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The Efficiency of Offshore Wind Energy Companies in the European Countries: A DEA Approach

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Abstract: Considering environmental issues such as greenhouse gas emissions associated with climate change and the depletion of fossil fuels, one of the possible solutions is the use of renewable energy sources. Wind energy is one of the most competitive and resilient energy sources in the world, which can play an important role in accelerating the global transition to green energy. The purpose of this study is to evaluate the allocative efficiency of 47 offshore wind energy companies in 9 European countries using the input-oriented BCC DEA model. The basic hypothesis is that by evaluating the relative efficiency of offshore wind energy companies in European countries, it is possible to determine a correlation between the results of efficiency between the two observed periods with slight deviations. The empirical results show no significant correlation between the score of relative efficiency and the country where the offshore wind energy company is located. On the other hand, the results are consistent with the basic hypothesis of this study. From the management perspective, significant improvements in all financial variables, i.e., tangible fixed assets, cash and cash equivalents, and current assets, are required to achieve relative efficiency. The model variables refer to the economic characteristics of offshore wind energy companies, indicating that only allocative efficiency was analysed, which is in contrast to previous studies.

Keywords: 47 offshore wind energy companies; electricity generation; assessment of allocative efficiency; nine European countries; input-oriented BCC DEA model

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Citation: Maradin, D.; Olgić Draženović, B.; Čegar, S. The Efficiency of Offshore Wind Energy Companies in the European Countries: A DEA Approach. *Energies* **2023**, *16*, 3709. https://doi.org/10.3390/en16093709

Academic Editor: Antonio Crespo

Received: 21 March 2023
Revised: 8 April 2023
Accepted: 23 April 2023
Published: 26 April 2023

1. Introduction

Greenhouse gas emissions associated with climate change and the depletion of fossil fuels have become one of the greatest challenges in the world. Considering these environmental issues, one of the possible solutions is the use of renewable energy sources. Renewable energy, apart from leaving open the possibility of using fossil fuels in the future, contributes significantly to the environmental aspect of sustainability. It is noted that renewable energy sources that use indigenous resources have the potential to provide energy services with zero or near-zero emissions of air pollutants and greenhouse gases [1]. Renewable energy sources can be considered additional forms of energy alongside existing conventional (fossil) power plants and will become even more important in the future [2]. Modern or new renewable energy sources (including small hydropower plants or modern biomass plants) emphasise sustainability and environmental preservation. Although investments in modern renewables are significant, they accounted for 12.6% of total final energy consumption in 2020 [3]. Wind energy also accounts for only a small share of global energy consumption, despite its widespread deployment. Nevertheless, the global penetration of wind energy is increasing, and its installed capacity has grown exponentially, i.e., it has almost quadrupled in the last decade [4]. In addition, technological innovation and economies of scale have established wind energy as one of the most competitive and resilient energy sources in the world. Compared to other renewable energy sources, wind energy has low maintenance costs. Further, achieving net-zero emissions requires various actions across a wide range of sectors. Wind energy can be one of the cornerstones of green recovery and play an important role in accelerating the global green energy transition [5]. Currently, the total global wind energy capacity is up to 837 GW and helps the world avoid over 1.2 billion tonnes of CO_2 annually, equivalent to the annual carbon emissions of South America [6]. Rapid progress in wind turbine installation is expected to continue in the future. Offshore wind energy is characterised by its sustainability and cleanliness and is one of the fastest-growing renewable energy sources in recent years [7]. It should be noted that offshore wind will be a key driver of the global energy transition towards climate change, with some industry stakeholders calling for an installed offshore wind capacity of over 1400 GW by 2050 [8]. To achieve this goal, the development of floating offshore wind will be pursued to deploy turbines in deeper waters and unlock up to 10 times more offshore wind resources than are possible with fixed-bottom turbines alone.

In the analysis of renewable energy, the focus is on the economic attributes and the evaluation of social and environmental impacts [9]. To ensure the development of the wind energy sector, it is necessary to pay attention to the management performance of wind energy companies. Therefore, the performance evaluation of different wind energy companies is crucial for the improvement of the energy sector. In this research, the measurement and assessment of offshore wind energy companies are carried out. It should be noted that the companies operate under the same conditions to evaluate their performance for business improvement. This means that all offshore wind energy companies generate electricity solely by using wind energy. This is one of the main assumptions of the Data Envelopment Analysis (DEA) method used in this study to determine relative efficiency. This nonparametric method has become one of the most widely used approaches to measuring and evaluating different power plants or energy companies. In view of the above, the basic hypothesis of this study is as follows: by evaluating the relative efficiency of offshore wind energy companies in European countries, it is possible to determine a correlation between the results of efficiency between the two observed periods with slight deviations.

This study makes the following specific contributions to previous literature:

- Existing offshore wind energy performance studies have focused on the technical and comprehensive characteristics of offshore wind farms. With the exception of one study evaluating capital and operating cost efficiency, the model variables in this study relate to the economic characteristics of offshore wind energy companies, meaning that only allocative (cost) efficiency was analysed.
- To the best of the authors' knowledge, there is only one study to date that incorporates both DEA models (CCR and BCC models) in the evaluation of offshore wind energy companies. This study also applied the two basic DEA models, and in choosing a model to measure and interpret relative efficiency, the BBC model was found to be more appropriate.
- Unlike previous research, the paper provides insight into the average number of projections or improvements that can make relatively inefficient offshore wind energy companies relatively efficient.

2. Literature Review

Many studies have been conducted to evaluate the relative efficiency of the power sector using the DEA methodology. In addition to electricity generation, the literature also includes measurements and evaluations of other electric power activities. It refers to electricity transmission [10], electricity distribution [11], and the electricity supply industry [12]. Färe, Grosskopf, and Logan [13] were the first researchers to use the DEA methodology in electricity generation and evaluated the relative efficiency of electric utilities in the state of Illinois between 1975 and 1979. Since then, many studies have provided a comprehensive review of the application of DEA models in the power industry (e.g., [14,15]).

