BEHZAD ADIBFAR PRODUCTIVE EFFICIENCY OF TURKISH WIND FARMS Bilkent University 2019

PRODUCTIVE EFFICIENCY OF TURKISH WIND FARMS: A TWO-STAGE DATA ENVELOPMENT ANALYSIS

A Master's Thesis

by

Behzad Adibfar

Graduate Program in

Energy Economics, Policy and Security

İhsan Doğramacı Bilkent University

Ankara

September 2019

To my dear parents

PRODUCTIVE EFFICIENCY OF TURKISH WIND FARMS: A TWO-STAGE DATA ENVELOPMENT ANALYSIS

The Graduate School of Economics and Social Sciences

of

İhsan Doğramacı Bilkent University

by

Behzad Adibfar

In Partial Fulfillment of the Requirements for the Degree of
MASTER OF ARTS IN ENERGY ECONOMICS, POLICY AND SECURITY

Graduate Program in Energy Economics, Policy and Security

…………………………………………………………..

İhsan Doğramacı Bilkent University
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September 2019

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Energy Economics, Policy, and Security.

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ABSTRACT

PRODUCTIVE EFFICIENCY OF TURKISH WIND FARMS: A TWO-STAGE DATA ENVELOPMENT ANALYSIS

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M.A. Program in Energy Economics, Policy and Security

Supervisor: Assoc. Prof. Dr. Fatma Taşkın

September 2019

This thesis estimates the relative productive efficiency of Turkish wind farms to discover their inefficiency reasons using a two-stage Data Envelopment Analysis (DEA). We choose three input variables and two output variables to conduct 4 different DEA models including input- and output- oriented CCR (Charnes, Cooper, Rhodes) and BCC (Banker, Charnes, Cooper) models. Sensitivity analysis is applied to DEA results to ensure the stability and robustness of the four models. In the second stage Tobit regression models are utilized to explore the exogenous factor that affect the efficiency of Turkish wind farm. DEA results indicate that 40% of Turkish wind farms were operating at preferable levels during 2017. Moreover, 42% of the wind farms should increase their operation levels by adding new installations, and 46% should decrease their capacity due to overinvestments. The sensitivity analysis confirms the robustness of DEA models in this thesis and reveals that amount of electricity generation as an output has substantial impact on the DEA results. Finally, Tobit regression results indicate age and site elevation do not have significant effect on the efficiency of Turkish wind farms. Furthermore, using Tobit regression, we discovered that Chinese and Indian made turbines have negative effect on the performance of Turkish wind farms.

Keywords: Data Envelopment Analysis (DEA), Productive Efficiency, Tobit Regression, Wind Farms,

ÖZET

TÜRKİYE RÜZGAR ENERJİ SANTRALLERİNİN ÜRETKEN VERİMLİLİĞİ: BİR İKİ-KADEMELİ VERİ ZARFLAMA ANALİZİ

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Yüksek Lisans, Enerji Ekonomisi ve Enerji Güvenliği Politikaları Programı

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Bu tez, Türkiye'deki rüzgar santrallerinin iki aşamalı Veri Zarflama Analizi (VZA) kullanarak, verimlilikleri tahmin etmek ve yüksek verimlilik nedenlerini araştırmayı amaçlamaktadır. Çalışmada ilk aşamada olarak girdi ve çıktı odaklı CCR ve BCC modelleri dahil olmak üzere 4 farklı VZA modeli, seçilen üç girdi ve iki çıktı değişkeni ile incelemiştir. İkinci aşamada, Türk rüzgar çiftliğinin verimliliğini etkileyen dışsal faktörleri belirlemek için Tobit regresyon modelleri kullanılmıştır. VZA sonuçları, Türkiye rüzgar santrallerinin % 40'ının 2017 yılında tercih edilen seviyelerde çalıştığını göstermektedir. Tanımlanan ölçek ekonomilerine göre, rüzgar santrallerinin % 42'sinin yeni tesisler ekleyerek işletme seviyelerini yükseltmesi ve % 46'sının fazla yatırımlar nedeniyle kullanım kapasitelerini azaltması gerektiğini göstermektedir.Girdi ve çıktı tanım farklılıklarının VZA sonuçları üzerindeki etkisinin incelemek için modelde duyarlılık analizi uygulanmıştır. Farkı girdi ve çıktı karışımlarına VZA sonuçlarının duyarlılığı araştırılmıştır. Kullanılan elektrik üretimi miktarının VZA sonuçları üzerinde en önemli bir etkisini olan çıktı olduğunu görülmüştür. Son olarak, Tobit regresyon analizde santral yaşı ve alan yüksekliğinin, Türk rüzgar santrallerinin verimliliği üzerinde önemli bir etkisi olmadığını sonucuna varılmıştır. Ayrıca, Tobit tahminleri Çin ve Hint türbinlerinin, Türk rüzgar santrallerinde en düşük verimlilik performansını gösterdiği görülmüştür.

Anahtar kelimeler: Rüzger Enerji Santralleri (RES), Tobit regresyon, Veri Zarflama Analizi (VZA), Üretken verimlilik

ABBREVIATIONS

BCC: Banker, Cooper, Charnes

CCR: Cooper, Charnes, Rhodes

CRS: Constant Returns to Scale

DEA: Data Envelopment Analysis

DMU: Decision Making Unit

DRS: Decreasing Returns to Scale

EMRA: Energy Market Regulatory Authority

GW: Giga Watt

GWEC: Global Wind Energy Council

GWh: Giga-Watt hour

IEA: International Energy Agency

IPCC: Intergovernmental Panel on Climate Change

IRENA: International Renewable Energy Agency

IRS: Increasing Returns to Scale

MENR: Ministry of Energy and Natural Resources

MFA: Ministry of Foreign Affairs

MW: Mega Watt

MWh: Mega-Watt hour

OECD: Organization for Economic Co-operation and Development

PWEM: Potential Wind Energy Map

RERSM: Renewable Energy Resources Support Mechanism

RTS: Returns to Scale

SE: Scale Efficiency

SFA: Stochastic Frontier Analysis

TWEA: Turkish Wind Energy Association

VRE: Variable Renewable Energy

VRS: Variable Returns to Scale

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CHAPTER I

INTRODUCTION

1.1 Introduction

Human activities (e.g. burning fossil fuels, clearing land for agriculture, and deforestation) since the industrialization era has led to significant accumulation of Green House Gases (GHG) in the atmosphere of Earth. These gases such as carbon dioxide, nitrous oxide, methane, etc. block heat from escaping out of the Earth's surface. According to the Intergovernmental Panel on Climate Change (IPCC), since 1870, there is a direct linear correlation between cumulative total CO_2 emissions and global mean surface temperature response (IPCC 2018). Consequently, the temperature of the Earth's surface has approximately increased by 1±0.2 °C in 2017 compared to pre-industrial levels, with an average increase of 0.2±0.1 °C per decade (IPCC 2018). The warmer surface of the Earth will increase evaporation and precipitation which drives the wet regions to be wetter and dry regions to be dryer. Moreover, melting polar glaciers on the surface of Earth will increase sea levels which could lead to devastating impacts on different regions. The impacts of climate change are already being perceived globally, and insufficient actions against this crisis would drive life on Earth to an irreversible situation. Thus, in a global attempt to reduce the global temperature to pre-industrial levels, within the United Nations

Framework Convention on Climate Change (UNFCCC), 197 parties signed the Paris Agreement on 22nd April 2016. According to this agreement, by 2050, member states should expand the portion of renewables and nuclear energy substantially in their energy portfolio. Besides, immediate steps required for energy efficiency plus capture and storage of carbon dioxide released by the combustion of fossil fuels. Hence, climate change and global warming along with the intensive surge in global energy demand accelerated energy transition toward the development of clean and sustainable sources of energy. Renewable energies and energy efficiency as the pillars of that transition are now applicable to the energy sector at a large scale thanks to available and cost-competitive technologies.

