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The Productive Efficiency Assessment of Wind Power Generation in the United States

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ABSTRACT

Wind power is the largest renewable energy source which produces a negligible amount of GHG emissions, have gained enormous attention, especially in the electricity generation sector over the past decade in the United States. In this study, a Data Envelopment Analysis (DEA) is developed to quantitatively evaluate the relative efficiencies of the 34 state's wind power productivity for the electricity generation. An output-oriented CCR (Charnes, Cooper, and Rhodes (1978)) and BCC (Banker, Charnes, and Cooper (1984)) models are applied to pre-determined two input and three output variables. The sensitivity analysis is conducted to test the robustness of the DEA models. The DEA results indicate that more than two-thirds of the states operate wind power efficiently even though there are only five states that reach the maximum efficiency score. Findings of this study shed some light on the current efficiency assessments of the states and the future of wind energy for both energy practitioners and policy makers.

KEYWORDS: Data Envelopment Analysis (DEA), Multi-Criteria Decision Making, Productive Efficiency, Wind Power.

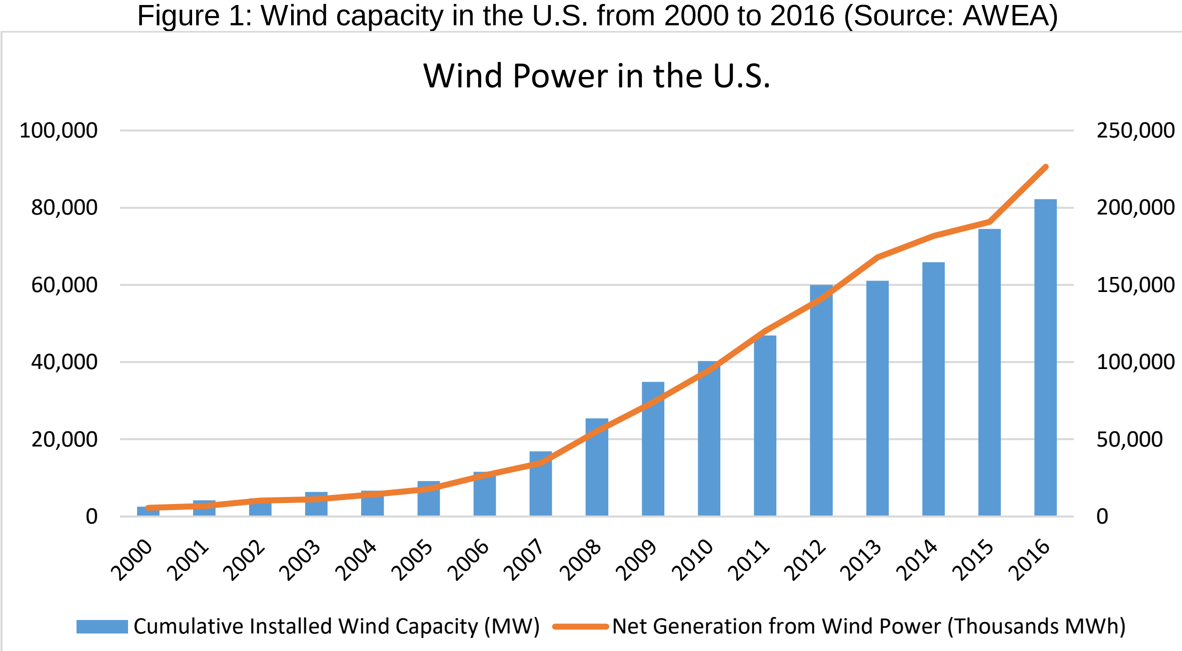
INTRODUCTION

Global warming is defined as the average temperature increase in Earth's surface, air, and oceans. It was first recognized by Fourier (1827), and Arrhenius (1897) developed the earliest model for the relationship between the temperature of the ground and carbon dioxide concentration. However, its perceived effects on human beings became more detectable and measurable within the last five decades. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the average global surface temperature increased by 0.85 ± 0.20°C (1.53 ± 0.36°F) since 1850 because of irrepressible increase of the concentration of greenhouse gasses such as carbon dioxide, methane, nitrous oxide, and chlorofluorocarbons. According to the previous report of the IPCC, if we will be successful to keep the level of the concentration of the greenhouses gasses constant, the global average surface warming would be about 0.2°C for a decade which may lead to severe problems in ecosystems all over the world. According to the scenario projections in this report, when the warming increases by 2°C, approximately 25% of the plant and animal species will be in danger of extinction. In addition, crop productivity will decrease leading to food scarcity in many regions of the world. Millions of people will have health problems because of increase in malnutrition. Moreover, deaths, diseases, and injuries will increase due to severe weather conditions. Climate change also results in significant rising of sea levels; this will lead islands in Asia, Africa, and the Caribbean to become vulnerable to storms surge, inundation, and erosion. A rising on sea level also the cause of some islands will even vanish. The report adds that, by 2020, climate change will cause between 75 and 250 millions of people to have fresh water problems in Africa. Shortly, climate change would cause many severe problems if the global warming is not restrained. Not surprisingly, global warming and climate change became the most critical environmental and political issue between countries. A total of 192 countries have signed the Kyoto Protocol which delimits the production of GHG emissions to fight global warming and climate change. More recently, 197 United Nations Framework Convention on Climate Change (UNFCCC) members have signed, and 129 of them ratified the Paris Agreement, which aims to reduce the global average temperature to pre-industrial levels. Therefore, renewable energy sources, which produce a negligible amount of GHG emissions, have gained enormous attention, especially in the electricity sector over the past decade.

