grid accessibility and logistics. This output is calculated as the distance of the wind farm to nearest medium sized city within 250 km with a population density above 1000 person/ km^2. It is desired that the connectivity is maximised and therefore this parameter has been inverted and used as an output of the model.
2) Electricity produced: this parameter measures the amount of estimated theoretical annual electricity produced by the wind farm using the average wind speed data for each location. Based on the Betz momentum theory the amount of mechanical energy that can be extracted from a free stream airflow by an energy convertor is limited to around 59% of E using the equation below:

$$E = \left(\frac{1}{2}\right) A\rho v^3 t$$

   Where A designates the swept area of the rotor ($A = \pi r^2$), ρ represents the air density, v is the average wind speed, and t is the time.

   Since an important goal of the wind farm is to maximize its electricity production, this parameter is chosen as an output.
3) Water depth: In order to take better advantage of energy resources at sea, the offshore wind industry is developing wind turbine concepts for deployments in deeper waters. Some offshore wind projects are now planned for instalment in water depths up to 50 m, which require a shift from the monopile foundation (which are used in about 96% of the presently commissioned wind farms) to novel foundation types such as floating structures [31]. The ability to produce energy efficiently at greater water depths is seen as a positive development and this parameter is therefore used in this analysis as an output.

The suitable number of inputs and outputs with relation to the number of DMUs is amongst the debated topics within the DEA literature. Banker et al. [21] suggest that the number of DMUs should be at least three times the number of inputs and outputs while [32] suggest that the number of DMUs should be two times greater the combined number of inputs and outputs, however this rule may not be imperative [22]. They point out that while in statistical regression analysis, the sample size can be a critical issue as it tries to estimate the average behaviour of a set of DMUs, DEA focuses on individual DMU performance. In that sense the number of DMUs under evaluation may be immaterial. For this analysis a combined number of 7 inputs and outputs and 71 DMUs are considered, which comfortably meets the suggested rules of [21] and [32].

3.2 Data description

It is suggested that for the DEA analysis a mixture of raw data (e.g. revenue, number of employees) and percentile/ratio data (e.g. returns on investment, profit per employee) can be used simultaneously [22]. The type of data used for this DEA analysis is raw data and none of the inputs or outputs have an equal value across all DMUs. The data related to the inputs and outputs has been retrieved from the literature [33], [10], and publically available data sources including online resources [24],[25]. The sample consists of 71 operational and in construction offshore wind farms and excludes any demonstration wind farms. The statistical description of the input and output data used for this analysis is described below in Table 2.

Parameters		Median	Min	Max	Standard deviation
x_1	Number of turbines	60	6	175	37
x_2	Cost(£ million/MW)	5.96	2.77	11.44	1.79
x_3	Distance to shore (1-5)	3.00	1	5	1.44
x_4	Area(km^2)	33.00	2	407	59.55
y_1	Connectivity(km)	80.25	6.45	250	66.77
y_2	Generated electricity (GWh)	977.67	48.12	5289	943.036
y_3	Water Depth(m)	19	2.5	42.5	10.006

Table 2: statistical summary of inputs and outputs

3.3 DEA Results and discussion

Tables 3 shows the result of the CCR DEA analysis of 71 offshore wind farms across five countries: United Kingdom, Germany, Denmark, Netherlands and Belgium. The table presents the efficiency scores for the wind farms and the reference set, i.e. the set of efficient units from which the inefficiency of non-efficient units is determined.

