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The effects of electricity prices on productive efficiency of states' wind power performances in the United States

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Abstract

Wind power is the largest renewable energy source, which produces a negligible amount of greenhouse gas (GHG) emissions, has gained enormous attention in the electricity generation sector over the past decade in the United States. In this study, a Data Envelopment Analysis (DEA) is implemented to quantitatively evaluate the relative efficiencies of the 39 states' wind power production for the electricity generation. Eight output-oriented CCR (Charnes, Cooper, and Rhodes) models are developed with different combinations of pre-determined four input and five output variables to investigate the effect of electricity prices on the productive efficiency and to test the robustness of the DEA models. The DEA results indicate that two-thirds of the states operate wind power efficiently. Although the high retail price of electricity has a significant contribution to the productive efficiency of the six states, it does not affect the relative efficiency scores of the nineteen states. The location and the size of operation are not advantage/disadvantage to operating wind power at the most productive scale.

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1. Introduction

Global warming, which is a long-term increase in the overall average temperature of the Earth's climate system, was first recognized by Fourier (1827). The primary cause of global warming is an irrepressible increase in the concentration of greenhouse gases (GHG) released by people burning fossil fuels. Arrhenius (1897) developed the first quantitative model to investigate the relationship between global surface temperature and carbon dioxide concentration. According to the National Oceanic and Atmospheric Administration (NOAA), the average global surface temperature increased by 0.65°C in the 21st century, and 2014, 2015 and 2016 were the three warmest years in a row since modern record-keeping began in 1880. According to the scenario projections in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the ecosystem will face severe problems such as endangered of animal and plant species, food scarcity, malnutrition, floods, and freshwater problems, if the global warming is not restrained. Hence, global warming and climate change became the most critical environmental and political issue between countries. As of March 2019, a total of 185 Parties (184 countries and the European Union (EU) cover more than 88% of global greenhouse gas emissions) have signed and ratified the Paris Agreement, which aims to reduce the global average temperature well below 2°C above pre-industrial levels, and limit to 1.5°C above the pre-industrial levels to mitigate the risks and impacts of climate change significantly. Therefore, renewable energy sources, especially wind power which produces a negligible amount of GHG emissions, have gained enormous attention in the electricity generation sector over the past decade in the United States.

Wind power is the most abundant renewable and sustainable energy source that generates electricity by converting the kinetic energy of wind. According to the American Wind Energy Association-AWEA's dataset, the cumulative installed wind power capacity is doubled since 2010, and wind power provided 5.55% of electricity demand in 2016. During 2016, 82.17 GW installed wind power generated almost 226.5 million megawatt-hours (MWh) electricity which avoided 160 million metric tons of carbon dioxide, and 88.5 billion gallons of water consumption. Besides, in 2015, the Department of Energy has reported the wind power will provide the 10% of U.S. electricity demand by 2020, 20% by 2030 and 35% by 2050 that emphasizes the importance of wind energy for the United States as a whole, and as well as for each state.

In the literature, there are more than four hundred Data Envelopment Analysis (DEA) – related articles for electricity generation sector, and they can be divided into two major streams of research evaluating the relative efficiency of decision-making units (DMUs). The first stream of research focuses on efficiency analysis of electricity distribution companies for different countries, and the second stream of research focuses on the energy efficiency of various operations. Two recent review studies cover both of these two streams. Mardani et al. (2017) review 144 published scholarly articles between 2006 and 2015 that include DEA application in energy efficiency, and Sueyoshi et al. (2017) provide a comprehensive literature review for DEA applied to energy and environment from the 1980s and 2010s.