International Energy Agency (IEA) has forecasted that renewables will have the fastest growth in the electricity sector, providing almost 30% of power demand in 2023, up from 24% in 2017. Hydropower will remain the largest renewable source, meeting 16% of global electricity demand by 2023, followed by wind (6%), solar photovoltaic (4%), and bioenergy (3%) (IEA, 2018). Among renewables, wind power has proven to be one of the cleanest and most reliable sources of energy. The global wind energy market has experienced remarkable growth since the second millennium due to availability, zero CO_2 emission during electricity generation, and advanced cost-competitive technology. Wind power is even preferable over hydropower because of sustainability and substantially low water consumption, specifically in countries facing a water crisis. Consequently, compared to only 17 GW in 2000, global installed wind power capacity surged to 564 GW by the end of 2018. With growing interests in wind power, more countries are increasing the share of this clean energy in their energy portfolio and Turkey’s energy market is not an exception.

Since the ratification Renewable Energy Resources Support Mechanism (RERSM) in 2005 and due to remarkable rising demand for energy and the desire to mitigate share of imported fossil fuels wind energy industry started to boom in Turkey. The cumulative installed wind power capacity of Turkey reached 6,516.2 MW in 2017 which compared to European countries, after Germany, France, Sweden, and the UK has the most installed capacity for wind energy. Currently, wind power supplies 7% of the electricity demand in Turkey which is the second largest source of renewable energy after hydraulic power. The official 2023 vision for wind capacity in Turkey is 20,000 MW. This target is arguable and with the recent trend in capacity addition, Turkey's installed wind capacity is expected to reach to a value of approximately 11,000 MW in 2023 (Melikoglu, 2018).

Development of wind industry in Turkey will continue to grow, however wind power is variable renewable energy (VRE) in which the electricity generation process is intermittent due to the fluctuating nature of wind. Hence, it is essential to develop a capacity to harness wind power in an efficient manner. Moreover, since the rapid expansion of the wind energy industry in Turkey, there is a gap in scholar research on performance assessment of the existing wind farms. The performance assessment of operating Turkish wind farms is pivotal: first to provide an insight to the productive efficiency level of the existing wind farms and to recognize the reasons for inefficiency in performance and launch policies to improve the efficiency of electricity generation process. And second, to present guideline for future investments in the Turkish wind energy industry and contribute to achieving sustainable development goals in this sector.

This study aims to empirically address the question of "whether Turkish wind farms have been generating electricity efficiently or not?". Using a two-stage Data Envelopment Analysis (DEA), a non-parametric non-stochastic technique first we appraise the relative productive efficiency level of 73 operating Turkish wind farms in year 2017. In this stage, three input and two output variables are determined to implement both input- and output-oriented efficiency models. Subsequently, in the second stage, Tobit regression models identify the effect of major factors e.g. age, site elevation, and brand of the turbines, on the performance level of the wind farms. Results of this study can guide the managers of the Turkish wind farms to formulate appropriate policies to improve the efficiency level of the wind farms and will shed some light on investment strategies in the Turkish wind industry.

The remainder of this study is organized as follows;
In Chapter II, Section 1 presents a historical review of the use of wind power. Section 2 explains the current status of the global wind market and in Section 3 a comprehensive overview of the Turkish electricity market and development of the wind energy market in the country is provided. Chapter III includes three sections in which Section 1 presents a thorough literature review for application of DEA methodology in the wind industry, Sections 2-4 provide the introduction of the DEA method, Tobit estimation technique, and sensitivity analysis. Section 5 presents the description of data used in the computation of productive efficiency which includes two output and three input variables. Section 6 presents the DEA results obtained from four common models in the literature. The results of the sensitivity which confirm the robustness and stability of different DEA models are also reported in this section. Moreover, this section presents the result of Tobit regression models which

are used to explain the effect of various determinants of productive efficiency in wind farms. Lastly, Chapter IV provides the conclusions and policy recommendations for the Turkish wind farms.

CHAPTER II

WIND POWER

2.1. A Brief History

The use of wind power as a source of energy goes back to early 5000 BC when the propel boats used wind energy along the Nile River. Years later, simple wind-powered pumps have been invented by Chinese. At the same time in Persia and the Middle East windmills with woven-reed blades has been implemented; this invention leads to extend the usage of wind pumps and windmills to produce more food by the end of the 11th century. Eventually, this technology had spread to the Western Hemisphere by European immigrants. King Hammurabi of Babylon has been known as the one who implemented the plan of using vertical-axis wind-powered machines to transfer fertile plains of the Euphrates and Tigris Rivers. Since A.D. 1350, Holland has used windmills to drain marshes and shallow lakes to turn them into productive agricultural lands.

The first practical horizontal windmills had been installed in Sistan, a region in Iran during the 9th and 7th centuries. These windmills became popular across the Middle East and spread to China and India. On the other hand, American colonies utilize wind power to run windmills to grind grains, pump water to settlements in the

Western United States, and also cutting woods. The first small wind-powered generators which also known as wind turbines have been invented in the late 1800s and early 1900s and been used widely since then, even though with the extension of power lines in the 1930s, the usage of wind pump and small wind turbines decreased dramatically. The small wind turbines continue to be popular to supply the electricity demand of remote and rural areas which connected them to the power grid.

The UK has been installed its first windmill at Weedley in Yorkshire at 1158. The Dutch started to use their windmills in the Rhine delta. These windmills had been used for farming or even drawing water from one place to another until the end of the 19th century when Scottish scientist introduce wind as an alternative source for producing electrical energy. The first renewable wind turbine invented by Scottish Professor James Blyth in 1887. Nevertheless, during the industrial revolution, most of the Dutch-style windmills replaced by steam-powered mills. In summary, windmills and water-driven mills have been used over 1200 years to power generators. By 1900, Denmark had about 2500 windmills installed, which had been used for mechanical loads like pumps and mills. At the same time, the American scientists were developing the larger wind turbine project to create large enough power stations to provide the electricity at a more affordable price. However, the first wind-powered turbine has not been installed until 1941. These turbines have greater abilities to provide distributable energy with less risk and stronger efficiency. The evolution that perfected procedure to create the components and features of the modern windmills took about 500 years. The combination of wood and metal has been used to prevent fires as a result of storms or other hazardous weather conditions. However, nowadays, this metal has been replaced with glass epoxy, fiberglass, aluminum, and even graphite composite materials.

Energy crisis in the 1970s had a great influence on energy production all around the world. Shortages in oil supply, led mankind develop ways to utilize alternative energy sources like wind, to produce electricity. With such developments, wind power generated electricity started to be used in small scales in more than 83 countries all over the world. Moreover, such wide usage and updates in its technologies, lead to installment and operation of the world's first offshore wind-powered generators in Denmark in 1973. Nowadays, based on the 2017 reports, Denmark generates its 43.4% electricity demand by using wind power generators. Such reports also listed Denmark alongside Spain and Germany as the most wind energy-producing countries of the European Union.

Turkey's first wind farm has been built in 1998 which led to establishing the Renewable energy law that includes financial incentive to develop the wind power plants. Not accessing to fossil fuel, make available renewable energy sources like wind power plants crucial for Turkey's economy. Furthermore, wind measurements that have been performed by the National Meteorology Institute indicated the potential of agricultural and even living areas for wind farm implementations. Such environment-friendly wind power generators convert the kinetic energy of wind into electricity.

In the last 20 years, with increasing concerns toward the development of cleaner energies in large scales to create energy security, wind farm development has been moved at a pace. Even with the reduction in government green subsidies, wind turbines provide the most electricity demand among the other types of renewable energy technologies including solar panels. Yet, wind power technology in the past had limited application because of the lack of economic benefits and supply stability. By the start of the twenty-first century, innovations in materials, construction, control designs, and other technologies had a great impact on the capacity and efficiency of the installed wind power generators.

In conclusion, the desire to produce more sustainable and clean energy makes wind turbines one of the most important alternative sources to supply future energy need. Wind-powered generators have been considered as an inevitable part of every development planning because of its merits in cost, ecological compatibility, sustainability, and ubiquity natures. On the other hand, wind speed and its fluctuations have been considered by engineers while designing the farm wind plants during the development of its technology. Moreover, in such wind farms, the generation schedule planned based on the day-ahead wind power forecast.