Wind Farms		Efficiency	Ref Set
1	Scroby Sands	0.84	3;4;31;44;
2	North Hoyle	0.89	3;4;31;58;
3	Kentish Flats	1.00	3
4	Burbo Bank	1.00	4
5	Burbo Bank Extension	1.00	5
6	Beatrice	0.92	12;44;58;
7	Hornsea project 1	1.00	7
8	East Anglia 1	1.00	8
9	Dudgeon	0.78	4;5;7;44;
10	Rampion	0.83	3;42;44;58;
11	Galloper	0.90	5;44;55;
12	Walney Extension	1.00	12
13	Walney Phase 1	0.79	44;47;49;58;66;
14	Walney Phase 2	0.79	4;31;44;49;58;
15	Race bank	1.00	15
16	Lincs	0.64	4;44;62;66;
17	London Array	0.99	3;7;62;
18	Lynn	0.87	4;31;44;49;66;
19	Teeside	0.75	44;48;49;66;
20	Thanet	0.74	3;4;31;44;58;
21	Sheringham Shoal	0.76	31;44;58;66;
22	Rhyl Flats	0.75	4;31;44;49;
23	Robin Rigg	0.62	3;12;44;62;
24	Ormonde	0.95	44;47;49;58;66;
25	Westermost rough	0.94	4;5;44;49;66;
26	West of duddon sands	0.79	3;4;44;62;
27	Gwynt y Mor	0.95	3;12;44;62;
28	Gunfleet Sands	0.65	4;44;62;66;
29	Greater Gabbard	0.74	3;4;7;12;62;
30	Humber Gateway	0.74	4;44;62;66;
31	Barrow	1.00	31
32	Amrumbank West	0.85	44;48;54;66;
33	Bard Offshore 1	1.00	33

34	Butendiek	0.80	44;54;62;66;
35	EN BW Baltic 1	0.76	44;47;49;58;66;
36	EN BW Baltic 2	0.92	44;47;49;66;
37	Dantysk	0.75	8;44;47;48;62;66;
38	Global Tech 1	1.00	38
39	Riffgat	0.93	48;49;54;66;
40	Sand bank	0.81	44;48;62;66;
41	Trianel windpark Borkum	1.00	41
42	Arkona	1.00	42
43	Borkum Riffgrunde 1	0.87	44;47;48;49;66;
44	Borkum Riffgrund 2	1.00	44
45	Merkur	0.90	7;44;47;50;66;71;
46	Nordergrunde	0.81	5;44;55;66;
47	Wikinger	1.00	47
48	Veja mate	1.00	48
49	Alpha Ventus	1.00	49
50	Nordsee One	1.00	50
51	Meerwind sud/ost	0.82	44;47;48;49;66;
52	Belwind	0.79	44;47;49;66;
53	Nobelwind	0.87	44;47;49;66;
54	Northwind	1.00	54
55	Thornton Bank 1	1.00	55
56	Thonton Bank 2	0.87	4;5;44;49;
57	Thornton Bank 3	0.81	44;49;55;66;
58	Rentel	1.00	58
59	Norther	0.84	12;31;44;58;
60	Egmond aan Zee	0.87	4;31;49;58;66;
61	Eneco Luchterduinen	0.92	31;49;58;66;
62	Gemini	1.00	62
63	Prinses Amalia	0.84	49;54;66;
64	Westermeerwind	0.73	3;4;7;62;
65	Anholt	0.71	3;7;12;62;
66	Middlegrunden	1.00	66
67	Rodsand 2	0.91	4;7;44;66;69;
68	Horns Rev 3	0.96	3;7;12;44;
69	Horns Rev 1	1.00	69
70	Nysted	0.47	4;31;44;66;
71	Horns Rev2	1.00	71

Table 3: Efficiency score of offshore wind farms

Table 4 and Figure 1 show the dominant wind farms with the highest frequency in the reference set. For instance, the first row in Table 4 shows that wind farm (Kentish Flat) appears as a reference point for 13 other wind farms (self-references are excluded). On a country level, Germany has the highest total reference set occurrences of any individual country. However, each country has a non-negligible number of reference set occurrences, as shown in Table 5. This is perhaps unsurprising given the communality of development of the European wind sector, with key manufacturing and operational stakeholders operating across the region. The shared experiential knowledge is also facilitated by Pan-European research funding and active industry bodies, which hold regular conferences and events. Nevertheless, an individual variance of efficiency can be seen within each country in Table 3. This implies that further sharing of good practice can still take within the sector in order to improve efficiency. There are several offshore wind farms across the region that feature particularly frequently in the reference sets in Table 4 and Figure 1. In this category, the three most dominating wind farms belong to Germany and Denmark, that appear as a reference for multiple, inefficient wind-farms across the whole set of countries with respect to the inputs and outputs considered. However, each country also contains at least one wind farm that dominates at least 10 other wind farms. It is hence recommended that further research takes place into the causal factors that are driving this efficiency at these wind farms on a case-by-case basis. Any factors that are not purely site or age dependent, such as logistical and operational practices, should be highlighted as good practice across the sector. The high level of German and Danish efficiency and high reference values are perhaps representative of the accumulated knowledge via a longer period of "learning through doing", as Denmark was a first mover in the general wind/offshore wind sector. The results of this paper confirm that German and Danish off-shore wind farms can still be looked to for highly efficient examples, although the other North-Western European countries also have their own examples. A further factor driving efficiency could be the location of component manufacturing facilities, a theme that is further discussed in Section 4.