There are two groups in the DEA literature, which are including wind power. The first group of studies compare the productive efficiency of wind power/plants with other energy sources. Ramanathan (2001) utilizes from DEA to compare risk assessment of eight power technologies that include wind power as well. Sarica and Or (2007) investigate operational and investment efficiency of 65 hydro, thermal and wind power plants in Turkey. San Cristobal (2011) examines the productive efficiency of 13 renewable energy sources in Spain, and Lins et al. (2012) evaluate performance assessment of 11 alternative energy sources in Brazil. Kim et al. (2015) investigate the investment efficiency of photovoltaic, wind power and fuel cell in Korea between 2007 and 2011. Saglam (2016, and 2018b) evaluates efficiency ranking of eight renewable energy technologies by applying four different ranking methodologies based on DEA. Ervural et al. (2018) consider wind power for a two-stage analytical approach to assess sustainable energy efficiency. Khanjarpanah et al. (2018) develop a multi-period double frontier network DEA model to sustainable location optimization of a hybrid wind-photovoltaic power plant with a real data of case study in Iran. The second group of studies focus on efficiency assessment of wind power/plants. Iglesias et al. (2010) evaluate the productive efficiency of 19 wind farms in Spain using DEA and SFA (Stochastic Frontier Analysis). Iribarren et al. (2013) evaluate operational efficiency of 25 wind farms in Spain combining DEA and LCA (Life Cycle Analysis), and Iribarren et al. (2014) develop two-stage DEA and EA (Emergy Analysis) for operational benchmarking evaluation of 25 wind farms in Spain. Ederer (2015) evaluates the capital and operating cost efficiency of offshore wind farms in the EU. Sameie and Arvan (2015) construct simulation based DEA model to compare 24 areas in Iran for wind farm feasibility. Wu et al. (2016) compare efficiency assessment of 42 wind farms in China using two-stage DEA and Tobit models. Niu et al. (2017) compare micrositing efficiency of 32 wind farms in China. Sağlam (2017a, 2017b) compares states' electricity production performances by developing four different DEA models. Sağlam (2017c, 2018a) evaluates productive efficiency of large-utility scale wind farms in the United States and Texas respectively by developing two-stage DEA and Tobit models. Pan et al. (2018) apply meta-frontier DEA model and a regression method to evaluate wind power generation efficiency and its influencing factors. Pambudi and Nananukul (2019) develop a hierarchical dual DEA model for the selection of wind turbine site in Indonesia. Khanjarpanah and Jabbarzadeh (2019) propose cross-efficiency DEA model for sustainable optimization of wind farm location in Iran. Xin-gang and Zhen (2019) evaluate the technical efficiency of China's wind power enterprise by using DEA model.

This study focusses the relative efficiencies of the 39 states' wind power performances for electricity generation by using Data Envelopment Analysis (DEA). This work extends the model presented by Sağlam (2017a, 2017b) by including the value of production variable into the analysis to investigate the effect of electricity prices on the productive efficiency of states' wind power. In this paper, comprehensive DEA models are implemented to pre-determined four input and five output variables to measure and compare the relative efficiencies of the states that are operating wind power. The sensitivity analysis is conducted to investigate the effect of the variables by introducing new models with the various combinations of pre-determined four input and five output variables of the original model.

The remainder of this paper is organized as follows: Section 2, presents an output-oriented DEA framework, for the CCR (Charnes, Cooper, and Rhodes). This section also describes the data in detail with the selection of input and output variables. Section 3, reports the DEA results of each approach with the sensitivity analysis. Finally, Section 4, provides a summary and some concluding remarks.

2. Methodology

2.1. Data Envelopment Analysis (DEA)

DEA is a non-parametric, multi-factor relative efficiency measure to evaluate and improve the efficiency of both manufacturing and service operations. Charnes et al. (1978) develop the DEA framework to calculate the relative efficiency score of DMUs. The model's objective is to maximize output variable(s) while keeping the current level of inputs fixed. The output-oriented CCR (Charnes, Cooper, and Rhodes) model can be formulated as a linear programming problem under constant returns to scale (CRS) assumption. The relative (global) technical efficiency score of the *k^th^* DMU (θ_k) with *n* number of DMUs, *s* number of output and *m* number of input variables, can be formulated as Equation 1:

$$
\begin{aligned}
\text{Max.} \quad & \theta_k + \varepsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i=1}^{m} s_i^-\right) & & \\
\text{s.t.} \quad & \theta_k y_{rk} - \sum_{j=1}^{n} y_{rj}\lambda_j + s_{rk}^+ = 0 & & r = 1, \ldots, s; \\
& x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_{ik}^- = 0 & & i = 1, \ldots, m; \\
& \lambda_j, s_i^-, s_r^+ \geq 0; & & j = 1, \ldots, n;\ i = 1, \ldots, m;\ r = 1, \ldots, s.
\end{aligned}
\tag{1}
$$

where s_r^+ and s_i^- represent non-negative slack variables for output and input constraints respectively. x_{ij} represents the amount of i^{th} input variable that is consumed by j^{th} DMU; y_{rj} represents the amount of r^{th} output variable that is produced by j^{th} DMU; and lastly λ_j represents structural variables.

2.2. Data Description

This study evaluates wind power performances of the 39 states that have utility-scale wind project(s) to generate electricity, by using pre-determined four input and five output variables.

2.2.1. Input Variables

In this study, we consider four input variables for the DEA formulation: (1) installed wind capacity, (2) number of wind turbines, (3) total project(s) investment, and (4) annual land lease payment.

The installed wind capacity is one of the most critical input variables because there is a strong correlation between the installed wind capacity and the electricity generation. Hence, it has a significant effect on the output variables and the technical efficiency scores of the states. The number of wind turbines is selected as the second input variable to include land requirement into the analysis. The total capital investment is chosen for the third input variable because the total system levelized cost of unit electricity production varies with the incentives and technological advancements over the years. Lastly, the average is chosen as the fourth input variable of this study because annual land lease ranges from $1,000 and $4,000 per MW installed capacity that depends on the individual wind turbine capacity, the capacity of the plant and the value of the land.

2.2.2. Output Variables

In this study, we consider five output variables for the DEA model: (1) net generation, (2) percentage of in-state energy production, (3) number of U.S. homes powered, (4) wind industry employment and (5) the value of generated electricity.

As discussed above, there is a strong correlation between the installed wind capacity and the generated electricity, so that the net electricity generation is one of the most critical output variables for this study. The wind power has a crucial role in each state to meet their Renewable Portfolio Standards (RPS) requirements. Hence, the percentage of wind power in-state electricity generation is selected as an output variable for the DEA analysis. The average household electricity consumption fluctuates state-by-state so that the number of U.S. houses powered by the in-state production is also selected as an output variable. There are more than 88,000 employers in the wind industry so that the distribution of them among the states is another output variable for the DEA analysis. Lastly, the average residential, retail price of electricity varies between ¢7.70 and ¢23.85 per kilowatt-hour (kWh), that cause a significant difference in the value of the production which is chosen the last output variable for the DEA models.

The dataset is collected from AWEA's state fact sheets. Table 1 summarizes the descriptive statistics of input and output variables. On average, a state in the sample have installed capacity of 1,938 MW with 1,266 wind turbines; have invested more than $3.6 to wind projects that pay about $5.5 million as annual land leases. Again, on average, a state in the sample generated 5,461GWh electricity that powered more than 446,600 homes with a value of $518.7 million.

Table 1: Descriptive statistics of the input and output variables

	DEA Input-Output Variables	Average	Minimum	Maximum	Stand. Dev.
Input 1	Installed Wind Capacity (MW)	1,938	2	18,531	3,214
Input 2	Number of Wind Turbines	1,266	1	10,751	2,177
Input 3	Total Project Investment ($)	3,631,641,026	4,000,000	32,700,000,000	5,771,414,291
Input 4	Annual Land Lease Payments ($)	5,491,026	50,000	50,000,000	8,555,976
Output 1	Net Generation (MWh)	5,461,891	5,091	53,132,361	9,269,178
Output 2	In-State Energy Production (%)	8.35	0.03	35.76	8.92
Output 3	Equivalent U.S. Home Powered	446,601	434	4,100,000	724,025
Output 4	Wind Industry Employment	2,194	50	24,500	4,155
Output 5	Value of Generated Electricity ($)	518,724,749	567,647	4,399,359,491	807,031,094

Table 2 presents the correlation matrix of input and output variables used in the DEA models. As seen from the table there are very strong positive correlations between all input and output variables in the model (except the second output variable). All the correlation coefficients values are significant even at 0.1%, which shows that all the input and output variables (except the second one) are very critical, and they are necessary for the DEA models. The second output variable, in-state energy production (%), has a relatively low positive correlation coefficient values between all the input and output variables, but they are still significant at 5%. Hence, we keep this out variable in our models because of states' RPS requirements that are discussed above.