However, wind farms future depends on settings the basis on solid and reliable science, engineering and economics. The advantage of the wind is its infinite magnitude orientation in the Sun's fusion energy which is trapped in the atmosphere. Furthermore, the implementation of wind turbines is rapid cause it takes about 2 years since they only require local regulations. On the other hand, with the world embarking to the third industrial revolution, namely, the Low Carbon Age, wind farms installation plays a pivotal role in sustainable development. Global studies indicated that in the next 40 years, wind farm technologies are going to improve and the generation cost will decrease more than 50% to generate more affordable and cleaner energy for the increasing population. Furthermore, nowadays advanced technologies create opportunities for various sized wind-powered generators to operate to charge batteries or even provide electricity demand of the whole nation. But, it should be noted that wind power is variable, so during the low seasons, alternative resources should be considered to supply the energy demand.

2.2. Global Wind Energy Market

Wind power is a mature and yet rapidly developing renewable energy technology. Considering the devastating consequences of climate change attempts to curb the reliance on fossil fuels and rapidly growing demand for energy, more countries include wind power in their energy mix. Advancement of wind power technology has made the sector more cost-competitive compared to conventional sources of energy which also intensifies incentives for investment in the wind energy sector. International Renewable Energy Agency (IRENA) estimates the cost of per kW of different wind power technologies in its annual reports. According to these reports, the average cost of wind turbines ranges from 527 USD/kW for the Chinese turbines to 980 USD/kW for the BNEF WTPI[1] technology in 2017. The average cost of turbines has plunged significantly in the last decade. For example, the Chinese wind turbines' price has decreased more than 53% since 2007 and the other wind turbines have experienced almost the same drop in the price since then (IRENA, 2017).

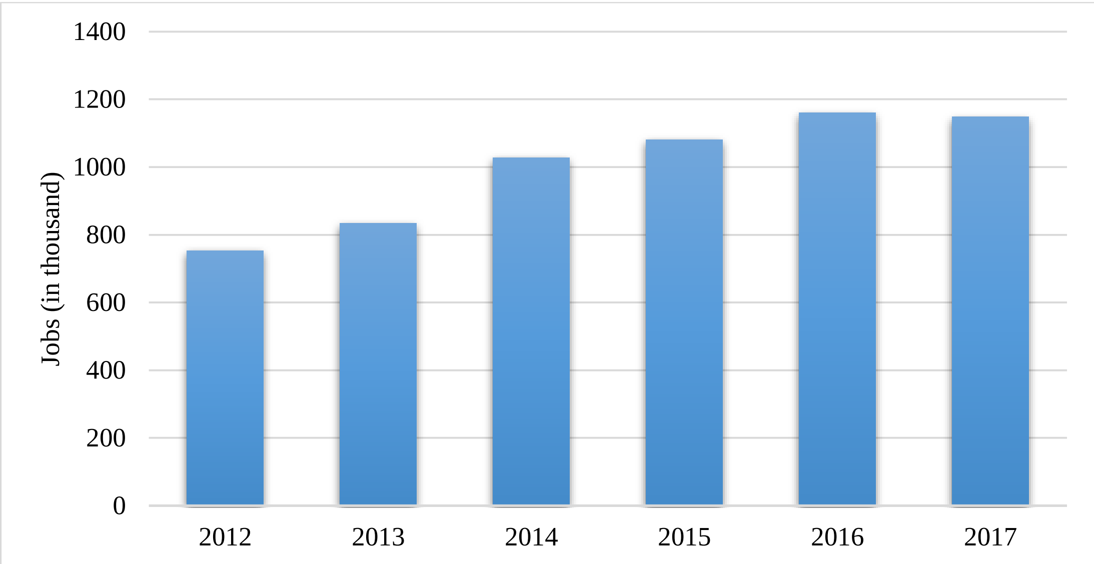

Figure 1. Worldwide Employments Provided by Wind Energy Sector. (Source: IRENA)

[1] Bloomberg New Energy Finance Wind Turbine Price Index

Since the fuel for wind power production is provided by nature each megawatt-hour generated by wind power costs significantly less compared to power plants fueled by the conventional sources of energy, where additional costs for the fuel increase the variable costs for electricity generation. Wind energy also provides effective contributions to the countries' economy. While the sector grows rapidly, job opportunities increase correspondingly, which range from technology expert to wind farms operator positions. Wind energy market, in 2017, has created more than 1.1 million jobs worldwide and the number is expected to increase with further developments in the sector as can be seen in Figure 2. Moreover, governments purchase electricity from the companies running wind farm projects at fixed prices based on 20-25 years contracts which contribute to price stability. Therefore, wind power development as a domestic source of energy decreases the vulnerability of energy consumers against the unpredictable and fluctuating prices of fossil fuels. Furthermore, since generating electricity by wind has zero CO_2 emissions, it is also contributing to decreasing environmental impacts and necessary governmental expenditures by cutting carbon costs imposed on the economy especially in developed countries.

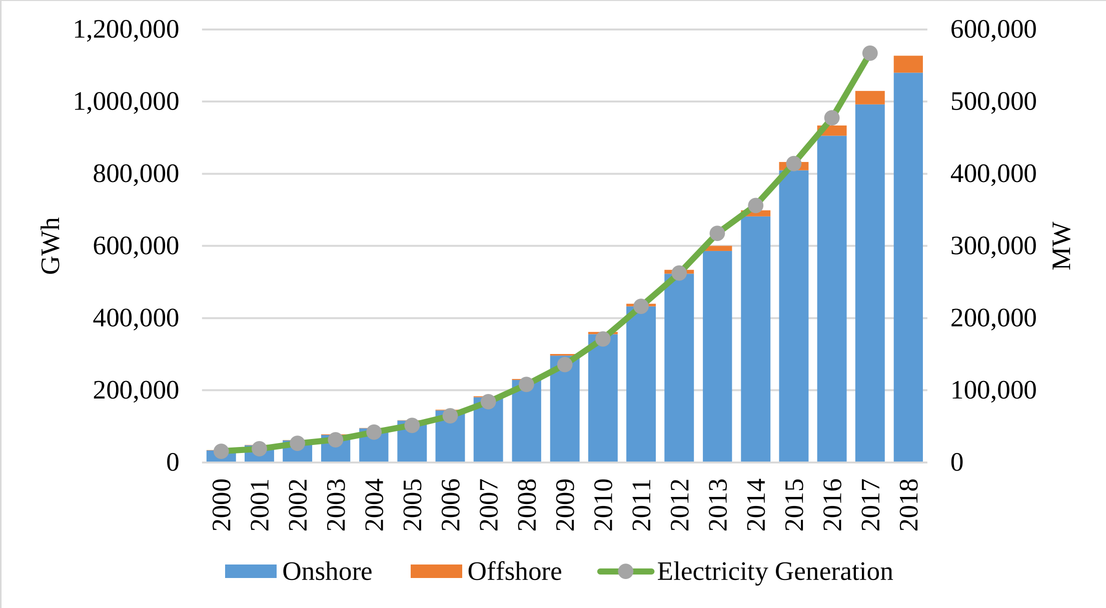

Figure 2. World Wind Energy Installed Capacity & Electricity Generation Development. (Source: IRENA)

In an exponential trend, since the second millennium, the global total installed wind capacity reached 564 GW by the end of 2018 and 1,134 TWh of electricity generated by wind in 2017. In this regard, in a decade, both total installed capacity and electricity generated by wind power increased by approximately fivefold which resulted to bring the share of wind energy in the global market to eight percent. Today China is the leading country in the wind power sector with 184,6 GW of cumulative installed capacity in 2018 due to the promotion of favorable governmental policies and the country’s high potential for wind energy. The second-largest wind market belongs to the US with a total installed wind capacity of 94.2 GW in 2018. In addition to China and the US, Germany (60 GW), India (35 GW), and Spain (23 GW) collectively form the top five wind markets. Figure 3 illustrates the top 10 countries by the highest installed wind power in their energy portfolio, in 2018.