Offshore wind farms	Country	Frequency
Kentish Flats	UK	13
Burbo Bank	UK	14
Burbo Bank Extension	UK	5
Hornsea 1	UK	8
East Anglia 1	UK	2
Walney Extension	UK	8
Race Bank	UK	1
Barrow	UK	12
Country total		**63**
Bard offshore 1	Germany	1
Trianel Wind Park	Germany	1
Arkona	Germany	2
Global Tech	Germany	1

Borkum Riffgrund 2	Germany	39
Wikinger	Germany	11
Veja mate	Germany	8
Alpha Ventus	Germany	20
Nordsee One	Germany	2
Country total		**85**
Thornton Bank 1	Belgium	4
Rentel	Belgium	10
North Wind	Belgium	5
Country total		**19**
Gemini	The Netherlands	14
Country total		**14**
Middlegrunden	Denmark	29
Horns Rev 2	Denmark	1
Horns Rev 1	Denmark	2
Country total		**32**

Table 4: reference set frequency of efficient wind farms

Figure 1 represents the reference set frequency information graphically corresponding to the frequency column of Table 4.

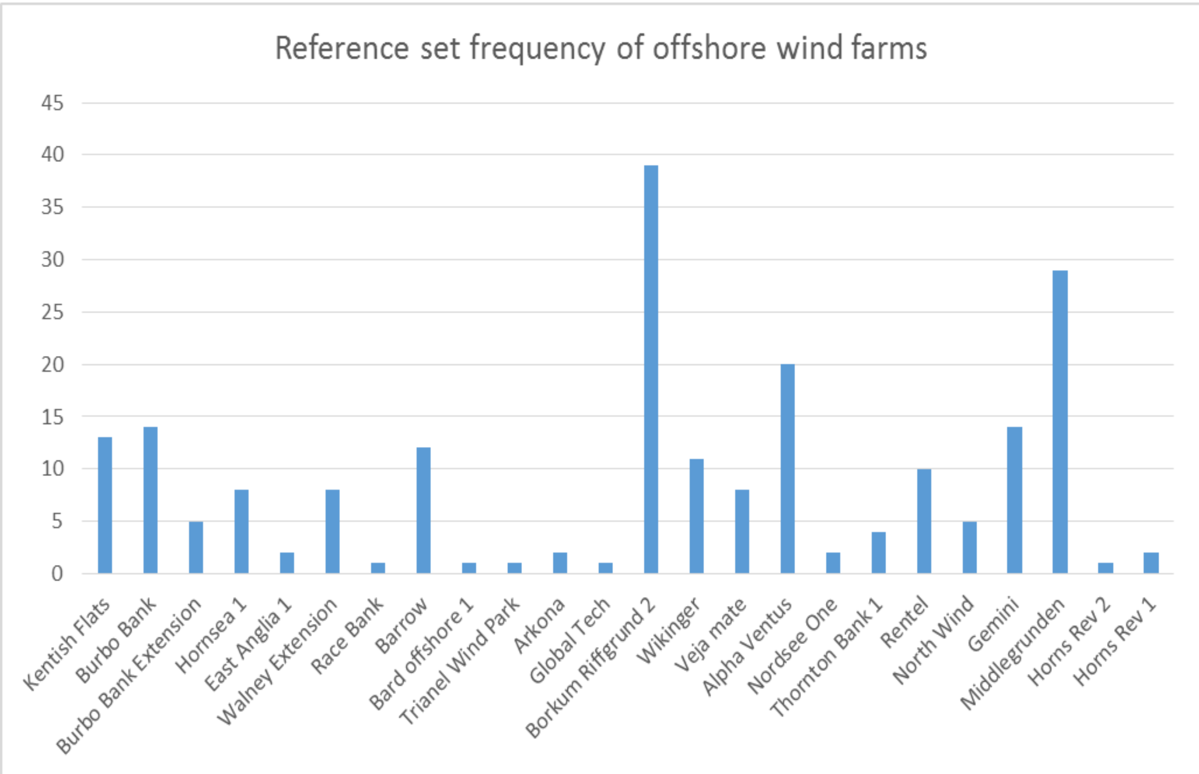

Figure 1: Reference Set frequency of Efficient Wind Farms

3.4 Statistical Analysis

It is important to determine whether the median efficiency rating of the wind farms located in different countries is significantly different. In order to conduct the test, three groups are created such that the wind farms located in Netherlands and Belgium form Group 1, Germany and Denmark form Group 2 and the wind farms located in the UK form Group 3. This categorization is done primarily because the