With regard to the evaluation of the relative efficiency of offshore wind energy companies, which is the subject of this study, there has been an increasing number of relevant studies in recent years.

Using the super-efficiency DEA method and the Tobit regression model, Yi-Chia et al. [16] investigated the factors affecting the environmental performance of offshore wind energy companies based on cross-sectional data from seven locations in Taiwan in 2019. The results suggest that the performance value could be further increased by improving the factors affecting efficiency. These factors included the age of the company, the number of internal committees, the number of shareholders, the amount of research and development, ISO 45,001, government policies, the quality of personnel, and wind speed. Wpd Taiwan Energy Co. had the best environmental performance, while Copenhagen Infrastructure Partners Association had the lowest efficiency score.

Benini and Cattani [17] measure the long-run capacity of offshore wind farms and estimate the technical efficiency of 26 offshore wind farms over a 13-year period using a fully parametric model and a semiparametric Stochastic Frontier Analysis (SFA) method. This allows production factors to have a nonlinear effect on the amount of electricity generated. Next, the estimated technical efficiency is regressed against the age of the offshore wind farms, taking into account technological change in the wind energy industry, to determine the resilience of technical efficiency to ageing. As explained in the methodology section, this is necessary because technical efficiency does not support technological change in the observed Decision Making Units (DMUs). The results show that technical efficiency ranges from 83% to 98% and does not decrease with age. The results suggest that offshore wind farms can be a long-term solution for the energy transition.

Akbari, Jones, and Treloar [18] evaluate the relative efficiency of 71 offshore wind farms in 5 northwestern European countries (the United Kingdom, Germany, Denmark, the Netherlands, and Belgium) using the DEA method, a Charnes-Cooper-Rhodes model (CCR model). This is in contrast to this study, where both the CCR and the additional Banker-Charnes-Cooper model (BCC model) are applied. The number of turbines, cost, distance to the coast, and area of wind farms are chosen as inputs, while connectivity to population centres, electricity generated, and water depth are considered outputs. The results of the analysis of the DEA show the following: (I) several offshore wind farms in Germany and Denmark were highlighted as dominant in the selected sample; (II) the average CCR efficiency score of all offshore wind farms is 87%; (III) the efficiency score is not evenly distributed across countries; and (IV) the result of the statistical analysis shows that the median efficiency scores of the wind farms are not statistically different from each other and therefore the wind farms have a relatively high average efficiency score across all countries studied in this analysis. Finally, the study provides offshore wind stakeholders and policymakers with a practical and holistic performance assessment by including economic, environmental, technical, and social inputs and outputs in the analysis.

Ederer [19] analysed the relative performance of offshore wind farms in terms of costs by using the two basic DEA models (CCR and BCC models) and scale efficiency. The analysis was divided into a static model to evaluate capital cost efficiency, which refers to all one-time expenditures associated with the development and installation until the acquisition of an offshore wind farm, and a dynamic model to examine operating cost efficiency, which refers to all annualised expenditures incurred after the date of acquisition until the decommissioning of an offshore wind farm. For the assessment of capital cost efficiency (specific capital cost is considered as input and installed capacity, distance to shore, and water depth are outputs), 22 observations, i.e., 22 offshore wind farms in selected European countries, were included, and for operating cost efficiency (specific operating cost is the input and installed capacity, distance to the port of operation, energy performance, and availability are outputs), 26 observations, i.e., 7 offshore wind farms, were included. The learning-by-doing rate for capital cost efficiency shows that efficiency increases with accumulated experience. Furthermore, the Tobit regression used in the study shows increasing capital cost efficiency as a function of time and decreasing operating cost efficiency as a function of year of operation.

Additionally, in analysing the offshore wind potential on the Atlantic and Mediterranean coasts of Morocco, Daoudi et al. [20] listed 14 offshore wind farm sites and classified them based on 6 criteria to prioritise their suitability for a wind farm. The most important criterion is the wind power density calculated with the Weibull distribution function over the period of 2016–2020. Through a dynamic and static study, the application of the new approach based on the DEA method revealed favourable sites with high potential for offshore energy generation.

On the other hand, several studies on onshore wind energy can be found in the literature where relative efficiency is measured and evaluated. Of note is a study in which Maradin, Cerović, and Šegota [21], using the DEA methodology, analysed the evaluation of the relative efficiency of electricity generation of 78 onshore wind power companies in 12 selected European countries, identifying the factors that improve the efficiency of the companies. To the authors' knowledge, this was the first study to analyse the comprehensive performance of onshore wind power companies, including their economic and technical characteristics. In addition, the paper provided insight into the modified form of the Cobb-Douglas production function (inputs of capital and fuel were used to produce outputs instead of labour and capital) in evaluating the efficiency of an onshore wind power company. Iglesias, Castellanos, and Seijas [22] evaluated only the productive efficiency of 57 onshore wind farms in Spain (Galicia region) during the period of 2001–2004 using the frontier methods of the DEA and SFA. The results show no significant changes in the annual efficiency scores for each observed wind farm. Ertek, Tunç, Kurtaraner, and Kebude [23] present a data-centric analysis of 74 commercial onshore wind turbines from leading manufacturers in the world. Among other methods, they provide benchmarking through the two DEA models to evaluate technical efficiency. Pestana Barros and Sequeira Antunes [24] evaluate the technical efficiency of 65 onshore wind farms in Portugal during the period of 2004–2008 using stochastic production econometric frontier models, considering ownership and unobserved managerial ability as factors affecting wind farm performance. Starting from the fact that the existing studies only measure the technical (productive) efficiency of onshore wind farms in one country (with the exception of the study by [21]), this research goes one step further and analyses the other approach, i.e., the allocative efficiency of offshore wind energy companies in nine European countries.