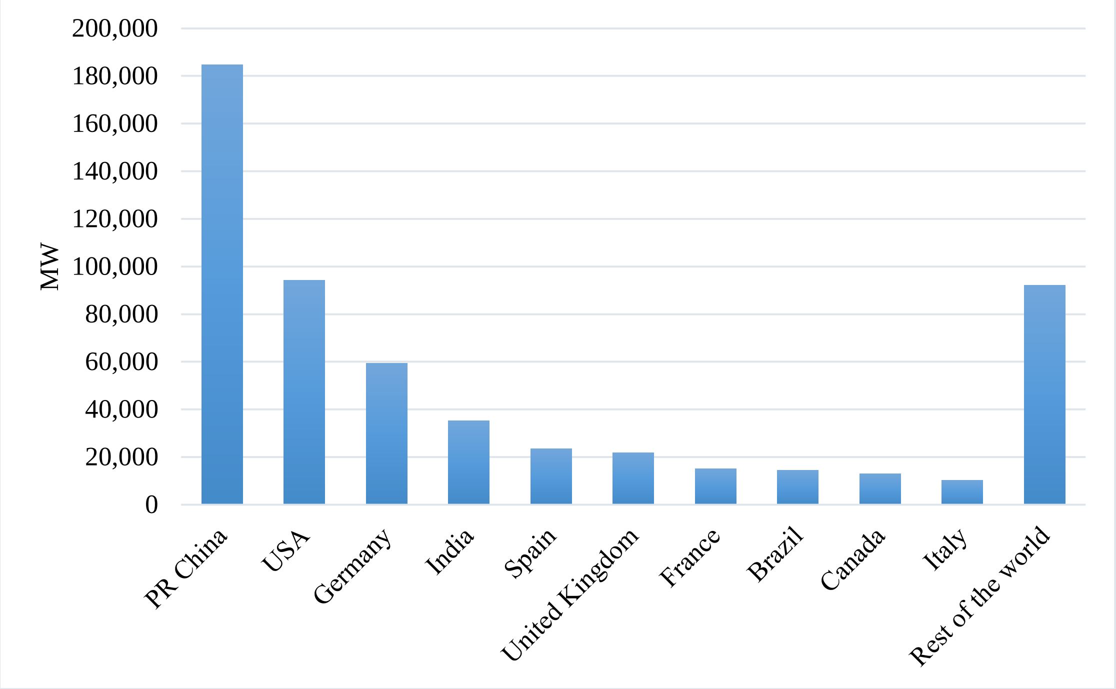

Figure 3. Top 10 Wind Markets in 2018. (Source: IRENA)

It is difficult to estimate new installation by private sector by excluding governmental supports such as renewable share objectives and auction/tender policies. However, the global wind energy industry is expected to grow further through existing supportive governmental policies and new business models continuously. Global Wind Energy Council (GWEC) Market Intelligence estimated that 300 GW of wind power capacity will be added to the global cumulative installed capacity until 2023 (GWEC, 2018). China is expected to still lead the wind market by 2023 however the market share will drop due to new installations in other regions of the globe. Owing an already developed wind market new installations in Europe will remain constant. In Asia excluding China, India is expected to have the most contribution to new installations whilst the government prefer wind over subsidizing coal. The new installations in North American states especially the US will expand further between 2019 and 2020. The offshore wind industry is also developing rapidly due to high potential in many regions and advanced cost-competitive technologies being offered in the market and it is expected to emerge as a large-scale global market in the next five years. Currently, nine percent of world new wind installation include offshore and this portion is expected to double in by 2023.

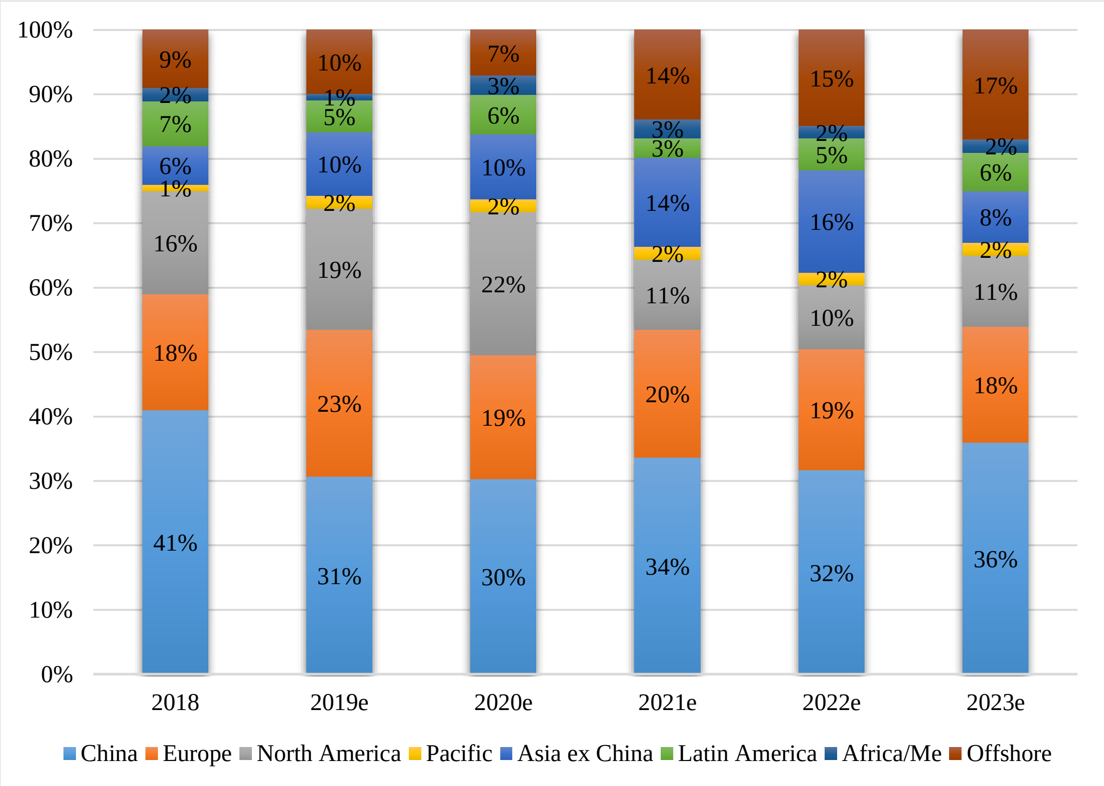

Figure 4. Near-Term New Wind Power Installations Vision by Regions

2.3. Wind Energy in Turkey

Turkey's economic development parallel to its growing population has lead the country's demand for energy to the all-time high point which comparing to the OECD countries, it has the largest positive change rate in energy demand over the last 15 years. (MFA, 2019) By the end of 2017, the electricity demand in Turkey has reached 297 TWh, which has been doubled since 2004 (Figure 5). Furthermore, according to government reports, the lowest expected electricity consumption amount could reach

453 TWh by the year 2030. Increasing demand for energy requires the development of electricity infrastructure, market liberalization, and establishing long term production visions.

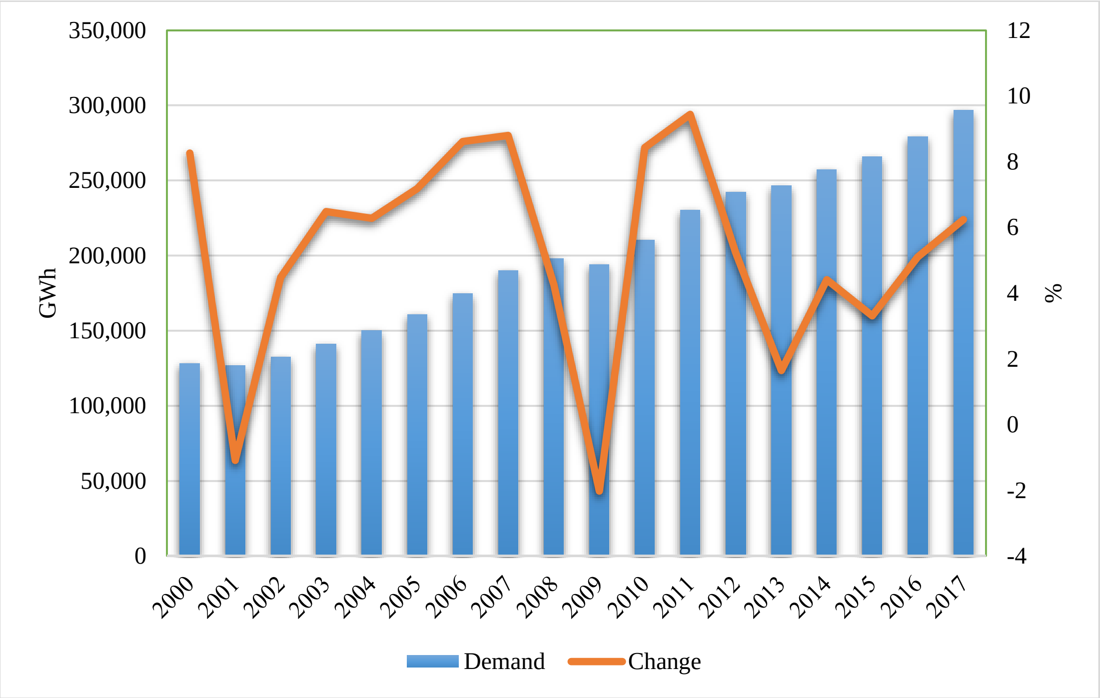

Figure 5. Demand for Energy in Turkey, 2000-2017. (Source: TEİAŞ)