number of wind farms in Netherlands, Belgium and Denmark are not large enough to be presented as an individual group for the Kruskal Wallis H test, hence these countries are grouped together (Belgium-Netherlands and Germany-Denmark) based on the geographical proximity and similarity, to form a group which is suitable for the statistical analysis using non-parametric tests [34]. In order to understand the distribution of the data, the Anderson-Darling test is conducted (Figure 2), which shows that the data is not normally distributed.

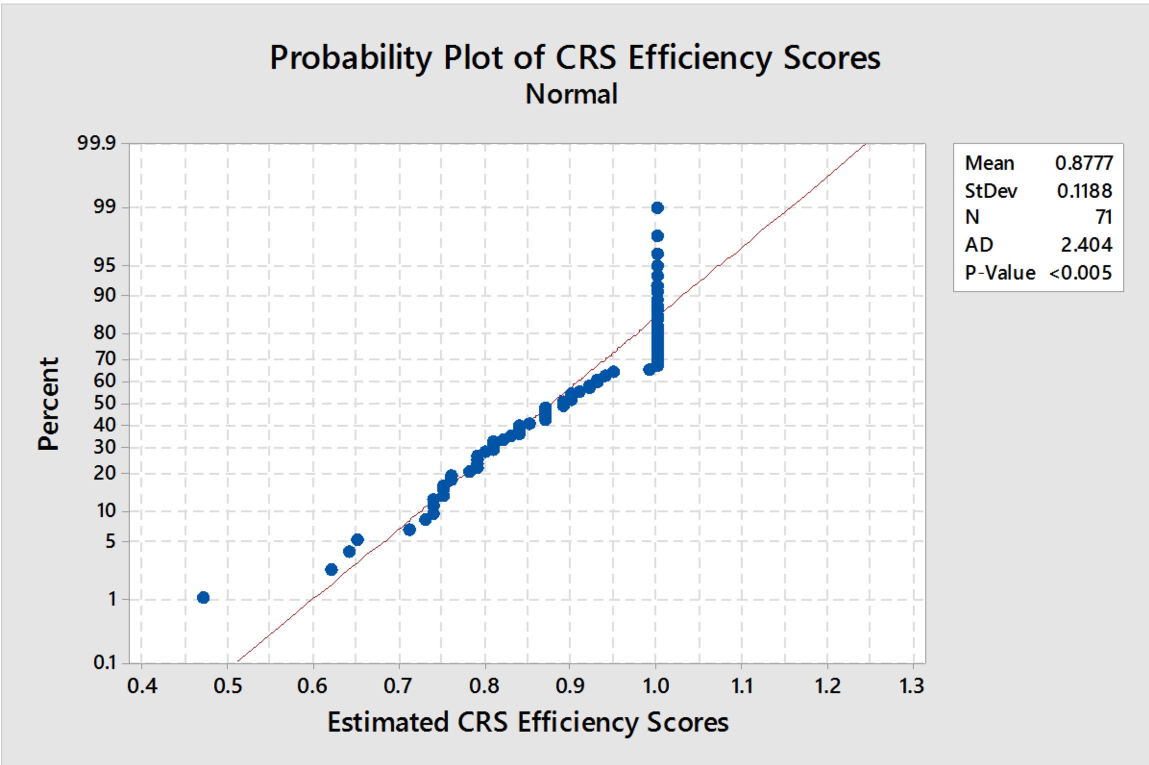

Figure 2: Anderson-Darling normality test of the DEA efficiency scores

The Kruskal-Wallis H test is conducted to understand if the median efficiency score of the countries are statistically significantly different from one another (i.e. whether the medians of two or more groups differ). The p-value is a probability that measures the evidence against the null hypothesis (i.e. the population medians are all equal) and lower probabilities provide stronger evidence against the null hypothesis. The DF (Degree of Freedom) is equal to n-1, where n represents the number of data groups, and the z-value indicates how the average rank for each group compares to the average rank of all observations, and the higher the absolute value, the further a group's average rank is from the overall average rank.