According to the United States Environmental Protections Agency (EPA) data, there are five main sources of GHG emissions in the United States: electricity production 29%, transportation 27%, industry 21%, commercial and residential 12%, and agriculture 9%. These values are consistent with the worldwide data of IPCC, where the electricity production has the highest contribution to the total of GHG emissions. The U.S. Energy Information Administration data shows that in 2016, about 65% of electricity was generated by burning of fossil fuels (natural gas 33.8%, coal 30.4%, and petroleum 0.6%) which are the primary sources of GHG emissions for the electricity production. About fifteen percent of electricity is generated by renewable energy sources, which produce a negligible amount of GHG emissions, in the United States.

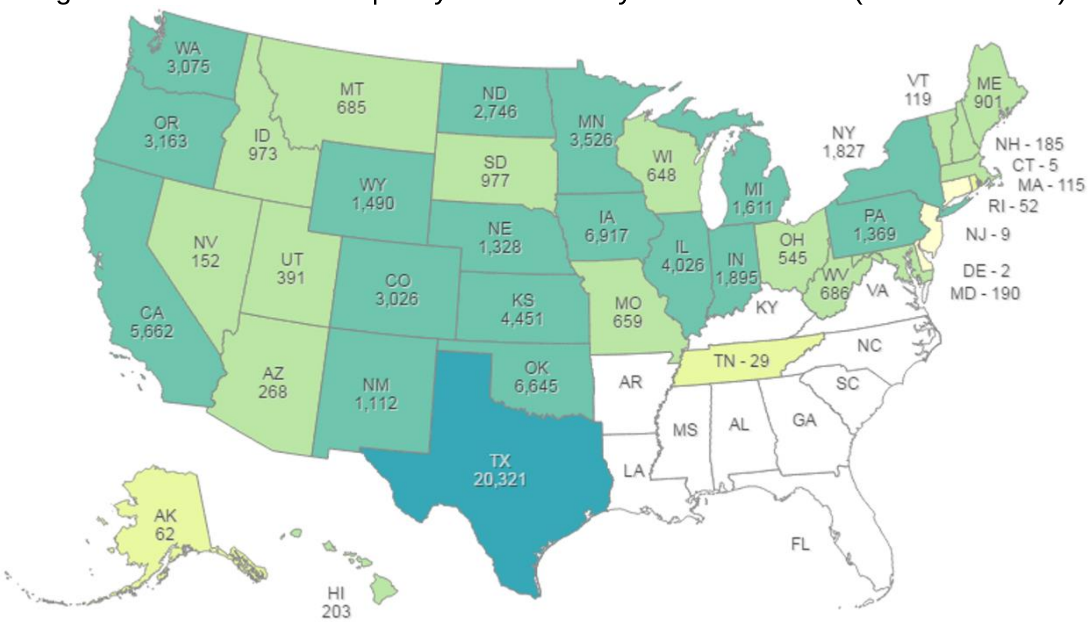
Wind power is the largest renewable and sustainable energy source that generates electricity by converting the kinetic energy of wind. As seen in Figure 1, wind power has gained enormous interest for electricity generation during the last decade in the U.S. The cumulative installed wind power capacity is doubled since 2010. According to the American Wind Energy Association (AWEA) 2016 Fourth Market Report, during 2016, 7.70 GW new wind power capacity was added in the U.S., and the cumulative installed wind power capacity reached 82.17 GW. Thus, 5.55% of electricity demand is provided by wind energy 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.