Therefore, the Turkish energy sector has experienced significant growth over the past decade. Since 2007, as the result of liberalization and privatization legislations in the electricity market, Turkey's total installed power capacity doubled and reached 85,200 MW generating 295 TWh of electricity (Figure 6). In its latest report, Turkish Ministry of Energy and Natural Resource (MENR) reveals that the country has 7,423 electricity production power plants, which according to their primary sources of energy are categorized as; 653 hydraulic, 42 coal, 249 wind, 48 geothermal, 320 natural gas, 5868 solar, and 243 other power plants. (MENR, 2019)

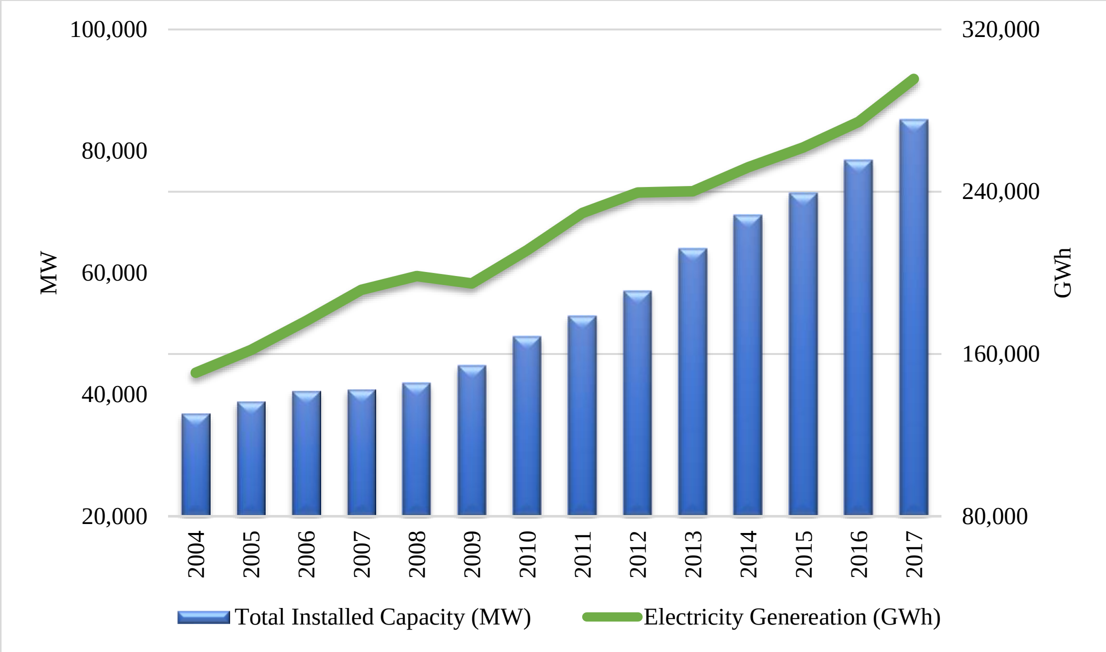

Figure 6. Turkey's Total Installed Capacity & Total Electricity Generation, 2004-2017. (Source: TEİAŞ)

By the end of 2017, 37% of Turkish electricity production was supplied by natural gas; 33% from coal, 20% from hydropower, 6% from wind, 2% from geothermal, and 2% from other sources. Figure 7 and 8 illustrate the share of primary sources of energy in Turkey regrading amount of electricity generation and installed capacity, respectively. Thermal sources, specifically natural gas and coal, by generating more than 70% of the electricity, predominate the country's energy portfolio. Additionally, more than half of the fossil fuels used for generating electricity was imported, leaving only 45.2% for the domestic resources to supply the country's rising energy demand. Hard coal is the only domestic conventional energy source of Turkey and there are policies to increase the number of coal-fired power plants. These policies, beside over-dependency on imported natural gas and lignite in order to generate electricity, could raise serious economic and environmental issues for the country. Thus, the Turkish policymakers have initiated strategies in order to mitigate the share of fossil fuels and by 2023, the government aims to raise the share of domestic energy sources to two-thirds by diversification of energy sources, increasing the share of renewables, and enhancing energy efficiency.

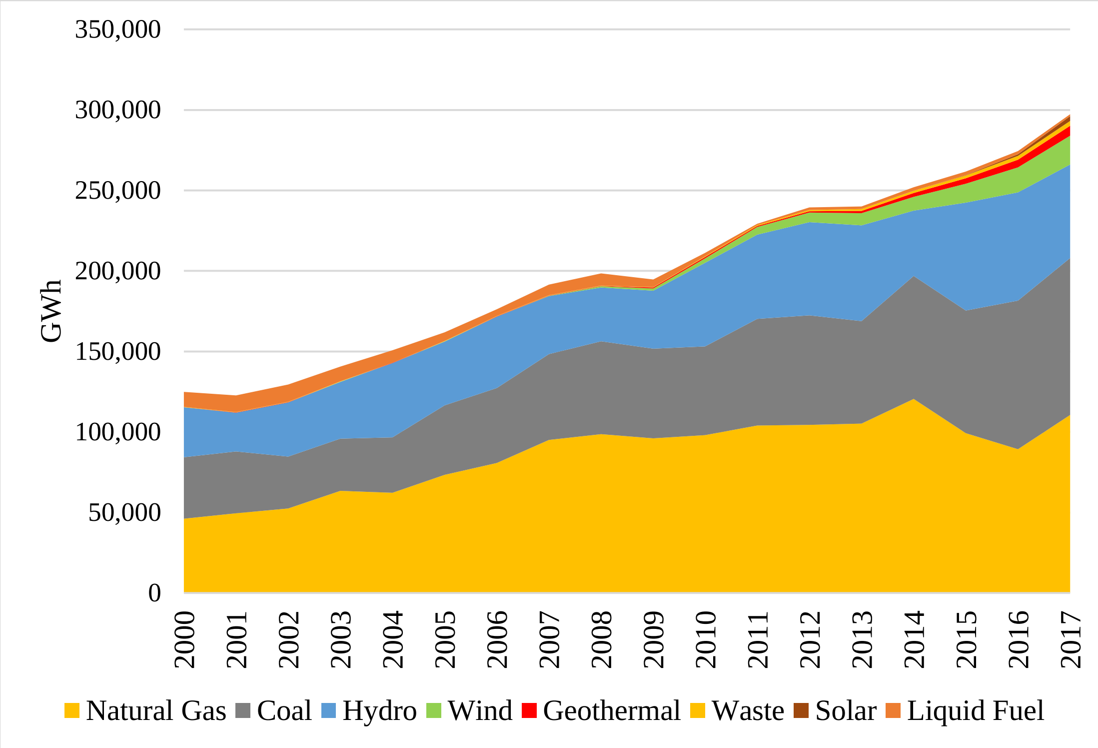

Figure 7. Development of Turkey's Electricity Generation by Primary Energy Resources, 2000-2017. (Source: TEİAŞ)

Even though Turkey does not possess significant conventional energy sources, the country has a high potential for renewable sources of energy. According to research by MENR, Turkey's renewable energy potential 136.6 GW. Assuming that this potential could be fully utilized, it is more than sufficient for the country's current and mid-term demand for electricity. As Table 1 presents, Turkey has significant potential for utilizing wind and solar power which together if fully developed have the potential to exceed the country's current total installed power capacity.