Finally, various studies can be found that address the following offshore issues: (I) a systematic literature review on the methods and theories used in decision-making for offshore wind power investment, followed by the characteristics, applicability of different methods, and discussion of representative literature during the period of 2010–2020 [7]; (II) the use of policy instruments and deployment of offshore wind power in the North Sea, viz., in Denmark, the United Kingdom, Germany, and the Netherlands between 1990 and 2020 [25]; (III) the proposed guidelines and policy implications in environmental licencing for offshore wind projects for new markets based on the research cases in the United Kingdom, Germany, Denmark, and Taiwan [26]; (IV) the analysis of the different approaches of Europe, China, and the United States to the development of the offshore wind energy industry [27]; (V) a new multi-attribute decision-making model to be applied to the location selection of offshore wind power stations [28]; (VI) the accuracy of wind speed distribution and compares offshore wind turbine performance predictions in Australia using three international reanalysis datasets: BARRA, ERA5, and MERRA-2 [29]; (VII) the development of an integrated offshore wind and wave energy system that could be one of the best solutions for the future of the ocean energy sector and the energy transition [30]. In the study of the development of the onshore wind energy market in the European Union, Germany and Spain are considered the main gross producers of electricity from wind energy in the EU. The study concludes that the cumulative installed wind power capacity will increase in most EU countries, highlighting that the highest growth will be in Croatia in 2022 [31]. Another study provides a comprehensive overview of the state of wind energy in terms of status, potential, and policy analyses and assessments, as well as recommendations for increasing the installed capacity of wind power [32]. In addition, there are studies that address climate change and its impact on the dynamic behaviour of an offshore wind turbine [33]; a review of the technical aspects of wind farm development, including the impact of offshore wind turbines and hybrid energy technologies [34]; analysing the positive and negative economic effects of renewable energy technologies [35]; or presenting the advantages and disadvantages of renewable energy sources in general without considering a single type of renewable energy [36].

3. Methodology

3.1. Data Envelopment Analysis Approach

DEA is a widely used method for calculating the relative efficiency of numerous DMUs operating under similar conditions. It is a type of nonparametric comparative performance analysis in which it is assumed that there are n DMUs to be evaluated, and not all DMUs are efficient. These DMUs convert multiple inputs to multiple outputs, so it is not possible (or we do not know) to develop a functional form, a relationship between them, but requires verification of the positive correlation between inputs and outputs. In other words, it is assumed that the increase in input influences the increase in output. DEA is based on mathematical programming and evaluates the efficiency of a DMU relative to a set of comparable DMUs. DEA forms an efficiency frontier, using efficient units as the standard for the best possible performance. DMUs that are not relatively efficient are below the efficiency frontier, and DEA then measures the amount of inefficiency (distance from the efficiency frontier) of inefficient units while making comparisons to the units with the best practices. DEA also provides a way for inefficient DMUs to reach an efficiency frontier based on projections, such as potential changes in inputs or outputs. When assessing relative efficiency using the DEA method, an input- or output-oriented DEA model can be assumed. Therefore, efficiency can indicate a certain/fixed level of output with a minimum level of inputs or the maximisation of output with the existing level of inputs. The methodology can be particularly useful in complex situations where there are numerous DMUs with multiple outputs and inputs that cannot be analysed using other techniques that may be too complicated for management decision-making purposes. For this reason, the DEA methodology is an interdisciplinary scientific method applied in various fields, such as financial institutions or the banking sector [37], schools, universities, hospitals, shopping centres, hotels, business units in forestry, municipal utilities, energy sector at the national level [38] and others.

Due to the limitations of the DEA method, it is important to emphasise that the minimum number of DMUs should be three times greater than or equal to the sum of the number of inputs and outputs. On the other hand, one of the advantages of the DEA method over traditional nonparametric methods is the use of multiple inputs and outputs that can be expressed in different units of measurement. The inputs represent the resources used, while the outputs represent the results obtained, their selection reflecting the interest of the analysts using the DEA method. In this study, inputs and outputs are expressed in U.S. dollars (USD), which represents the allocative (cost) efficiency of offshore wind energy companies. In fact, the relative efficiency of the studied companies is fully evaluated in monetary units, which is in contrast to previous studies where mostly only technical (production) efficiency was evaluated. According to Farrell [39], "technical efficiency of a firm means its success in producing as large an output as possible from a given set of inputs, while allocative efficiency (the original Farrell term is price efficiency) means that a firm uses the various factors of production in the best proportions, in view of their prices. The overall efficiency of the firm is equal to the product of the technical and price efficiencies."

3.1.1. CCR Model

One of the basic DEA models is the CCR model, which is based on the assumption of constant returns to scale (CRS) and whose efficiency is defined as the ratio of output to input, with higher output per unit of input reflecting greater efficiency [40]. Suppose there are n DMUs that convert m inputs $(x_i, i = 1, 2, \ldots, m)$ into s outputs $(y_r, r = 1, 2, \ldots, s)$. The idea of the CCR model is to form virtual inputs $(v_1 x_{1o} + \ldots + v_m x_{mo})$ and virtual outputs $(u_1 y_{1o} + \ldots + u_s y_{so})$ for each DMU$_j$ included in the analysis using the output weights $(u_r)(r = 1, \ldots, s)$ and input weights (v_i) $(i = 1, \ldots, m)$ and solve the following fractional programming problem [41].