Figure 1: Wind capacity in the U.S. from 2000 to 2016 (Source: AWEA)



This study focuses on the 34 states who have utility-scale wind project(s). Figure 2 illustrates the cumulative installed wind power capacity of each state of the U.S. which was ended up with 82.17 GW by the end of 2016. Almost 25% of the wind power of the U.S. have been installed in Texas (TX, 20,321 MW). Iowa (IA) and California (CA) follow Texas with the cumulative installed wind power capacities of 6,917 MW and 5,662 MW respectively. On the other hand, the lowest installed wind power capacities belong to New Jersey (NJ) 9 MW, and Delaware (DE) 2 MW. The 11 states (Alabama (AL), Arkansas (AR), Connecticut (CT), Florida (FL), Georgia (GA), Kentucky (KY), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Virginia (VA)) do not have any utility-scale wind power.

Figure 2: Installed wind capacity in the U.S. by the end of 2016 (Source: AWEA)



In this study, linear programming problems are modeled to quantitatively evaluate the relative efficiencies of the 34 states' wind power performances for electricity generation by using multi-criteria decision-making tool. A comprehensive DEA models are applied to pre-determined two input and three output variables to measure and compare the relative efficiencies of the states that are operating wind power. The output-oriented CCR (Charnes, Cooper, and Rhodes (1978)) and BCC (Banker, Charnes, and Cooper (1984)) models are developed to investigate the effects of the variables from different aspects. The sensitivity analysis is conducted with the various combinations of input and output variables of the original model for the purpose of the robustness of DEA. Lastly, the findings of this study shed some light on the current efficiency assessments of the states and the future of wind power for both energy practitioners and policy makers.

The remainder of this paper is organized as follows: Section 2, provides a brief literature review for DEA-related articles in the energy sector and the wind industry. Section 3, presents an overview of the DEA framework, for the output-oriented CCR and BCC models. Section 4, describes the data in detail with the selection of input and output variables. Section 5, reports the DEA results of each approach with the sensitivity analysis. Finally, Section 6 provides a summary and some concluding remarks.

LITERATURE REVIEW

Data Envelopment Analysis (DEA), is a very popular management tool for evaluating and improving the efficiency of both manufacturing and service operations. It was developed by Charnes et al. (1978). The DEA has been studied by a large number of researchers for various applications in: education (Palocsay and Wood, 2014), banking (Paradi and Zhu, 2013), transportation (Zhou et al., 2014), health (Kemp, 2015), and environment (Goto et al., 2014). In the literature, there are more than thirty DEA – related articles for the energy sectors. Bagdadioglu et al. (1996) applied DEA to discover the relationship between privatization and ownership on the efficiency of Turkish electricity supply industry. Sueyoshi and Goto (2001) studied the performance of the electric power in Japan. Miliotis (1992) looked at Greece electricity distribution districts, Forsund and Kittelsen (1998) compared electricity distribution companies in Norway, by using DEA efficiency scores. Chen (2002) studied the cross efficiency of the electricity distribution sector in Taiwan, Pacudan and Guzman (2002) looked at the effectiveness of electricity distribution in the Philippines. Resende (2002) studied Brazilian electricity companies, and Korhonen and Syrjanen (2003) studied the efficiency of electricity distribution in Finland.

Boyd and Pang (2000) studied the linkage between energy efficiency and productivity in two segments of the glass industry. They compared the level of electricity and fossil fuel intensity by using regression analysis. They also showed that there is a strong correlation between energy intensity and productivity. Ramanathan (2001) applied DEA to the comparative risk assessment of eight different energy supply technologies. He concludes that solar photovoltaic and nuclear power are the most efficient energy sources. Jha and Shrestha (2006) used DEA to measure the efficiency of hydroelectric plants in Nepal. Chien and Hu (2007) apply DEA to the 45 OECD and non-OECD economies to determine the effects of renewable energy sources on the technical efficiency. They used macroeconomic data such as labor, capital stock, and energy consumption for the input variables where the real GDP served as the only output variable. They concluded that there was a positive correlation between use of renewables and technical efficiency and a negative correlation with the traditional energy. Jayanthi et. al. (2009) applied DEA to U.S. photovoltaic industry. Cristobal (2011) applied DEA to evaluate the efficiency of the renewable energy sources in Spain. Kasap and Kiris (2013) develop an AHP and DEA approach to evaluate electricity generation companies of OECD countries. More recently, Chiu et al. (2016) compared productivity efficiencies of G20 countries by using DEA and Malmquist Index. Saglam (2016) compares the efficiencies of the eight major renewable energy sources that generate electricity using four different analytical approaches. Saglam (2017a) develops a two-stage DEA to quantitatively evaluate the relative efficiencies of the 39 state's wind power performances. Saglam (2017b) applies a two-stage DEA to quantitatively evaluate the relative efficiencies of the 236 large utility-scale wind farms in the United States.