Table 1 Economic Potential of Renewable Energy Sources in Turkey (Source: MENR)

Renewable Energy Sources	Potential (MW)	Installed Capacity in 2017 (MW)	Capacity Factor	2023 Vision of Installation (MW)	Average Annual Electricity Generation Potential (GWh/yr)
Hydro	36,000	27,273	%44	36,000	144,000
Wind	48,000	6,516	%30	20,000	60,000
Solar	50,000	3,420	%20	3,000	7,500
Geothermal	600	1,064	%84	600	4,400
Biomass	2,000	477.4	%80	2000	14,000
Total	136,600	38,750.4	-	61,600	229,900

Regarding wind power, Turkey is amongst the world's leading countries to expand its wind installed capacity. Starting from 2009, wind power has gained significant importance in Turkey's energy mix and it has become the second-largest renewable source of energy after hydropower.

According to the Potential Wind Energy Map (PWEM), theoretically, Turkey has roughly 48,000 MW potential to harness wind power (38,000 MW onshore & 10,000 MW offshore). The total area which is equivalent to this potential is just 1.30% of the total surface area of Turkey. Besides, it has been estimated that under the current electricity network infrastructure, Turkey has 10,000 MW potential of wind power. This potential could hit 20,000 MW by implementing necessary development in electricity transmission and distribution infrastructures. Turkey has set the target to

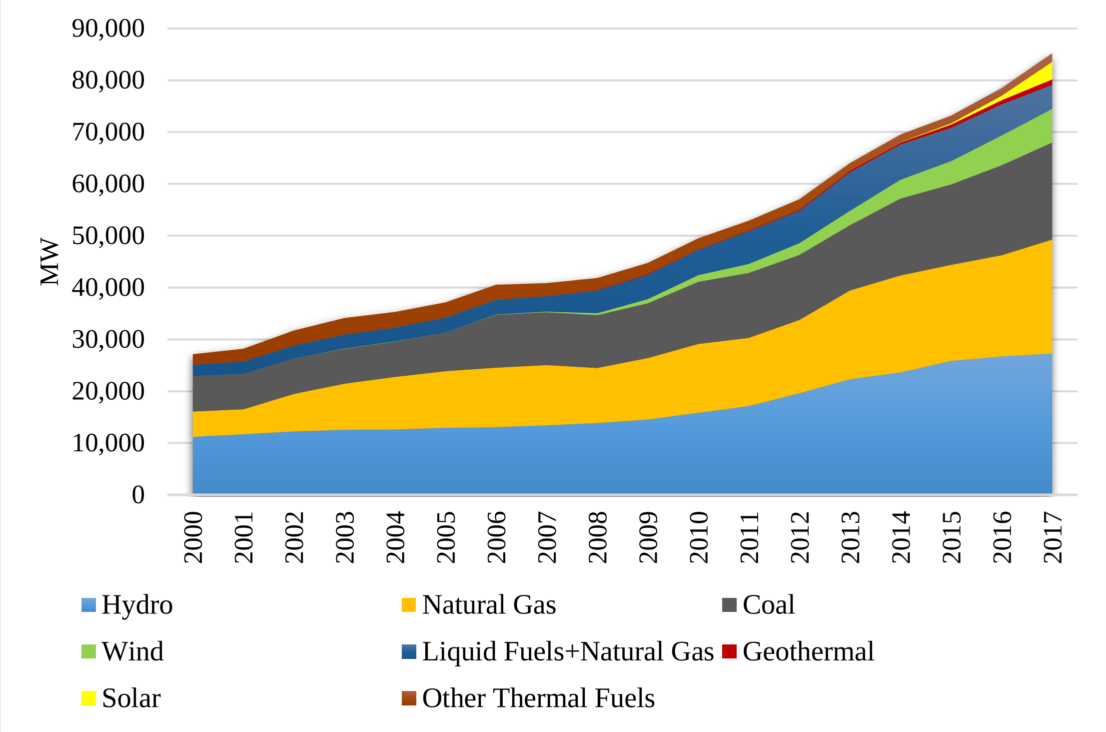

Figure 8. Development of Turkey's Installed Capacity by Primary Energy Resources (Source: TEİAŞ)

reach 20,000 MW of wind power installed capacity by 2023. The cumulative installed wind power capacity reached 6,516.20 MW by the end of 2017. The nominal generating capacity for wind energy in 2004 was only 18.90 MW. Since then, wind power installed capacity surged exponentially as a result of governmental subsidies and private sector's investments. In Turkey, wind power generated 17,903.80 GWh of electricity by 164 wind power plants in 2017, 144 of them generated 16,667.92 GWh of electricity under the Renewable Energy Resources Support Mechanism (RERSM). Figure 9 illustrates the cumulative and new installed wind power capacity of Turkey between 2004 and 2017.

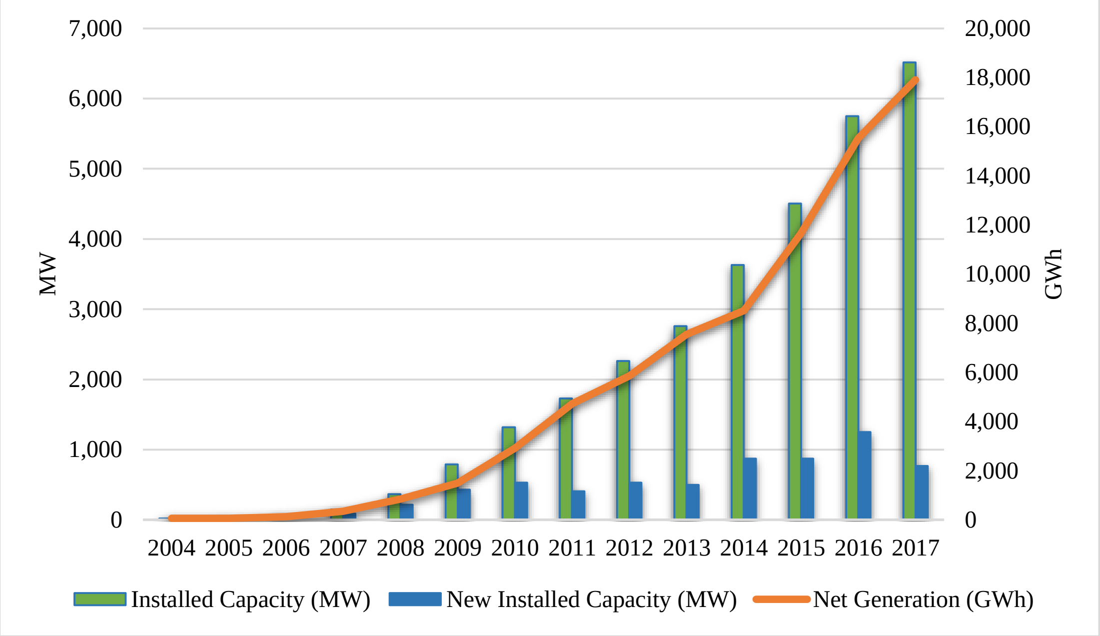

Figure 9. Wind Energy in Turkey, 2004-2017 (Source: TEİAŞ)

Diversification of energy sources toward renewables and implementation of efficiency policies are inevitable for Turkey to reach 2023 vision. The limited wind power potential of Turkey compared to countries like China and the US demands comprehensive research and analysis of the existing wind farms before the establishment of new capacity. Moreover, examination of current wind farms is crucial for increasing the efficiency of electricity generation in order to propel the production to the optimum point.

CHAPTER III

LITERATURE REVIEW, METHODOLOGIES, AND EMPIRICAL RESULTS

3.1. Literature Review

Developed by Charnes (1978) Data Envelopment Analysis (DEA) is a non-parametric and non-stochastic linear programming, technique to evaluate the relative performance of homogeneous Decision Making Units (DMUs). DEA has opened up numerous possibilities for benchmarking cases which have been resistant to other approaches by solving the complex (often unknown) nature of the relationships between the multiple inputs and multiple outputs involved in many of activities. This method has also proven to be a reliable benchmarking tool in the energy sector and it has been utilized by a vast number of scholars focused on energy efficiency issues. Regarding the application of DEA method in the energy sector, (Mardani, Zavadskas, Streimikiene, Jusoh, Khoshnoudi, 2017) present a comprehensive literature review of 144 articles published between 2006 and 2015 on the DEA applications in energy sector. This survey categorizes the examined articles into nine application areas: environmental efficiency, economic and eco-efficiency, energy efficiency issues, renewable and sustainable energy, water efficiency and other application areas.