Model 1

$$\max_{v,u} \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \ldots + u_s y_{so}}{v_1 x_{1o} + v_2 x_{2o} + \ldots v_m x_{mo}} \tag{1}$$

subject to:

$$\frac{u_1 y_{1j} + \ldots + u_s y_{sj}}{v_1 x_{1j} + \ldots v_m x_{mj}} \leq 1 \qquad (\mathrm{j} = 1, \ldots, n) \tag{2}$$

$$v_1, v_2, \ldots, v_m \geq 0 \tag{3}$$

$$u_1, u_2, \ldots, u_s \geq 0 \tag{4}$$

The optimal values for the weights (u_r) $(r = 1, \ldots, s)$and (v_i) $(i = 1, \ldots, m)$ are obtained from the CCR model for each DMU and determined from the output and input data of all DMUs in the peer group of the data. The constraints (2) mean that the maximum value of the objective function θ is equal to or less than 1, or that the maximum efficiency result of the DMU under consideration can be 100%. This model can be rewritten as follows [42]:

Model 2

$$\max \quad \theta = \sum_{r=1}^{s} u_r y_{ro} \tag{5}$$

subject to:

$$\sum_{r=1}^{s} u_r y_{rj} \leq \sum_{i=1}^{m} v_i x_{ij} \quad (j = 1, \ldots, n) \tag{6}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{7}$$

$$v_1, v_2, \ldots, v_m \geq 0 \tag{8}$$

$$u_1, u_2, \ldots, u_s \geq 0 \tag{9}$$

Model 3 represents an input-oriented CCR model that determines optimal slack values to reach the efficiency frontier.

Model 3

$$\text{Min} \quad \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{10}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad (i = 1, \ldots, m) \tag{11}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad (r = 1, \ldots, s) \tag{12}$$

$$\lambda_j \geq 0 \quad (j = 1, \ldots, n) \tag{13}$$

The ε in the objective function is not Archimedean as infinitely small or smaller than any real positive number. If an optimal solution $(\theta^*, \lambda^*, s^{-*}, s^{+*})$satisfies $\theta^* = 1$, λ= 1, input slacks $s^{-*} = 0$,and output slacks $s^{+*} = 0$, then DMU$_o$ (DMU under consideration) is relatively efficient [41] and is on the efficiency frontier. Otherwise, it is relatively inefficient and lies below the efficiency frontier. The input-oriented Model 3 optimises the slack values to achieve the efficiency frontier, called projections (target values) on the efficiency frontier, which can be calculated as follows:

Inputs:

$$\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \ (i = 1, \ldots, m) \tag{14}$$

Outputs:

$$\widehat{y}_{ro} = y_{ro} + s_i^{+*} \ (r = 1, \ldots, s) \tag{15}$$

3.1.2. BCC Model

The BCC model is another commonly used DEA model based on the assumption of variable returns to scale (VRS) with a piecewise linear efficiency frontier [43]. It differs from the CCR model (Model 3) only in that it includes the convexity constraints:

$$\sum_{j=1}^{n} \lambda_j = 1, \lambda j \geq \ 0 \quad \forall j \tag{16}$$

Model 4 represents an input-oriented BCC model that obtains optimal slack values to achieve the piecewise linear efficiency frontier. Due to the difference in the efficiency frontier compared to the CCR model, the BCC efficiency scores are better than or at least the same as the CCR efficiency scores for all the DMUs studied compared to the CCR model. Therefore, it is very important to consider the type of returns to scale before evaluating the DMUs.

Model 4

$$\text{Min} \quad \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{17}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \quad (i = 1, \ldots, m) \tag{18}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad (r = 1, \ldots, s) \tag{19}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{20}$$

$$\lambda_j \geq 0 \quad (j = 1, \ldots, n) \tag{21}$$

$$s_i^- \geq 0 \tag{22}$$

$$s_r^+ \geq 0 \tag{23}$$

The definition of BCC efficiency [41] states that if the optimal solution of the BCC model $(\theta_B^*, \lambda^*, s^{-*}, s^{+*})$satisfies $\theta_B^* = 1$and $s^{-*} = 0, s^{+*} = 0$, the DMU_o is BCC efficient and lies on the efficiency frontier, otherwise the BCC is inefficient and lies below the efficiency frontier. As in the case of the CCR model, the projections for all inefficient DMUs can be calculated as follows.

Inputs:

$$\widehat{x}_{io} = \theta^* x_{io} - s_i^{-*} \quad (i = 1, \ldots, m) \tag{24}$$

Outputs:

$$\widehat{y}_{ro} = y_{ro} + s_i^{+*} \quad (r = 1, \ldots, s) \tag{25}$$

Figure 1 shows the graphical representation of the CCR and BCC models.

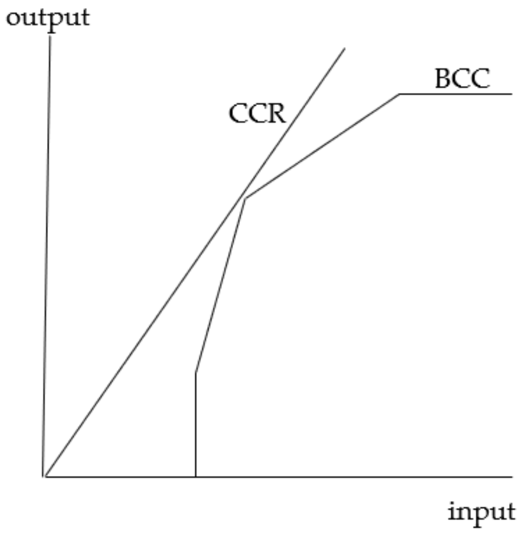

Figure 1. CCR and BCC models.

DEA models are based on the assumption that there is a set of admissible possibilities. This set is formed by all possible combinations of inputs and outputs and is bounded by so-called efficient frontiers. Efficient units are those whose combinations of inputs and outputs lie on the efficient frontier [44]. Inefficient units, on the other hand, lie below the efficient frontier.