In this study, we use DEA to compare the efficiencies of the 34 state's wind power performances for electricity generation by using multi-criteria decision-making tool. We develop one of the most comprehensive DEA models are applied to pre-determined two input and three output variables to measure and compare the relative efficiencies of the states that are operating wind power. The output-oriented CCR (Charnes, Cooper, and Rhodes (1978)) and BCC (Banker, Charnes, and Cooper (1984)) models are developed to investigate the effects of the variables from different aspects. The sensitivity analysis is conducted with the various combinations of input and output variables of the original model for the purpose of the robustness of DEA. Therefore, the results of this study shed some light on the future of these technologies for the policy makers.

DATA ENVELOPMENT ANALYSIS (DEA)

DEA is a non-parametric, multi-factor relative efficiency measure for evaluating and improving the effectiveness of both manufacturing and service operations. Charnes et al. (1978) introduced the DEA framework to calculate the relative efficiency score with the division of the weighted sum of outputs and a weighted sum of inputs to obtain decision-making units (DMU). Equation 1 formulates the scenario where we have N number of maximized DMUs, which are achieved by s number of output and m number of input variables:

$$
\begin{aligned}
& max \quad E_e = \frac{\sum_{k=1}^{s} v_{ke} y_{ke}}{\sum_{i=1}^{m} u_{ie} x_{ie}} \\
& s.t. \quad \frac{\sum_{k=1}^{s} v_{ke} y_{kj}}{\sum_{i=1}^{m} u_{ie} x_{ij}} \le 1; \;\; j = 1, 2, 3, \dots, n \\
& v_{ke}, u_{ie} \ge 0; \;\; k = 1, 2, 3, \dots, s; \;\; i = 1, 2, 3, \dots, m
\end{aligned} \tag{1}
$$

where, E_e is the maximized efficiency score which belongs to the e^{th} DMU.

The Output-Oriented CCR Model

The output-oriented model's objective is to maximize output variable(s) while keeping the current level of inputs fixed. The output-oriented CCR model can be formulated as a linear programming problem under constant returns to scale (CRS) assumption. The relative technical efficiency score of the k^{th} DMU (ζ_k) can be computed as follows:

$$
\begin{aligned}
\text{Max.} \quad & \zeta_k + \varepsilon \left(\sum_{r=1}^{s} s_r^{+} + \sum_{i=1}^{m} s_i^{-} \right) \\
\text{s.t.} \quad & \zeta_k y_{rk} - \sum_{j=1}^{n} y_{rj} \lambda_j - s_{rk}^{+} = 0 \qquad r = 1,2, \dots, s; \\
& x_{ik} - \sum_{j=1}^{n} x_{ij} \lambda_j - s_{ik}^{-} = 0 \qquad i = 1,2, \dots, m; \\
& \lambda_j, s_i^{-}, s_r^{+} \ge 0; \qquad j = 1,2, \dots, n; \; i = 1,2, \dots, m; \; r = 1,2, \dots, s.
\end{aligned} \tag{2}
$$

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

The Output-Oriented BCC Model

The output-oriented BCC model can be formulated by adding a convexity constraint to the Equation 2. The relative pure efficiency score of the kth DMU (ξ_k) of BCC model under variable returns to scale (VRS) assumption can be formulated as Equation 3:

$$
\text{Max.} \quad \xi_k + \varepsilon \left(\sum_{r=1}^{s} s_r^{+} + \sum_{i=1}^{m} s_i^{-} \right) \tag{3}
$$

$$\text{s.t.} \quad \xi_k y_{rk} - \sum_{j=1}^{n} y_{rj}\lambda_j - s_{rk}^{+} = 0 \qquad r = 1,2,\dots,s;$$
$$x_{ik} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_{ik}^{-} = 0 \qquad i = 1,2,\dots,m;$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j, s_i^{-}, s_r^{+} \geq 0; \qquad j = 1,2,\dots,n;\ i = 1,2,\dots,m;\ r = 1,2,\dots,s.$$

Scale efficiency score can be obtained by calculating the ratio of CCR technical efficiency score and BCC pure technical efficiency score.

DATA DESCRIPTION

This study evaluates wind power performances of the 34 states that have utility-scale wind project(s) to generate electricity, by using pre-determined two input and three output variables.

Input Variables

In this study, we consider two input variables for the DEA analysis: (1) installed wind capacity, (2) number of wind turbines. Table 1 presents the related data for these input variables.

Installed wind capacity:

The installed wind capacity is one of the most important input variables because there is a strong correlation between the installed wind capacity and the generated electricity. So that, it has a significant effect on the output variables and the technical efficiency scores of the states. The most common installed capacity unit is megawatt (MW). The installed wind capacity ranges between 2 MW and 20,321 MW which are installed in Delaware (DE) and Texas (TX) respectively. The average installed wind capacity is 2,408 MW, and eighteen states have installed more than 1,000 MW of wind power.