Country	N	Median	Average rank	Z
Belgium-Netherlands	13	0.87	36.4	0.08
Germany-Denmark	27	0.93	40.6	1.47
United Kingdom	31	0.87	31.8	-1.5
Overall	71		36	
H=2.72 DF=2 p-value=0.257				

Table 5: Kruskal-Wallis test for efficiency score vs country

The results in Table 5 show that there are no significant differences between the median efficiency score of the three country groups (p-value=0.257). Therefore, while the median efficiency scores are different, no statistically significant difference can be concluded from the data. This supports the rationale given in Section 3.3 of a connected north-western European offshore wind sector with a diffusion of expertise and knowledge across the region meaning that significant differences of efficiency, when considering the input and output factors of this study, do not appear.

It is noted that the UK offshore wind farms tend to be larger than their continental counterparts, which may be a factor that could give a potential efficiency advantage. However DEA is a relative rather than an absolute efficiency measurement technique, and hence concentrates on the level of output achieved (including electricity generated) per unit of input (including turbines and area). This effect could potentially diminish the role of an absolute measure of the size of the wind farm (e.g in GW) when determining efficiency. One possible hypothesis for the median efficiency score of UK being slightly, although not statistically, lower than that of the Germany-Denmark group is found in [35], which gives the location of the component manufacturers for European offshore wind farms as principally located in Germany and Denmark, with consequent longer and more complex supply chains to offshore wind farms in the UK. Although proving this hypothesis is beyond the scope of the DEA analysis in this paper, it is a plausible argument and in line with the DEA results that the longer UK supply chains are causing the slightly lower levels of efficiency at UK offshore wind farms.

3.5 Sensitivity analysis

A sensitivity analysis is conducted to determine the effects of the elimination of inputs $(x_1, \ldots, x_4)$and outputs $(y_1, \ldots, y_3)$ on the DEA efficiency scores. The efficiency scores are reported in Table 6, where Y = the variable is included, and N=the variable is removed from the model. In models 1,2,3 and 4 one of the input variables has been removed, and in models 5,6,7 one of the output variables has been removed at a time.

	Original model	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
x_1=No. of turbines	Y	N	Y	Y	Y	Y	Y	Y
x_2=Distance to shore	Y	Y	N	Y	Y	Y	Y	Y
x_3=Cost	Y	Y	Y	N	Y	Y	Y	Y
x_4=Area	Y	Y	Y	Y	N	Y	Y	Y
y_1=Electricity production	Y	Y	Y	Y	Y	N	Y	Y
y_2=Connectivity	Y	Y	Y	Y	Y	Y	N	Y
y_3=Water depth	Y	Y	Y	Y	Y	Y	Y	N
Average CCR efficiency score	0.87	0.85	0.85	0.75	0.8	0.74	0.79	0.64

Table 6: Sensitivity analysis results

The average efficiency score of the original model including all the inputs and output variables is higher compared to the other 7 models (0.87). This is to be expected as allowing the units more dimensions by which they can gain their efficiency, normally, results in a higher efficiency score, conversely removing a measure can result in a lower efficiency score. Removing the input related to cost, in model 3 results in the lowest average efficiency (0.75) and removing the water depth output leads to the lowest efficiency (0.64). The results of the sensitivity analysis shows that all the inputs and outputs, and especially the cost and the water depth have an effect on the efficiency score of the wind farms.