(Zhou, Ang, Poh, 2008) provide a thorough literature survey on the application of data envelopment analysis (DEA) to energy and environmental studies by a classification of 100 publications related to the fields. Also, in an exhaustive review, (Sueyoshi, Yuan, Goto, 2017) summarize previous research efforts of 693 DEA-related articles published from the 1980s to 2010s. The study indicates that more than 400 articles applied DEA methodology to energy issues including electricity generation, transmission & distribution network, renewables, energy efficiency, etc.

The accelerated development of wind power industry in recent years has promoted the significance of efficiency evaluation of wind farms. In this regard, DEA has also proven to be a promising method in the literature of the efficiency analysis of wind power sector. This literature is divided into two categories; the first category deals with the efficiency analysis of wind power technology compared to other technologies, and the second category analyze the efficiency of a group of wind farms as decision making units (DUMs). Within the first group of studies, which compare the efficiency of wind power technology with other electricity generation technology following examples are presented; (Lins et al., 2012) analyze the performance of alternative energy sources of Brazil from socioeconomic and environmental aspects. The study justifies that the Brazilian government should prioritize policies which encourage investments in technologies using solid wastes to generate electricity. (Kim, Lee, Park, Zhang, Sultanov , 2015) utilize DEA to assess the efficiency of investments in three major sources of renewable energy in Korea including photovoltaics, wind power, and fuel cells. The results indicate wind power as the most efficient renewable energy technology in Korea from the perspective of government investment. (Sarıca, Or, 2007) implement DEA to evaluate investment and operational efficiencies of 65 thermal, hydro, and wind power plants, owned by both private and public sectors in Turkey. The study concludes the scale efficiency of renewable source power plants decreases exponentially with respect to the size of plant for both investment and operational efficiencies. In addition, the results show that wind power plants in Turkey have the highest DEA efficiency values regarding their operational and investment performances. (Ramanathan, 2001) combines divergent characteristics of eight different energy supplying technologies by associating DEA and Comparative Risk Assessment (CRA), benchmarking them to comprehendible rankings. The findings rate nuclear and solar PV technologies as the most efficient supply of energy. Further arguments by the study reveal that large land requirement of renewable technologies is the main obstruction for large deployment of them. (Sağlam, 2018) applies DEA to predetermined input and output variables to compare efficiencies of the eight major renewable energy sources including; wind power (onshore & offshore), solar photovoltaic (crystalline & thin film), solar thermal, geothermal, biomass, and hydropower. According to the results of this DEA analysis, geothermal and biomass outrank rest of the studied renewable energy sources regarding the efficiency of the performance. Moreover, the study claims that land requirement, as input, plays a crucial role in DEA modeling of renewable energy technologies. (Sağlam, 2017)

Within the second category of DEA studies in the wind power sector, researchers attempt to evaluate the productive efficiency of a group of wind farms as the DMUs. Table 2 summarizes most recent studies regarding performance assessment of the wind farms. (Wu, Hu, Xiao, Mao, 2016) evaluates productive efficiency of 42 large-scale wind farms in China using DEA in the first stage to determine efficiency scores of wind farms. In the second stage, Tobit regression has been utilized to find a correlation between DEA scores and uncontrollable variables such as the age of wind farms and wind curtailment rate. The results confirm that efficiency scores of all wind farms are relatively high, however, half of the wind farms are overinvested regarding installed wind power capacity, and about 48% have the potential of reducing the auxiliary electricity consumption. (Iribarren, Vázquez-Rowe, Rugani, Benetto, 2014) synthesize DEA and Life Cycle Assessment (LCA) to benchmark the operational and environmental performance of 25 wind farms in Spain. Average reductions of 19–45% in the consumption of selected inputs were considered to be feasible when current WFs have to be reconstructed or substituted by new farms at the same location. It was also quantitatively verified that these reductions would result in lower environmental impacts (average reductions of 18–29%).

Table 2. Summary of literature on application of DEA in wind industry

Publication	DMUs	Methods	Input variables	Output variables
Wu et al. (2016)	42 wind farms in China	DEA and Tobit	Installed capacity Auxiliary electricity consumption Wind power density	Electricity generated Availability
Sağlam (2017)	95 wind farms in Texas	DEA and Tobit	Installed capacity Number of wind turbines Wind power density	Net generation Capacity factor
Sağlam (2018)	236 wind farms in the USA	DEA and Tobit	Installed capacity Number of wind turbines Wind power density	Net generation Value of production Homes powered
Iglesias et al. (2010)	57 wind farms in Spain	DEA and SFA	Installed capacity Labour Interposed surface Wind speed Fuel	Availability factor Active energy
Ederer (2015)	22 offshore wind farms	DEA and Tobit	Specific capital costs	Installed capacity Distance to shore Water depth

(Iglesias, Castellanos, Seijas, 2010) simultaneously apply DEA and Stochastic Frontier Analysis (SFA) methodologies to measure the productive efficiency of a group of wind farms in Spain between 2001 and 2004. The study claims that there is a strong correspondence between the results of the application of both methods on the same data set showing high average technical efficiencies for almost 75% of the DMUs. (Sağlam, 2018) conduct a two-stage performance assessment for 95 large utility-scale wind farms in Texas using DEA in the first stage to determine efficiency scores and Tobit regression method in the second stage in order to find the reasons of ineficiencies. DEA results indicate that half of the wind farms were operated efficiently in Texas during 2016. Additionally, Tobit regression models indicate that elevation of the site, rotor diameter, hub height, and brand of the turbine have significant contributions to the relative efficiency scores of the wind farms, and the age of turbine has a negative impact on the productive efficiency of the wind farms. (Ederer, 2015) utilizes DEA as an operations research tool in order to evaluate the relative capital and operating cost efficiency of offshore wind farms based on their main characteristics. The results revealed that using average cost as an input for evaluating the performance of the off-shore wind farms is insignificant and more sophisticated cost assessments should be applied to appraise the productive efficiency levels of offshore wind farms.

3.2. Data Envelopment Analysis (DEA)

This linear programming based technique appraise the relative performance of homogeneous entities by maximizing the ratio between the weighted sum of outputs and the weighted sum of inputs (Charnes, Cooper, Rhodes, 1978). The weights are not predetermined but rather assigned by the model, avoiding bias resulting from subjectively assigned weights similar to the Analytic Hierarchy Process (Merkert, Hensher, 2011). Therefore, when there is not an apparent market for valued outputs or even when other possible sources for reasonably supportable systems of weights are not readily available, the DEA can be proposed as a reliable method.

The general mathematical equation in order to maximize the relative efficiency score of unit k with x input and y output can be formulated as follows;

$$\text{Max } h_k = \frac{\sum_j^m u_j y_{jk}}{\sum_i^n v_i x_{ik}} \qquad (1)$$

s.t.

$$\frac{\sum_j^m u_j y_{jk}}{\sum_i^n v_i x_{ik}} \leq 1$$

$$u_j, v_i \geq 0; \;\; k = 1, 2, \dots, t; \;\; i = 1, 2, \dots, n; \;\; j = 1, 2, \dots, m$$

Where h_k is the efficiency score for k_{th} DMU, u_j and v_i are respectively the weights of output and input of the k_{th} unit which are determined by the model.