The number of wind turbines:

The number of wind turbines is selected as the second input variable to include land requirement into the analysis. The capacity of an installed wind turbine varies. Although older version wind turbines generate only 0.5 MW, the modern turbines generate up to 3 MW. This difference has a significant effect on annual land leases as well because the new generation wind turbines require much less land than the older generation wind turbines for the same capacity, which makes it another important input variable.

Output Variables

In this study, we consider three output variables for the DEA analysis: (1) net generation, (2) percentage of in-state energy production, (3) number of U.S. homes powered. Table 1 presents the related data for these output variables.

Net generation:

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. Hence, the net electricity production for the calendar year 2016, is selected for the first output variable.

In-state energy production:

Renewable Portfolio Standards (RPS) have been mandated by 29 states across the U.S. which require certain targets for a proportion of in-state electricity production through the renewable energy sources by a certain target year. The wind power has a critical role for each state to meet their RPS requirements. Thus, the percentage of wind energy in-state electricity generation is selected as an output variable for the DEA analysis.

The number of U.S. homes powered:

The average household electricity consumption fluctuates state-by-state so that the number U.S. houses powered with the in-state production is also selected as an output variable.

The Data

The data set is collected from American Wind Energy Association's U.S. wind energy state facts. Table 1 summarizes the descriptive statistics of input and output variables.

Table 1: Descriptive statistics of the input and output variables

DEA Input-Output Variables	Mean	Min	Median	Max	Standard Deviation
Installed Wind Capacity (MW)	2,408	115	1,220	20,320	3,676
Number of Wind Turbines	1,533	56	734	11,590	2,395
Net Generation (Thousands MWh)	6,653	237	3,543	57,551	10,482
% of In-State Energy Production (%)	10.00	0.50	7.01	36.59	9.58
Equivalent U.S. Home Powered	615,517	22,000	327,500	5,300,000	966,516

RESULTS AND DISCUSSIONS

DEA Results

The relative efficiency scores of the 34 states are calculated by Equations 2 and Equation 3 for the output-oriented CCR and BCC models. Table 2 presents the efficiency scores for both of the models. The ranking of states is given for each model. The scale efficiency scores for the output-oriented models are calculated by the ratio of the technical efficiency of the CCR model and pure technical efficiency of the BCC model. Returns to scale information is obtained from the dual problem of the CCR models. For a given DMU, returns to scale is identified increasing returns to scale (IRS) if the sum of the dual weights is less than 1, and it is identified decreasing returns to scale (DRS) if the sum of the dual weights is greater than 1.

Table 2 indicates that the efficiency scores of the wind power productivity of the 34 states are relatively high, and they vary from 0.552 to 1.000 for the output-oriented CCR model. The average relative efficiency score is 0.839. The relative efficiency scores of the output-oriented BCC model range from 0.556 to 1.000 and the average relative efficiency score is 0.868, which is only about 3% higher than the average relative efficiency scores of CCR model. Hence, BCC efficiency score is at least as good as the corresponding CCR efficiency score. Therefore the average BCC efficiency score is higher than the average CCR efficiency score. Moreover, the number of efficient DMUs in BCC models is greater than the number of efficient DMUs in CCR models.

According to the CCR models, there are only five states (HI, MD, NM, SD, and VT) reach the maximum efficiency score, 1.000. Moreover, 22 state's CCR efficiency score exceeds 0.80, and 16 of them exceed 0.90. In the output-oriented BCC model, ten states reach the maximum efficiency score, and 25 state's BCC efficiency score exceeds 0.80, and 18 of them exceed 0.90. These results indicate more than two-thirds of the states operate wind farms efficiently, and their wind power productivity is relatively high. This can be explained by a high percentage of the installed capacity of the wind power is relatively new in most of these states. Relatively newly installed wind power helps to improve the relative efficiency scores of those states because of two reasons. First, technological developments in wind turbines during the last decade allow generating more electricity per wind turbine, which positively affects wind power productivity and the efficiency scores of the states. Second, relatively new projects are much cheaper because of the technological advancements, and they may have more federal and state tax and investment incentives.

Table 2 presents the scale efficiency scores for the output-oriented models. The scale efficiency scores of the output-oriented model range from 0.637 to 1.000, and the average scale efficiency score is 0.969. Moreover, the scale efficiency scores of 31 states out of 34 states exceed 0.9 for the output-oriented model. Nevertheless, there are only five states (HI, MD, NM, SD, and VT) that reach the maximum efficiency score which indicates constant returns to scale, in other words, these states are operating wind power at the most productive scale size. There are five increasing returns to scale (IRS) states (MA, MT, NV, NH, WI) which may increase their productivity efficiency with investing on the more productive wind turbines. There are 24 decreasing returns to scale (DRS) states where the invested capital and equipment is greater than the optimum production scale. As discussed above, expensive and less productive old technologies are the main reasons for the state of DRS. In addition, Table 2 indicate the benchmarking peer group for each inefficient states for both output-oriented CCR and BCC models.