4 Conclusions

In this study the estimated efficiency of 71 offshore wind farms across five European countries including Germany, United Kingdom, Netherlands, Belgium and Denmark has been assessed using a DEA CCR method, and the reported average CCR efficiency score of the offshore wind farms is 87% . This cross European analysis is useful to understand the current state of the industry and shall provide a benchmark for future analysis as well as providing further insight on the factors affecting the efficiency of wind farms which is shown in the sensitivity analysis. Several offshore wind farms in Germany, and Denmark have been highlighted as dominating a range of wind farms across multiple North Western European countries. Further investigating of the properties of these wind farms is recommended on a case by case basis in order that the logistical and operational factors where good practice can be replicated are distinguished from non-replicable factors that are specific to those sites. Some offshore wind farms from the other nations on the other hand, do dominate a number of other wind farms across the region, but not at the level of the most highly efficient German and Danish farms. Further investigations are hence recommended into the distinct nature of German and Danish wind farms, again to assess the replicability of good practice.

The slightly higher, although not statistically significant, efficiency and high reference levels of the German wind farms is in part due to the relative input-output basis of the DEA analysis, but also has other potential underlying causes. This paper highlights one potential cause, the length and complexity of the component supply chains from the German-Danish base to the UK offshore wind farms. This applies to both the construction phases of future and the operational phase of current and future wind farms. At the time of writing, there is significant political uncertainty between the UK and the European Union that may affect future supply chains and hence the efficiency of future UK wind farms. Therefore, it is recommended that this aspect is monitored and mitigated as possible as political developments unfold. The general relationship between length of supply chains and efficiency of offshore wind farms is worthy of further investigation in other geographical regions, particularly where there exists a long distance between the component manufacturing base and the offshore wind farm locations. However, transferal to onshore wind farms is not possible due to the different operating conditions giving rise to some new inputs or outputs and removal of others.

The results of the DEA analysis show that the efficiency score is not evenly spread across the countries, however, the result of the statistical analysis shows that the median efficiency scores of the wind farms are not statistically different from one another and therefore wind farms show a relatively high average efficiency score across all the countries studied in this analysis.

The Offshore wind industry is an attractive and rapidly growing source of marine renewable energy and there is a need to assess the performance of this technology on a broad scale i.e. assessing as many decision making units as possible. This study offers a practical and holistic performance assessment to the offshore wind stakeholders and policy makers by including economic, environmental, technical and social inputs and outputs in the analysis.

4.1 Future research

In this analysis the CCR-DEA has been used, however, other DEA variants could be applied for a comparative study in which more comprehensive results could be drawn. Secondly, DEA is a descriptive analytical technique that allows decision makers to understand the relative level of efficiency of a set of units rather than providing prescriptive decision making suggestions. Whilst understanding the relative efficiency of offshore wind values is valuable, the authors also suggest that future research may focus on employing other descriptive methods, and providing recommendations on the prescriptive improvement actions to increase the efficiency of inefficient wind farms through the use of other multi-criteria decision making methods.

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5 Appendix

		Inputs				Outputs		
	Offshore wind farms	No.turbine	Social Impact	Area km^2	combined(million £ /MW)	annual energy production (GWh)	Connectivity	Water depth
1	Scroby Sands	30	5	4	3.25	142.4326	0.030186	5
2	North Hoyle	30	4	10	3.29	164.8836	0.033063	8.5
3	Kentish Flats	30	5	10	2.77	180.2663	0.049661	3.5
4	Burbo Bank	25	4	10	3.52	212.3322	0.063561	2.5
5	burbo bank extension	32	4	40	6.00	1166.521	0.04894	8.5
6	Beatrice	84	4	131	5.95	1477.845	0.007617	42.5
7	Hornsea project 1	174	1	407	5.40	5289.842	0.006887	30.5
8	East Anglia 1	102	1	205	6.20	3005.043	0.010766	35.5
9	Dudgeon	67	2	55	6.45	1798.595	0.014147	18
10	Rampion	116	4	79	6.24	1966.147	0.029577	29
11	Galloper	56	2	113	7.44	1855.832	0.010544	27
12	Walney extension	87	3	149	3.58	1530.626	0.019795	37
13	Walney Phase 1	51	4	28	6.49	793.8238	0.02503	21
14	Walney Phase 2	51	3	45	7.08	998.4333	0.02106	27
15	Race bank	91	2	62	5.54	2371.951	0.012837	15
16	Lincs	75	5	41	6.70	1202.676	0.01215	12
17	London array	175	3	122	6.86	3596.732	0.020775	11.5
18	Lynn	27	5	10	3.14	256.0966	0.012524	9
19	Teeside	27	5	4	6.20	281.0292	0.020247	12
20	Thanet	100	4	35	4.72	600.8877	0.023836	18.5
21	Sheringham	88	3	35	5.61	1125.632	0.017536	18.5