3.2. Data and the Model

This study includes and analyses 47 offshore wind energy companies from 9 European countries, namely Belgium (number of offshore wind energy companies (n) in the sample = 2), Estonia (n = 1), Finland (n = 1), France (n = 4), Germany (n = 9), Poland (n = 1), Spain (n = 2), Sweden (n = 2), and the United Kingdom of Great Britain and Northern Ireland (n = 25). Offshore wind energy companies were selected for the research sample based on the availability of data from the relevant database ("Orbis Europe"). Only those companies that exclusively use wind energy (and supply to the electricity grid) to generate electrical energy were included in the sample. This is the only activity of the studied companies, so the companies that generate electrical energy from different energy sources are excluded from the sample. In this way, one of the basic assumptions of the DEA method, that the companies are comparable among themselves and operate under similar conditions, is fulfilled (cf. [45]). The inputs and output of the model are determined and presented with the following variables:

Inputs:

1. Tangible fixed assets refer to the value of wind turbines owned by a company (expressed in thousands of USD);
2. Cash and cash equivalent refer to total cash liquid assets (expressed in thousands of USD);
3. Current assets refer to the total amount of short-term assets owned by a company (expressed in thousands of USD).

Output:

1. EBIT (Earnings Before Interest and Taxes) refers to earnings before interest and taxes and is a measure of a company's profitability that includes all revenues and expenses except interest and tax expenses (expressed in thousands of USD).

The model variables presented refer to the economic characteristics of offshore wind energy companies, which means that only allocative (cost) efficiency was analysed. Tangible fixed assets are the value of offshore wind turbines (in addition to other forms of tangible fixed assets, such as real estate, equipment, land, and others). Although tangible fixed assets are used in business operations over a long period of time, this study evaluates the contribution of property to business efficiency only for the period of the observed years. Cash and cash equivalents of offshore wind energy companies refer to highly liquid short-term assets of a company. In this study, it is reported as a separate variable because of its importance in determining relative efficiency or inefficiency. Another important input variable with relevant economic value is current assets, which refer to short-term assets that an offshore wind energy company expects to use up, convert to cash, or sell within one year or one operating cycle. The variable EBIT is used as the only output of the model. This variable directly shows the success of the offshore wind energy company, i.e., its financial performance in the considered years 2019 and 2020. In addition to analysing profitability, EBIT can also be used to evaluate the relative efficiency of the company, as it eliminates the effects of financing decisions, statutory tax rates, and the application of different accounting principles. Considering only one (mentioned) quantitative variable does not allow a complete assessment of relative efficiency, as other qualitative variables and/or other quantitative variables on the output side are missing. The limitations of the analysis are thus acknowledged in the study, as the focus was on the assessment of allocative (cost) efficiency.

In the wind energy industry, the use of labour is not required once the company starts operations because it is a highly technologically automated industry. Studies show that for every 20 MW of installed capacity, only one or two full-time employees are required to operate and maintain the wind energy company. In addition to the theoretical basis, empirical studies show a very low correlation between labour input and other observed variables [21]. This is the reason why this study does not include labour input as one of the fundamental factors in production processes in the evaluation of relative allocative efficiency.

After selecting 3 inputs and 1 output variable in the model to evaluate the relative (allocative) efficiency of 47 offshore wind energy companies, the statistics of the observed variables used for the DEA method are summarized below (Table 1).

Table 1. Statistics of inputs and output in the DEA model for 2019 and 2020.

	Tangible Fixed Assets		Cash & Cash Equivalent		Current Assets		EBIT	
	2019	2020	2019	2020	2019	2020	2019	2020
Max	2,589,153	2,996,115	173,763	158,207	1,252,313	1,196,154	299,885	359,841
Min	10.07	9.58	0.07	0.03	3.71	6.28	89.56	23.21
Avg.	507,115	558,954	24,744	18,076	100,000	105,238	63,310	121,472
SD	644,258	722,453	43,253	30,816	221,661	220,461	60,259	71,735

Source: Authors' calculation evaluated by the Data Envelopment Analysis method using the software package DEA-Solver Professional Release 11.0.

Due to the fact that a number of wind energy companies generated a loss in the observed years (14 companies in 2019 and 13 companies in 2020) and are therefore not suitable for measuring relative efficiency, note that all values of the EBIT variable are increased for 26,100 monetary units (USD) in 2019 and 79,500 monetary units (USD) in 2020. This eliminates the negative value of the variable and allows evaluation of the relative efficiency of the positive values of the company, which is one of the important assumptions of the DEA methodology. It is possible to make data translation (shifting) without changing the efficiency frontier so that the classification of DMU entities as inefficient or efficient (due to the mentioned data transfer) is invariable or translation invariant [46]. Since negative values are not possible, in the mathematical programming of the DEA method, the value zero (0) is replaced by a very low positive value (10–8) with the same result of relative efficiency. When selecting suitable input and output variables, a positive correlation must be assumed, as shown in the following Table 2.

Table 2. Coefficients of inputs and output correlation in 2019.

	Tangible Fixed Assets	Cash & Cash Equivalent	Current Assets	EBIT
Tangible fixed assets	1	0.75345	0.43219	0.83128
Cash & cash equivalent	0.75345	1	0.56563	0.61764
Current assets	0.43219	0.56563	1	0.64641
EBIT	0.83128	0.61764	0.64641	1

Source: Authors' calculation.

The most important condition in the DEA methodology should be a positive correlation between inputs and outputs, as well as between mutual inputs and mutual outputs. Tables 2 and 3 show that all inputs and outputs have a positive correlation coefficient. In 2019, the coefficient between the tangible fixed asset input and the output of EBIT is the highest (0.83128), indicating a high correlation between the variables, i.e., an increase in assets increases the profit of the company. The same variables had the highest correlation (0.68774) between input and output in 2020.

Table 3. Coefficients of inputs and output correlation in 2020.

	Tangible Fixed Assets	Cash & Cash Equivalent	Current Assets	EBIT
Tangible fixed assets	1	0.7296	0.4884	0.68774
Cash & cash equivalent	0.7296	1	0.48178	0.34794
Current assets	0.4884	0.48178	1	0.4791
EBIT	0.68774	0.34794	0.4791	1

Source: Authors' calculation.