Sensitivity Analysis

One of the most important limitations of DEA framework is that the relative efficiency scores are strictly dependent on the input and output variables. So that, the efficiency scores are affected significantly by any outlier or measurement error in the data set. The best way to overcome this problem is constructing new models with different combinations of input and output variables of the original model. For the purpose of sensitivity analysis, five new models are built, by removing input and output variable(s) from the original model (M1) which includes two input and three output variables. Table 3 presents the input and output variable combinations of the six different models.

Table 2: The Relative Efficiency Scores of the 34 States								
	CCR MODEL			BCC MODEL				
States	Efficiency Score	Rank	Peer Group	Efficiency Score	Rank	Peer Group	Scale Efficiency	RTS
AZ	0.6523	32	HI, MD.	0.6531	33	HI, KS, MD.	0.9988	DRS
CA	0.7652	24	NM.	0.8106	24	KS, TX.	0.9440	DRS
CO	0.9631	8	NM, SD.	0.9811	11	KS, NM.	0.9816	DRS
HI	1.0000	1	-	1.0000	1	-	1.0000	CRS
ID	0.7901	23	HI, MD.	0.8041	25	KS, MD, OK, SD.	0.9825	DRS
IL	0.8330	18	NM, SD.	0.8496	20	KS, NM.	0.9805	DRS
IN	0.8092	21	HI, SD.	0.8115	23	KS, NM, SD.	0.9972	DRS
IA	0.9107	13	HI, SD.	1.0000	1	-	0.9107	DRS
KS	0.9977	6	HI, SD.	1.0000	1	-	0.9977	DRS
ME	0.6609	31	MD, VT.	0.7609	26	OK, SD, VT.	0.8686	DRS
MD	1.0000	1	-	1.0000	1	-	1.0000	CRS
MA	0.6369	33	NM, SD.	1.0000	1	-	0.6369	IRS
MI	0.9120	12	HI, SD.	0.9152	16	HI, KS, SD.	0.9965	DRS
MN	0.9360	11	NM, SD.	0.9594	13	KS, NM.	0.9756	DRS
MO	0.5524	34	HI, MD.	0.5560	34	HI, KS, MD.	0.9935	DRS
MT	0.9443	9	NM, SD.	0.9466	14	HI, NM.	0.9976	IRS
NE	0.9032	15	HI, MD.	0.9102	17	HI, KS, MD, SD.	0.9923	DRS
NV	0.8023	22	HI, MD.	0.8751	19	MD, VT.	0.9168	IRS
NH	0.9058	14	MD, VT.	0.9192	15	MD, VT.	0.9855	IRS
NM	1.0000	1	-	1.0000	1	-	1.0000	CRS
NY	0.6769	29	HI, SD.	0.6799	31	HI, KS, SD.	0.9957	DRS
ND	0.9435	10	HI, MD.	0.9629	12	KS, MD, OK, SD.	0.9799	DRS
OH	0.7306	25	HI, MD.	0.7339	27	HI, KS, MD.	0.9955	DRS
OK	0.9687	7	HI, MD.	1.0000	1	-	0.9687	DRS
OR	0.7076	27	HI, SD.	0.7138	29	KS, NM.	0.9913	DRS
PA	0.8216	20	HI, MD.	0.8348	21	KS, MD, OK.	0.9841	DRS
SD	1.0000	1	-	1.0000	1	-	1.0000	CRS
TX	0.8895	17	HI, SD.	1.0000	1	-	0.8895	DRS
UT	0.6889	28	HI, MD.	0.6905	30	HI, KS, MD.	0.9977	DRS
VT	1.0000	1	-	1.0000	1	-	1.0000	CRS
WA	0.8248	19	HI, MD.	0.8313	22	KS, MD, OK.	0.9921	DRS
WV	0.6657	30	HI, MD.	0.6679	32	HI, KS, MD.	0.9968	DRS
WI	0.7266	26	NM, SD.	0.7278	28	HI, NM, SD.	0.9984	IRS
WY	0.9016	16	NM.	0.9096	18	KS, NM.	0.9912	DRS
Mean	0.8389			0.8678			0.9687	
Min	0.5524			0.5560			0.6369	
Max	1.0000			1.0000			1.0000	
Stdev	0.1289			0.1278			0.0664	

Table 3: Input-Output Variables of 6 Models.					
	Input 1	Input 2	Output 1	Output 2	Output 3
Model 1 (M1)	X	X	X	X	X
Model 2 (M2)	X	X	X	X	
Model 3 (M3)	X	X	X		X
Model 4 (M4)	X		X	X	X
Model 5 (M5)	X		X		X
Model 6 (M6)	X		X	X	

Table 4 indicates the relative efficiency scores of each state for the output-oriented CCR models for the six different models. Also, it presents the summary statistics of these six models and contribution of each model to the overall performances of each state. As expected, the efficiency scores of the original model are at least as good as the rest of the other models because the original model is the most comprehensive regarding the number of input and output variables. Therefore, the average efficiency score of Model 1 (M1) is greater than the average efficiency scores of the remaining models.