	shoal							
22	Rhyl flats	25	4	10	4.14	237.1265	0.022961	7.5
23	Robin Rigg	58	4	18	3.77	348.5148	0.01348	6
24	Ormonde	30	4	10	5.93	647.5133	0.025062	19
25	Westermost rough	35	4	35	5.65	933.457	0.031868	17
26	West of duddon sands	108	3	67	6.76	2114.329	0.029766	19
27	Gwynt y mor	160	4	68	4.91	1688.189	0.025198	22.5
28	Gunfleet sands	48	5	16	4.48	439.0244	0.0191	6.5
29	Greater Gabbard	140	2	146	5.98	2239.777	0.011171	20.5
30	Humber gateway	73	5	27	6.44	1029.778	0.023769	13.5
31	Barrow	30	5	10	3.56	265.3192	0.038863	14
32	Amrumbank west	80	1	33	6.51	1561.375	0.005701	22.5
33	Bard offshore	80	1	59	10.29	1735.606	0.00429	40
34	Butendiek	80	2	33	7.89	1566.17	0.004597	19.5
35	EN BW Baltic 1	21	4	7	6.22	134.739	0.014989	17.5
36	EN BW Baltic 2	80	2	30	6.84	1149.14	0.008387	31
37	Dantysk	80	1	66	7.15	1654.155	0.003985	25
38	Global tech 1	80	1	42	6.98	1583.224	0.004443	39.5
39	Riffgat	30	1	6	8.07	601.8295	0.005943	20.5
40	Sand bank	72	1	47	8.06	1811.052	0.003742	27.5
41	trianel windpark borkum	40	1	23	4.96	399.2861	0.00532	30
42	Arkona	60	2	39	4.14	1055.604	0.00669	24.5
43	borkum riffgrunde 1	78	1	36	6.27	1588.658	0.00562	26
44	Borkum Riffgrund 2	56	1	36	5.76	2130.341	0.005534	27
45	Merkur	66	1	39	5.73	1101.627	0.005476	30
46	Nordergrunde	18	4	3	6.04	407.8694	0.010706	7
47	wikinger	70	1	34	5.96	1175.707	0.006682	38
48	Veja mate	67	1	51	8.33	2329.999	0.00423	40
49	Alpha ventus	12	1	4	6.74	200.5886	0.005626	29
50	Nordsee One	54	1	35	5.21	1205.254	0.006043	28.5
51	Meerwind sud/ost	80	1	40	6.88	1561.375	0.006161	25.5
52	Belwind	55	1	13	5.71	676.9664	0.010679	16
53	nobelwind offshore wind farm	50	1	22	6.24	730.95	0.010817	26.5
54	North wind offshore wind farm	72	2	14	7.53	1392.785	0.007758	19
55	Thornton Bank 1	6	3	2	7.89	146.8953	0.012967	20
56	Thonton bank 2	30	3	12	4.56	734.4764	0.012997	13
57	Thornton Bank 3	18	3	7	9.88	333.3458	0.012885	16
58	Rentel	42	2	23	4.53	738.9227	0.012399	29
59	Norther	44	3	38	4.52	774.1095	0.013955	19.5
60	Egmond aan Zee	36	4	24	5.08	278.2169	0.042655	16.5
61	Eneco	43	3	16	4.83	400.1407	0.02845	20

	Luchterduinen							
62	Gemini	150	1	70	7.54	3640.003	0.006981	33
63	Prinses Amalia	60	3	17	11.44	558.3359	0.027681	21.5
64	Westermeerwin d	48	3	16	3.63	414	0.017857	5
65	Anholt	111	3	116	5.00	1589.021	0.012744	15.5
66	Middlegrunden	20	1	10	10.63	48.12018	0.154921	4.5
67	Rodsand 2	90	1	34	3.60	577.453	0.007085	9
68	Horns Rev 3	49	3	144	3.47	977.6694	0.006063	15.5
69	Horns Rev 1	80	1	21	3.16	379.8203	0.006031	8.5
70	Nysted	72	5	26	5.02	359.1439	0.007334	7.5
71	Horns Rev2	91	1	33	3.43	583.8692	0.005709	13