The DEA model can be used to evaluate relative efficiency in terms of CRS and VRS. Returns to scale can be expressed as the rate at which output increases when inputs are increased proportionally. In forming the DEA model, the next step in this research is to choose the appropriate DEA model considering the envelope, i.e., constant or variable returns to scale, and given the orientation towards input or output. Without a more detailed analysis, it is not possible to predict the performance of 47 offshore wind energy companies in terms of returns to scale. Therefore, it is necessary to measure and evaluate the relative efficiency using constant (Model 3) and variable (Model 4) returns to scale for the observed years. Finally, according to the results, whether CRS or VRS, is making a choice.

Table 4 shows the results of the relative efficiency of 47 offshore wind energy companies (DMUs) evaluated by the DEA method using the software package DEA-Solver Professional Release 11.0 and applying constant and variable returns to scale. The obtained results point out a significant difference and a significantly larger number of efficient (θ * = 1) companies (DMUs) evaluated with VRS, especially in 2019. In addition, the average efficiency score with variable returns is significantly higher than with constant returns for both 2019 and 2020, indicating that offshore wind energy companies operate with VRS. However, there is another argument for using VRS. It is argued that for a model with VRS, i.e., the BCC model, translational invariance is possible [46], as mentioned earlier.

Table 4. Relative efficiency with the use of constant and variable returns to scale.

	2019		2020	
Relative Efficiency Score	**CCR Model (CRS)**	**BCC Model (VRS)**	**CCR Model (CRS)**	**BCC Model (VRS)**
Number of efficient DMUs [1]	4	15	3	7
Number of inefficient DMUs	43	32	44	40
Average efficiency score	0.1619	0.546	0.148	0.4542
Max. efficiency score	1	1	1	1
Min. efficiency score	0	0.0001	0	0.0001

Source: Authors' calculation. [1] Because of the constraints in the software package, the number of fully efficient and weakly efficient entities with the highest efficiency score ($\theta^* = 1$) is shown.

The final selection of the DEA model is made by considering the orientation. In assessing relative efficiency, the DEA model can be oriented towards inputs or outputs. The input-oriented DEA model aims to minimise the values of inputs used for the same level of outputs, while the output-oriented DEA model maximises the possible values of outputs using the same values of inputs. In this research, the relative efficiency of offshore wind energy companies is presented based on the input-oriented DEA model. The main reason for choosing the input-oriented DEA model is to better interpret the results of this research. Moreover, the input-oriented DEA model with VRS (BCC model) is suitable for translation invariance in terms of output but not in terms of inputs [47]. This means that it is possible to transform the negative values of the output variables into positive values. As mentioned above, some offshore wind energy companies have made a loss (the negative value of the EBIT variable) in the observed years. By applying the translation invariance procedure, all values of the EBIT variable were increased by 26,100 monetary units (USD) in 2019 and 79,500 monetary units (USD) in 2020, thus transforming them into positive values. Due to the translation invariance, the efficiency frontier has not changed, i.e., the number of efficient DMUs remains the same despite the changed values of the EBIT variable.

4. Empirical Results

The relative efficiency of 47 offshore wind energy companies is evaluated using the input-oriented BCC model, which indicates variable returns to scale. Table 5 below shows the score and rank of the relative efficiency of 47 DMUs in 2019 and 2020, as well as the 9 countries they belong to.

Table 5 lists all 47 offshore wind energy companies (DMUs) classified into 2 groups: relatively efficient DMUs ($\theta^* = 1$) and relatively inefficient DMUs ($\theta^* < 1$). In assessing relative efficiency based on the 2019 data, 15 DMUs were found to be relatively efficient, while 32 DMUs were found to be relatively inefficient. Based on 2020 data, it can be seen that 7 companies (DMUs) were classified as relatively efficient, while 40 DMUs were classified as relatively inefficient. This can already be seen in Table 4, which shows the scores for relative efficiency.

As shown in Table 5, there is no significant relationship between the value of relative efficiency and the country where the offshore wind energy company is located. In other words, the results obtained by the model indicate that the relative efficiency of the offshore wind energy companies is not determined by external factors related to the specific circumstances in each country where the analysed offshore wind energy companies operate but by internal factors in the form of financial variables, i.e., tangible fixed assets, cash and cash equivalents, and current assets.

Table 5. Relative efficiency of 47 offshore wind energy companies (DMUs).