Table 4 also presents summary statistics for each state's performances with six different models. The contribution of each model to each state is shown in Figure 3. According to the overall average of six models, New Mexico (NM) is the most efficient state for operating the wind power that reached the maximum efficiency score in all of the six models. Colorado (CO), Hawaii (HI), Kansas (KS), and South Dakota (SD) follow NM in order, where their overall average efficiency scores are greater than 0.95. Moreover, 14 state's overall CCR efficiency score exceeds 0.90. Missouri (MO) is the least efficient state for operating the wind power. Maine (ME), Massachusetts (MA), and Arizona (AZ) follow MO in order, where the overall average efficiency scores are less than 0.65.

Figure 3: Comparison of Efficiency Scores of the Output Oriented CCR Models

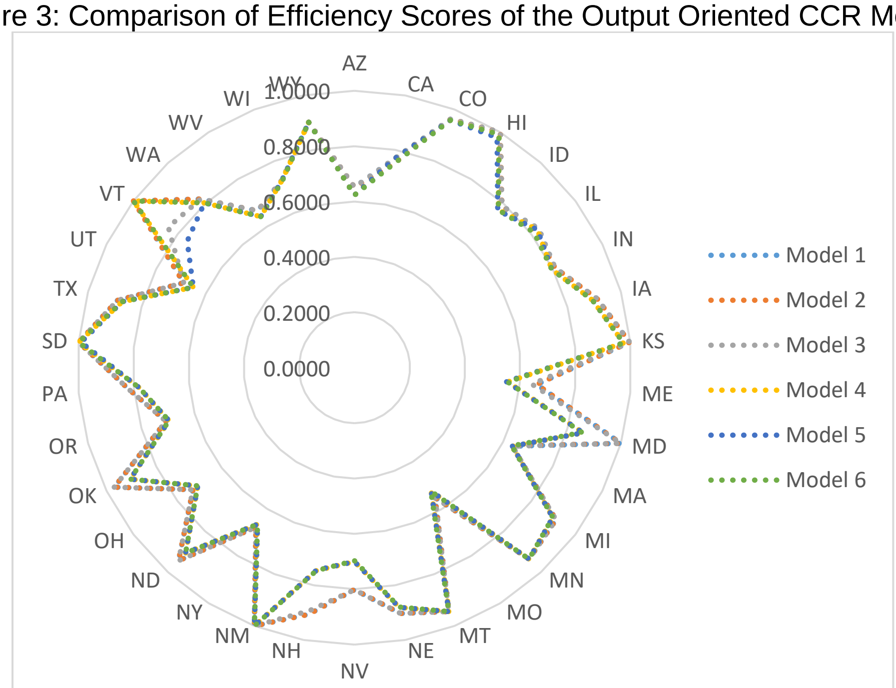


Table 4: Efficiency Scores of the Output Oriented CCR Models

States	M1	M2	M3	M4	M5	M6	Mean	Min	Max	Stdev
AZ	0.652	0.652	0.652	0.623	0.623	0.623	0.638	0.623	0.652	0.016
CA	0.765	0.745	0.765	0.765	0.765	0.745	0.759	0.745	0.765	0.010
CO	0.963	0.963	0.963	0.958	0.958	0.958	0.961	0.958	0.963	0.003
HI	1.000	1.000	1.000	0.991	0.977	0.991	0.993	0.977	1.000	0.009
ID	0.790	0.790	0.790	0.771	0.767	0.771	0.780	0.767	0.790	0.011
IL	0.833	0.819	0.833	0.827	0.827	0.812	0.825	0.812	0.833	0.008
IN	0.809	0.809	0.809	0.795	0.795	0.795	0.802	0.795	0.809	0.008
IA	0.911	0.911	0.911	0.893	0.893	0.893	0.902	0.893	0.911	0.010
KS	0.998	0.998	0.998	0.976	0.976	0.976	0.987	0.976	0.998	0.012
ME	0.661	0.661	0.643	0.556	0.551	0.556	0.605	0.551	0.661	0.056
MD	1.000	1.000	1.000	0.859	0.859	0.853	0.928	0.853	1.000	0.078
MA	0.637	0.634	0.637	0.637	0.637	0.634	0.636	0.634	0.637	0.001
MI	0.912	0.912	0.912	0.897	0.897	0.896	0.904	0.896	0.912	0.008
MN	0.936	0.936	0.936	0.935	0.935	0.935	0.936	0.935	0.936	0.000
MO	0.552	0.552	0.552	0.525	0.525	0.524	0.539	0.524	0.552	0.015
MT	0.944	0.944	0.944	0.944	0.944	0.944	0.944	0.944	0.944	0.000
NE	0.903	0.903	0.903	0.880	0.880	0.879	0.891	0.879	0.903	0.013
NV	0.802	0.801	0.802	0.701	0.701	0.696	0.751	0.696	0.802	0.056
NH	0.906	0.906	0.893	0.746	0.743	0.746	0.823	0.743	0.906	0.086
NM	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000
NY	0.677	0.677	0.677	0.665	0.665	0.665	0.671	0.665	0.677	0.007
ND	0.944	0.944	0.944	0.906	0.906	0.905	0.925	0.905	0.944	0.021
OH	0.731	0.731	0.731	0.709	0.709	0.709	0.720	0.709	0.731	0.012
OK	0.969	0.969	0.969	0.904	0.904	0.904	0.936	0.904	0.969	0.035
OR	0.708	0.708	0.708	0.697	0.697	0.697	0.702	0.697	0.708	0.006
PA	0.822	0.822	0.822	0.781	0.781	0.780	0.801	0.780	0.822	0.022
SD	1.000	1.000	1.000	1.000	0.992	1.000	0.999	0.992	1.000	0.003
TX	0.889	0.889	0.889	0.871	0.871	0.871	0.880	0.871	0.889	0.010
UT	0.689	0.689	0.689	0.651	0.651	0.651	0.670	0.651	0.689	0.021
VT	1.000	1.000	0.842	1.000	0.758	1.000	0.933	0.758	1.000	0.107
WA	0.825	0.825	0.825	0.805	0.805	0.805	0.815	0.805	0.825	0.011
WV	0.666	0.666	0.666	0.642	0.642	0.642	0.654	0.642	0.666	0.013
WI	0.727	0.725	0.727	0.724	0.724	0.722	0.725	0.722	0.727	0.002