The original model (M1) includes four input and the first four output variables. The second model is constructed (M2) by adding the value of production variable on the original model to investigate the effect of electricity prices on the relative efficiency scores of the states. The sensitivity analysis is conducted by removing (or adding) input and output variable(s) from (or to) the original model for the robustness of the DEA models. Table 3 presents the input and output variables of the eight different models under four groups to evaluate the effect of electricity of prices on the productive efficiency of states' wind power operations. Group 1 models (M1 and M2) consider the full set of input-output variables, Group 2 and Group 3 models include physical investment and monetary cost respectively into account. Group 4 models discard all the output variable except net generation and its value.

Table 2: Correlation matrix of input and output variables

	Input 1	Input 2	Input 3	Input 4	Output 1	Output 2	Output 3	Output 4
Input 2	0.928 (0.000)							
Input 3	0.998 (0.000)	0.944 (0.000)						
Input 4	0.987 (0.000)	0.932 (0.000)	0.989 (0.000)					
Output 1	0.997 (0.000)	0.905 (0.000)	0.992 (0.000)	0.980 (0.000)				
Output 2	0.408 (0.010)	0.338 (0.035)	0.410 (0.010)	0.363 (0.023)	0.441 (0.005)			
Output 3	0.996 (0.000)	0.910 (0.000)	0.993 (0.000)	0.979 (0.000)	0.999 (0.000)	0.451 (0.004)		
Output 4	0.965 (0.000)	0.844 (0.000)	0.954 (0.000)	0.952 (0.000)	0.973 (0.000)	0.389 (0.015)	0.966 (0.000)	
Output 5	0.987 (0.000)	0.962 (0.000)	0.991 (0.000)	0.982 (0.000)	0.981 (0.000)	0.438 (0.005)	0.984 (0.000)	0.940 (0.000)

Table 3: Input-Output combinations of eight models

	Groups	Group 1		Group 2		Group 3		Group 4	
	Models	M1	M2	M3	M4	M5	M6	M7	M8
Input-Output Variables Combinations	Input 1	X	X	X	X			X	X
	Input 2	X	X	X	X			X	X
	Input 3	X	X			X	X	X	X
	Input 4	X	X			X	X	X	X
	Output 1	X	X	X	X	X	X	X	X
	Output 2	X	X	X	X	X	X		
	Output 3	X	X	X	X	X	X		
	Output 4	X	X	X	X	X	X		
	Output 5		X		X		X		X

3. Results and Conclusions

Equations 1 calculates the relative efficiency scores of the 39 states for the output-oriented CCR models that are presented in Table 4. Model 1 (M1) results are consistent with the results of the previous study (Sağlam (2017b)). Although the relative efficiency scores range from 0.358 and 1.000, the average relative efficiency score is relatively high (0.830). There are only six states (DE, NE, NJ, MI, OK, and VT) that are operating wind power at the most productive scale size, and they reach the maximum efficiency score, 1.000. However, 25 states' the relative efficiency score exceeds 0.80, and 14 of them exceed 0.90.

Table 4: Efficiency scores of the output-oriented CCR models.