Rank (2019)	Score (2019)	DMUs	Country	Rank (2020)	Score (2020)
1	1	AMRUM-OFFSHORE WEST GMBH	Germany	1	1
1	1	AN AVEL BRAZ OFFSHORE	France	1	1
1	1	DUDGEON OFFSHORE WIND LIMITED	United Kingdom	1	1
1	1	GYM OFFSHORE ONE LIMITED	United Kingdom	1	1
1	1	INNER DOWSING WIND FARM LIMITED	United Kingdom	1	1
1	1	RWE BERGHEIM WINDPARKBETRIEBSGESELLSCHAFT MBH	Germany	1	1
1	1	GYM OFFSHORE TWO LIMITED	United Kingdom	10	0.9839
1	1	GYM OFFSHORE THREE LIMITED	United Kingdom	11	0.9216
1	1	BEATRICE OFFSHORE WINDFARM LIMITED	United Kingdom	18	0.4896
1	1	GODE WIND 1 OFFSHORE WIND FARM GMBH & CO. OHG	Germany	19	0.4777
1	1	GREATER GABBARD OFFSHORE WINDS LIMITED	United Kingdom	20	0.4678
1	1	GODE WIND 2 OFFSHORE WIND FARM P/S GMBH & CO. OHG	Germany	23	0.413
1	1	SEARENERGY OFFSHORE HOLDING GMBH & CIE. KG	Germany	29	0.2936
1	1	BARROW OFFSHORE WIND LIMITED	United Kingdom	31	0.2461
1	1	NEART NA GAOITHE OFFSHORE WIND LIMITED	United Kingdom	36	0.0991
16	0.9736	LYNN WIND FARM LIMITED	United Kingdom	9	0.9958
17	0.952	RWE RENEWABLES UK ROBIN RIGG EAST LIMITED	United Kingdom	12	0.891
18	0.7121	THANET OFFSHORE WIND LIMITED	United Kingdom	15	0.6423
19	0.6897	NORTH HOYLE WIND FARM LIMITED	United Kingdom	13	0.8752
20	0.6408	GLOBAL TECH I OFFSHORE WIND GMBH	Germany	24	0.3557
21	0.6205	SUURHIEKKA OFFSHORE OY	Finland	1	1
22	0.5911	RODSAND 2 OFFSHORE WIND FARM AB	Sweden	27	0.3309
23	0.5797	SCIRA OFFSHORE ENERGY LIMITED	United Kingdom	25	0.3409
24	0.5346	BORKUM RIFFGRUND 2 OFFSHORE WIND FARM GMBH & CO. OHG	Germany	22	0.4365
25	0.4681	ASPIRAVI OFFSHORE	Belgium	21	0.4563
26	0.4296	RWE RENEWABLES UK ROBIN RIGG WEST LIMITED	United Kingdom	17	0.5045
27	0.4208	ABERDEEN OFFSHORE WIND FARM LIMITED	United Kingdom	26	0.3328
28	0.4107	MEDITERRANEAN OFFSHORE WIND ENERGY SL	Spain	32	0.2196
29	0.3915	SVEA VIND OFFSHORE AB	Sweden	8	0.9999
30	0.3885	RAMPION OFFSHORE WIND LIMITED	United Kingdom	14	0.8676
31	0.3776	RWE RENEWABLES UK SCROBY SANDS LIMITED	United Kingdom	16	0.5604
32	0.3236	ASPIRAVI OFFSHORE II	Belgium	28	0.3141
33	0.3232	MERKUR OFFSHORE GMBH	Germany	33	0.2032
34	0.2424	WALNEY (UK) OFFSHORE WINDFARMS LIMITED	United Kingdom	34	0.1291
35	0.2135	BLYTH OFFSHORE DEMONSTRATOR LIMITED	United Kingdom	30	0.2466
36	0.1822	LINCS WIND FARM LIMITED	United Kingdom	35	0.119
37	0.1736	HIIUMAA OFFSHORE TUULEPARK OU	Estonia	37	0.0746
38	0.0064	PARC EOLIEN OFFSHORE DE PROVENCE GRAND LARGE	France	42	0.0016
39	0.0056	RWE OFFSHORE WIND POLAND SP. Z O.O.	Poland	41	0.0017
40	0.0041	MORAY OFFSHORE WINDFARM (WEST) LIMITED	United Kingdom	39	0.0067
41	0.0026	EAST ANGLIA OFFSHORE WIND LIMITED	United Kingdom	38	0.0389
42	0.002	OW OFFSHORE SL	Spain	44	0.0011
43	0.0018	EOLIENNES OFFSHORE DES HAUTES FALAISES	France	40	0.0054
44	0.001	KINCARDINE OFFSHORE WINDFARM LIMITED	United Kingdom	45	0.0009
45	0.0006	DOTI DEUTSCHE OFFSHORE- TESTFELD- UND INFRASTRUKTUR-GMBH & CO. KG	Germany	46	0.0007
45	0.0006	EOLIENNES OFFSHORE DU CALVADOS	France	43	0.0015
47	0.0001	MORAY OFFSHORE WINDFARM (EAST) LIMITED	United Kingdom	47	0.0001

Source: Authors' calculation evaluated by the Data Envelopment Analysis method using the software package DEA-Solver Professional Release 11.0.

On the other hand, the results are consistent with the basic hypothesis of this study, which is as follows: by evaluating the relative efficiency of offshore wind energy companies in European countries, it is possible to determine a correlation between the results of efficiency between the two observed periods with slight deviations. More specifically, although there are notable differences in the score results of relative efficiency, the correlation is significant with slight deviations in the ranking of the analysed offshore wind energy companies in the observed years, i.e., in 2019 and 2020. This is confirmed by the fact that several offshore wind energy companies are ranked the same in the efficiency score in the observed years 2019 and 2020. This is true for six companies that are relatively efficient in both 2019 and 2020, as well as for companies that are ranked the same under the following numbers: 33, 34, 37, and 47. In addition, there are a few companies that are ranked nearly equally in 2019 and 2020. For example, Aberdeen Offshore Wind Farm Limited is ranked as 27th most efficient company in 2019 and as 26th most efficient company in the following year 2020.

The assessment of relative efficiency implemented by the DEA method not only provides an estimate of the current level of relative efficiency but is also of great importance in the field of efficiency management of offshore wind energy, as it provides information on how to eliminate relative inefficiency and identifies sources and amounts of inefficiency. Therefore, for a relatively inefficient offshore wind energy company to be able to become relatively efficient, it is necessary to make projections or improvements and "shift" some of the factors to the efficiency frontier. These projections or improvements are the basic objectives of this research, and besides the determination, a solution to the problem of inefficiency is proposed. When applying the input-oriented DEA model, in order to achieve relative efficiency ($\theta^* = 1$), it is necessary to reduce the input variables while maintaining the existing output, i.e., the required changes or projections (in percentage) of each variable should be reduced.

To determine the amount of relative inefficiency of offshore wind energy companies in general, significant importance is given to determining the average amounts or average improvements for each observed input in the model (tangible fixed assets, cash and cash equivalents, and current assets). With such average adjustments (the reduction of factors), a possible achievement of relative efficiency at the aggregate size level is suggested. The average percentage improvements for relatively inefficient offshore wind energy companies are shown in Table 6 below.

Table 6. Average improvements for relatively inefficient offshore wind energy companies (DMUs) (%).