WY	0.902	0.902	0.902	0.902	0.902	0.902	0.902	0.902	0.902	0.000
Mean	0.839	0.838	0.833	0.810	0.802	0.808	0.822	0.800	0.839	0.020
Min	0.552	0.552	0.552	0.525	0.525	0.524	0.539	0.524	0.552	0.000
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.107
Stdev	0.129	0.129	0.126	0.134	0.130	0.135	0.128	0.130	0.129	-

SUMMARY AND CONCLUSION

This study evaluates the relative productive efficiencies of the 34 state's wind power performances by using multi-criteria decision-making tool. DEA is conducted for the output-oriented CCR and BCC models by using predetermined two input and three output variables.

The DEA results indicate more than two-thirds of the states operate wind power efficiently, and their productivity is relatively high as well. However, there are only five states (HI, MD, NM, SD, and VT) that are operating wind energy at the most productive scale size. In addition, five states (MA, MT, NV, NH, WI) may increase their productivity efficiency with investing more in the more productive wind technologies. Besides, there are 24 states overinvested to the wind power on the optimum production scale. As discussed above, the results illustrate that early installed wind power was more expensive and less productive than the current installed wind power. One of the primary reason is declining cost of wind energy over the period with technological advancements in manufacturing and material solutions of wind turbines.

The sensitivity analysis is conducted with the various combinations of input and output variables of the original model for the purpose of the robustness of DEA. According to the overall average of six models, New Mexico (NM) is the most, and Missouri (MO) is the least efficient state for operating the wind power. Colorado (CO), Hawaii (HI), Kansas (KS), and South Dakota (SD) follow NM in order, where their overall average efficiency scores are greater than 0.95. Moreover, 14 state's overall CCR efficiency score exceeds 0.90. Maine (ME), Massachusetts (MA), and Arizona (AZ) follow MO in order, where the overall average efficiency scores are less than 0.65.

Based on the findings of this study, some relevant suggestions are given as follow: First, the current wind technology is much more productive and reliable than relatively old technology, so that the states which have old technology wind turbines should replace them with current technology to increase their productivity level. Second, the 11 states that do not have any utility-scale wind power may start their efficient wind power generation with small-scale wind farms with benchmarking HI, MD, NM, SD, and VT. Third, the policymakers should continue federal incentives to keep wind energy attractive for the investors, and the bills should cover an extended period to obtain stable growth in the industry. Lastly, Renewable Portfolio Standards (RPS) should be ratified by each state.

In conclusion, it is hoped that the findings of this study shed some light on the current efficiency assessments of the 34 state's wind power for both energy practitioners and policy makers.

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