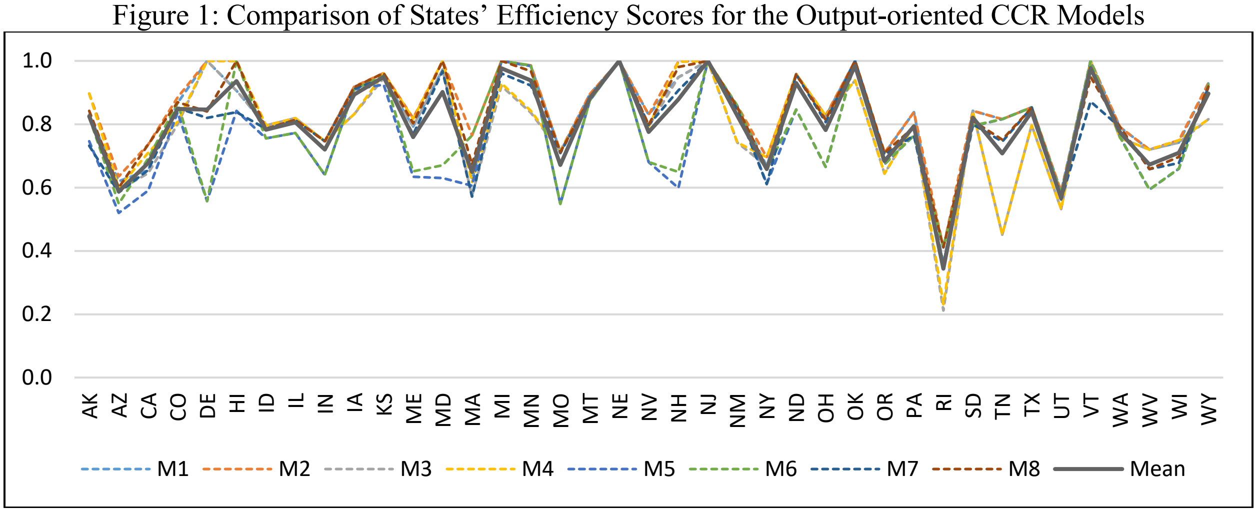
States	M1	M2	M3	M4	M5	M6	M7	M8	Mean	Min	Median	Max	S.D.
AK	0.830	0.897	0.830	0.897	0.747	0.822	0.732	0.842	0.825(19)	0.732	0.830	0.897	0.060
AZ	0.620	0.635	0.593	0.600	0.519	0.549	0.585	0.600	0.588(37)	0.519	0.596	0.635	0.037
CA	0.655	0.736	0.645	0.710	0.591	0.691	0.655	0.736	0.677(32)	0.591	0.673	0.736	0.050
CO	0.868	0.885	0.800	0.807	0.837	0.868	0.852	0.869	0.848(15)	0.800	0.860	0.885	0.031
DE	1.000	1.000	1.000	1.000	0.557	0.557	0.820	0.840	0.847(16)	0.557	0.920	1.000	0.194
HI	0.906	1.000	0.906	1.000	0.842	1.000	0.838	1.000	0.937(8)	0.838	0.953	1.000	0.072
ID	0.795	0.795	0.795	0.795	0.756	0.756	0.785	0.785	0.783(23)	0.756	0.790	0.795	0.017
IL	0.819	0.819	0.819	0.819	0.772	0.772	0.813	0.814	0.806(21)	0.772	0.816	0.819	0.021
IN	0.746	0.747	0.746	0.747	0.640	0.640	0.746	0.747	0.720(28)	0.640	0.746	0.747	0.049
IA	0.919	0.919	0.832	0.832	0.910	0.910	0.912	0.917	0.894(12)	0.832	0.911	0.919	0.038
KS	0.945	0.961	0.945	0.961	0.925	0.954	0.945	0.961	0.950(6)	0.925	0.950	0.961	0.013
ME	0.793	0.819	0.793	0.817	0.634	0.651	0.768	0.803	0.759(27)	0.634	0.793	0.819	0.074
MD	0.972	1.000	0.972	1.000	0.630	0.670	0.967	1.000	0.902(10)	0.630	0.972	1.000	0.156
MA	0.622	0.764	0.574	0.617	0.606	0.764	0.571	0.673	0.649(36)	0.571	0.619	0.764	0.078
MI	1.000	1.000	0.921	0.929	1.000	1.000	0.960	1.000	0.976(5)	0.921	1.000	1.000	0.035
MN	0.983	0.986	0.836	0.842	0.983	0.986	0.922	0.968	0.938(7)	0.836	0.976	0.986	0.065
MO	0.712	0.715	0.712	0.715	0.548	0.548	0.709	0.712	0.672(34)	0.548	0.712	0.715	0.076
MT	0.895	0.895	0.879	0.879	0.874	0.874	0.883	0.883	0.883(13)	0.874	0.881	0.895	0.008
NE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000(1)	1.000	1.000	1.000	0.000
NV	0.830	0.830	0.793	0.793	0.680	0.680	0.798	0.798	0.775(25)	0.680	0.795	0.830	0.060
NH	0.949	0.998	0.949	0.998	0.598	0.649	0.906	0.980	0.879(14)	0.598	0.949	0.998	0.161