Tangible Fixed Assets		Cash & Cash Equivalent		Current Assets	
2019	**2020**	**2019**	**2020**	**2019**	**2020**
47.42	54.78	58.85	70.14	46.19	63.28

Source: Authors' calculation.

Table 6 shows the various amount of projections or average improvements for relatively inefficient offshore wind energy companies to become relatively efficient. Particularly highlighted are the extremely high values in both 2019 and 2020, from 46.19% to 70.14%. Such enormous values of projections indicate that the financial inputs of offshore wind energy companies will radically decrease. Although this research does not show the average improvements for each relatively inefficient offshore wind energy company, the empirical results suggest that about 10 companies (DMUs) have a value of projections above 99% for each input variable. This means that the companies have double resource capacity, which should be halved to become relatively efficient. It should also be noted that the average improvements for each observed input are higher in 2020 than in 2019, which is consistent with the relative efficiency results that show there are fewer relatively efficient offshore wind energy companies in 2020 (7 DMUs) than that in 2019 (15 DMUs). In addition, the average efficiency score in 2020 is lower (0.4542) than that in 2019 (0.546). This can be explained by the fact that the quality of management of offshore wind energy companies should be necessarily higher in 2020 than in the previous year. From the management's perspective, significant efforts and improvements in all financial variables, i.e., tangible fixed assets, cash and cash equivalent, and current assets, are required to achieve relative efficiency.

To conclude, offshore wind energy companies should, on average, reduce tangible fixed assets by 47.42% in 2019 and 54.78% in 2020, cash and cash equivalents by 58.85% in 2019 and 70.14% in 2020, and variable current assets by 46.19% in 2019 and 63.28% in 2020 to achieve relative efficiency. The economic impact of the proposed reduction of inputs would ensure the "return" to the equilibrium point of the company.

It should be noted that this study does not examine the direct impact of the country and its reforms on the value of relative efficiency. This is indirectly contained in the economic variables (inputs and outputs) of the model.

5. Discussion and Policy Implications

Based on the results of this research, it is quite clear that they imply numerous considerations, especially in the field of managerial decision-making but also in the formation of public policies. The given information related to the necessary adjustments, i.e., amounts of projections and improvements by the relatively inefficient offshore wind energy companies, is of particular importance for all stakeholders involved in the renewable energy sector, especially in the wind energy sector. Ensuring exactly specified projections to eliminate inefficiencies would improve company performance, increase efficiency, and make the best use of resources. By increasing efficiency, more resources would be available for the company to use to further improve its operations and performance or to further stimulate its economic activity. This could also contribute to the growth of the company as a whole. If a company performs functions and activities efficiently, i.e., faster, more cost-effectively, and more competently than its competitors, it can achieve various benefits, such as higher profit levels and greater customer satisfaction.

In addition, the efficiency of the company could have an impact on the competitiveness of other companies in the industry. Therefore, efficiency is important for a company to gain a competitive advantage over its rivals. Consequently, competitiveness ensures market dominance. On the other hand, efficient offshore wind energy companies can contribute to the growth and development of the wind energy industry by ensuring a reliable and sufficient power supply.

Since the world's first offshore wind farm was installed in Vindeby off the southern coast of Denmark in 1991, wind energy potential has been critical if Europe is to achieve its goals of reducing carbon emissions by at least 55% by 2030 compared to 1990 and becoming carbon neutral by 2050. Europe's leadership in offshore renewables can be based on the enormous potential offered by the European Union's seas, from the North Sea and the Baltic Sea to the Mediterranean, from the Atlantic to the Black Sea, as well as the seas around the EU's outermost regions. The EU Offshore Renewable Energy Strategy envisages an installed capacity of at least 60 GW for offshore wind by 2030, rising to 300 GW by 2050 [48].

6. Conclusions

Offshore wind energy has emerged as a viable alternative to conventional energy resources to reduce greenhouse gas emissions and thus affect climate change. Today, the offshore wind industry faces the challenge of becoming competitive and thus significantly reducing the cost of electricity from offshore wind. In view of this, there is a need to measure and evaluate the operational performance of offshore wind energy companies. Therefore, the purpose of this study is to evaluate the allocative efficiency of 47 offshore wind energy companies in 9 European countries in 2019 and 2020 using the input-oriented BCC DEA model. The basic hypothesis is that by evaluating the relative efficiency of offshore wind energy companies in European countries, it is possible to determine a correlation between the results of efficiency between the two observed periods with slight deviations. The empirical results show no significant correlation between the score of relative efficiency and the country where the offshore wind energy company is located. On the other hand, the results are consistent with the basic hypothesis of this study. From a management perspective, significant improvements in all financial variables, i.e., tangible fixed assets, cash and cash equivalents, and current assets, are required to achieve relative efficiency. This pan-European analysis is useful in understanding the current state of offshore wind energy companies and is intended to provide a benchmark for future analysis as well as further insight into the financial factors that influence wind farm efficiency. Certain limitations of this study lie in the limited research period of only two years due to data availability. A better analysis of the performance evaluation of offshore wind companies would be possible through a dynamic component of efficiency, the so-called "DEA window analysis", which represents the change in efficiency over time. To fill this research gap, further research should examine relative efficiency over several years to provide a clearer picture of company performance.

Author Contributions: Conceptualization, D.M. and S.Č.; methodology, D.M.; formal analysis, S.Č.; resources, S.Č.; data curation, D.M.; writing—original draft preparation, D.M.; writing—review and editing, B.O.D.; visualization, B.O.D.; supervision, B.O.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The research data are taken from the "Orbis Europe" database (https://orbiseurope.bvdinfo.com, accessed on 15 January 2023).

Acknowledgments: This work has been fully supported by/supported in part by the University of Rijeka, Croatia under the project "New Energy Paradigm—How to Reconciliate Sustainability and Feasibility", and project numbers "uniri-drustv-18-61" and "uniri-drustv-18-255-1424".

Conflicts of Interest: The authors declare no conflict of interest.

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