NJ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000(1)	1.000	1.000	1.000	0.000
NM	0.856	0.858	0.742	0.742	0.856	0.858	0.848	0.853	0.827(18)	0.742	0.854	0.858	0.052
NY	0.667	0.696	0.667	0.696	0.612	0.657	0.611	0.661	0.658(35)	0.611	0.664	0.696	0.033
ND	0.958	0.958	0.958	0.958	0.846	0.846	0.957	0.957	0.930(9)	0.846	0.958	0.958	0.052
OH	0.824	0.827	0.824	0.827	0.665	0.665	0.807	0.814	0.781(24)	0.665	0.819	0.827	0.072
OK	1.000	1.000	0.938	0.938	1.000	1.000	1.000	1.000	0.985(3)	0.938	1.000	1.000	0.029
OR	0.708	0.709	0.644	0.644	0.673	0.674	0.704	0.709	0.683(31)	0.644	0.689	0.709	0.029
PA	0.838	0.838	0.796	0.796	0.764	0.764	0.765	0.791	0.794(22)	0.764	0.794	0.838	0.030
RI	0.358	0.411	0.212	0.232	0.358	0.411	0.358	0.411	0.344(39)	0.212	0.358	0.411	0.079
SD	0.842	0.842	0.841	0.841	0.794	0.795	0.800	0.811	0.821(20)	0.794	0.826	0.842	0.023
TN	0.816	0.816	0.451	0.451	0.816	0.816	0.745	0.751	0.708(30)	0.451	0.783	0.816	0.161
TX	0.853	0.853	0.796	0.796	0.853	0.853	0.853	0.853	0.839(17)	0.796	0.853	0.853	0.026
UT	0.588	0.588	0.532	0.532	0.580	0.580	0.563	0.571	0.567(38)	0.532	0.575	0.588	0.023
VT	1.000	1.000	1.000	1.000	1.000	1.000	0.872	0.949	0.978(4)	0.872	1.000	1.000	0.046
WA	0.791	0.791	0.756	0.756	0.760	0.760	0.791	0.791	0.774(26)	0.756	0.775	0.791	0.017
WV	0.720	0.720	0.720	0.720	0.594	0.594	0.658	0.658	0.673(33)	0.594	0.689	0.720	0.056
WI	0.742	0.749	0.742	0.749	0.659	0.660	0.677	0.697	0.709(29)	0.659	0.719	0.749	0.040
WY	0.930	0.930	0.816	0.816	0.925	0.925	0.917	0.919	0.897(11)	0.816	0.922	0.930	0.050
Mean	0.829	0.846	0.789	0.801	0.754	0.774	0.797	0.824	0.802	0.717	0.821	0.846	0.054
Min	0.358	0.411	0.212	0.232	0.358	0.411	0.358	0.411	0.344	0.212	0.358	0.411	0.000
Median	0.838	0.842	0.800	0.816	0.760	0.764	0.807	0.814	0.821	0.742	0.826	0.842	0.046
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.194
Stdev	0.143	0.136	0.165	0.166	0.163	0.157	0.142	0.139	0.140	0.162	0.144	0.136	0.045

The slack variables of the results indicate two main reasons for the low-efficiency scores. First, some states still use less efficient and less productive wind turbines which lead low-efficiency scores. For example, California (CA) has 8,413 active wind turbines for 5,662 MW installed capacity, even though it may maintain the same output level with 3,272 wind turbines. Therefore, old technology wind turbines should be replaced with the current technology to increase the productivity level. Second, excess capital investment leads to low-efficiency scores for the states.

Although there are seven states may improve their productivity level by investing, 25 states overinvested to the wind energy regarding their optimum production scale. The slack variables show that on average each state invests 8.76% (about $160 million) more than their needs to reach the same output level. Again, CA has the highest excess investment regarding the dollar amount ($1.55 billion), because of its early and expensive investments into the less productive wind technologies.

The second model (M2) takes the average retail price of electricity into account by adding the value of the state's total electricity production as an output variable. In M2, two more states (MD, HI) reach the maximum efficiency score beside the six states in the original model. In addition, six states (AK, CA, HI, MA, NH, NY) significantly increase their relative efficiency score by taking advantage of the high retail price of electricity even though some of them have genuine disadvantages such as sitting low-speed areas. Surprisingly, the electricity prices do not affect the relative efficiency scores of the nineteen states. This finding shows that it is possible to operate wind power at the most productive scale size, even though a state may have comparative disadvantages such as the retail price of electricity. For example, Oklahoma (OK) has one of the lowest electricity price (¢7.72 per kWh); it reaches the maximum efficiency score in both of these models.

Figure 1: Comparison of States' Efficiency Scores for the Output-oriented CCR Models



As mentioned above, eight different models are constructed of four groups for the sensitivity analysis. Table 4 presents the relative efficiency scores of each state for the eight different models, and Figure 1 illustrates the fluctuation of the relative efficiency scores. Also, Table 4 presents the summary statistics of these eight models and the contribution of each model to the overall performances of each state. The Spearman's rank correlation coefficient test is conducted between the models to test the robustness of the DEA models. The correlation coefficient values between the original model (M1) and the other seven models range from 0.71 to 0.97 with p = 0.000. Hence, there is a strong positive association between the models at the 0.1% significance level. As seen from the table, the original model has the highest efficiency scores for the states because it is the most comprehensive DEA model including four input and five output variables. When the model comparison is constructed in each group, the highest percentage changes have occurred at the same states (AK, CA, HI, MA, NH, NY) that proves the robustness of the DEA models. According to the overall average of eight models, Nebraska (NE) and New Jersey (NJ) are the most efficient states for operating the wind power that reaches the maximum efficiency score in all of the eight models. This is a fascinating finding because NE and NJ are located under different wind patterns. Also, NE has a large installed wind power capacity where NJ has only 9 MW installed capacity. This finding indicates that the location and the size of operation are not advantage/disadvantage to operating wind power at the most productive scale. Besides, Rhode Islands (RI) is the least efficient state for operating the wind power at each one of the eight models because of its very low production, which is 697 MWh per MW where the average is 2,564 MWh per MW installed capacity.

4. Conclusions

This study focusses the relative efficiencies of the 39 states' wind power performances by including the value of production variable into the analysis to investigate the effect of electricity prices on their productive efficiency. The output-oriented CCR model is applied for the DEA. The sensitivity analysis is conducted by introducing three new groups using pre-determined four input and five output variables.

The critical findings of this study are listed as follow: First, two-thirds of the states (26 states) operate wind power efficiently. Second, early large investments in less productive wind technologies are the primary reason for the states' low-efficiency scores (Sağlam (2017b)). Third, the high retail price of electricity has a critical contribution to the productive efficiency of the six states; it has no significant effect on the relative efficiency 19 states. Fourth, the low-electricity price is not a disadvantage to operate wind power efficiently (i.e., Oklahoma), but high electricity price is a critical incentive for the locations that have genuine drawbacks (i.e., California, low wind speed). Lastly, the location and the size of operation are not advantage/disadvantage of operating wind power at the most productive scale. Based on these findings, the following recommendations can be listed: First, the price of electricity should be taken into account to evaluate the productive efficiency of the energy sources. Second, old technology wind turbines should be replaced with the current technology to improve states' productivity level. Lastly, well-designed economic incentives should be expanded to achieve the first milestone of the wind vision report.
In conclusions, it is hoped that the findings of this study shed some light on the effects of electricity on the efficiency assessments of the states and the future of wind power for both energy practitioners and policymakers.

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