In the literature of DEA, CCR (Charnes, Cooper, Rhodes) and BCC (Banker, Charnes, Cooper) models are the most prominent models used by scholars in different research areas. The two models are based on the law of returns to scale which describes the rate of change in outputs relative to the associated change in the inputs of any production process in the long term. The CCR model (Charnes et al., 1978) evaluates the overall technical efficiency of DMUs based on the Constant Returns to Scale (CRS) hypothesis which indicates that any change in outputs is proportional to change in inputs. The BCC model (Banker, Charnes, Cooper, Clarke, 1989), on the other hand, measures the pure technical efficiency of DMUs based on the Variable Returns to Scale (VRS) assumption in which there is not particular proportion between changes in outputs and inputs. Both models appoint an efficiency score to each DMU ranging from zero to one. Those DMUs obtain maximum score establish an efficient production frontier whereby, scores and the inefficiency level of the other DMUs can be determined relative to the frontier. Moreover, the scale efficiency of the DMUs can be calculated by the ratio of efficiency scores of the CCR and BCC models. A scale efficient DMU has the optimal size of operations in which any alteration on the size will drive the unit to inefficiency. The CCR and the BCC both can be categorized based on two models; input-orientation model and output-orientation model. The former model minimizes the inputs while fixing the outputs, however, the latter model conversely maximizes the outputs while keeping the inputs constant.

To simplify the analysis, take an example which is restricted to one input variable and one output variable; Figure 10. Demonstrates the CCR and BCC efficiency frontier for seven presumed DMUs. Points A, B, C, D, E, F, and G represent the different input and output combinations of presumed DMUs. The dashed radial line (Oz) represents the CCR frontier based on CRS assumption in which among the DMUs only recognizes the points B and C as the most efficient units. Yet, the piece-wise solid line ABCD illustrates the BCC frontier under the VRS assumption. Points A, C, and D also become efficient in the BCC model while points E, F, and G are the inefficient DMUs. As it is obvious, the BCC frontier under the VRS assumption is more flexible and envelope more efficient DMUs than the CCR frontier.

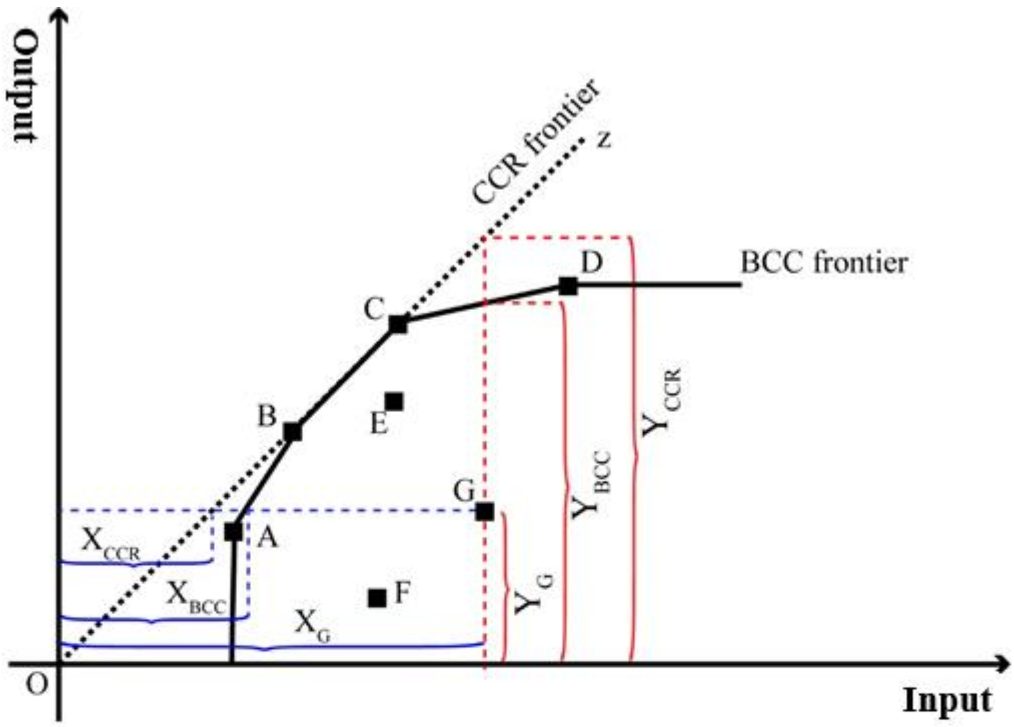

Figure 10. Graphical Illustration of CCR and BCC Frontiers

Taking point G as an example, input-oriented and output-oriented CCR, BCC, and Scale Efficiency (SE) scores for this DMUS can be calculated as the ratios included in the following table;

Table 3. Summary of CCR, BCC, and SE calculations for point G in figure 10.

Input-oriented models	Output-oriented models
$\theta_{CCR} = \frac{X_{CCR}}{X_G}$	$\varphi_{CCR} = \frac{Y_G}{Y_{CCR}}$
$\theta_{BCC} = \frac{X_{BCC}}{X_G}$	$\varphi_{BCC} = \frac{Y_G}{Y_{BCC}}$
$\theta_{SE} = \frac{X_{CCR}}{X_{BCC}}$	$\theta\varphi_{SE} = \frac{Y_{BCC}}{Y_{CCR}}$

Returning to general DEA formulation, Equation (1) has n+m+t+1 constraint however if we formulate it in dual form number of the constraints will decrease to n+m.

Therefore, in order to simplify the calculations, it is common to solve the DEA models in dual forms.

Following equations represent the formulation of input- and output-oriented CCR and BCC models.

1. Input-oriented models:

$$\text{Min.} \quad \theta_k - \varepsilon\left(\sum_{i=1}^{n} s_{ik}^{-} + \sum_{j=1}^{m} s_{jk}^{+}\right)$$

$$\text{s.t.}$$

$$\theta_k x_{ik} - \sum_{r=1}^{s} x_{ir}\lambda_r - s_{ik}^{-} = 0; \qquad (2a)$$

$$y_{jk} - \sum_{r=1}^{s} y_{jr}\lambda_r + s_{jk}^{+} = 0;$$

$$\lambda_r, s_{ik}^{-}, s_{jk}^{+} \geq 0; \;\; r = 1, 2, \ldots, s; \;\; i = 1, 2, \ldots, n; \;\; j = 1, 2, \ldots, m$$

$$\text{Min.} \quad \omega_k - \varepsilon\left(\sum_{i=1}^{n} s_{ik}^{-} + \sum_{j=1}^{m} s_{jk}^{+}\right)$$

$$\text{s.t.}$$

$$\omega_k x_{ik} - \sum_{r=1}^{s} x_{ir}\lambda_r - s_{ik}^{-} = 0; \qquad (2b)$$

$$y_{jk} - \sum_{r=1}^{s} y_{jr}\lambda_r + s_{jk}^{+} = 0;$$

$$\sum_{r=1}^{s} \lambda_r = 1$$

$$\lambda_r, s_{ik}^{-}, s_{jk}^{+} \geq 0; \; k = 1, 2, \ldots, t; \;\; i = 1, 2, \ldots, n; \;\; j = 1, 2, \ldots, m$$

2. Output-oriented models:

$$\text{Max.} \quad \varphi_k + \varepsilon\left(\sum_{i=1}^{n} s_{ik}^{-} + \sum_{j=1}^{m} s_{jk}^{+}\right)$$

s.t.

$$\varphi_k y_{jk} - \sum_{r=1}^{s} y_{jr}\lambda_r + s_{jk}^{+} = 0; \tag{3a}$$

$$x_{ik} - \sum_{r=1}^{s} x_{ir}\lambda_r - s_{ik}^{-} = 0;$$

$$\lambda_r, s_{ik}^{-}, s_{jk}^{+} \geq 0;\ k = 1, 2, \dots, t;\ \ i = 1, 2, \dots, n;\ \ j = 1, 2, \dots, m$$

$$\text{Max.} \quad \psi_k + \varepsilon\left(\sum_{i=1}^{n} s_{ik}^{-} + \sum_{j=1}^{m} s_{jk}^{+}\right)$$

s.t.

$$\psi_k y_{jk} - \sum_{r=1}^{s} y_{jr}\lambda_r + s_{jk}^{+} = 0; \tag{3b}$$

$$x_{ik} - \sum_{r=1}^{s} x_{ir}\lambda_r - s_{ik}^{-} = 0;$$

$$\sum_{r=1}^{s} \lambda_r = 1$$

$$\lambda_r, s_{ik}^{-}, s_{jk}^{+} \geq 0;\ k = 1, 2, \dots, t;\ \ i = 1, 2, \dots, n;\ \ j = 1, 2, \dots, m$$

Where θ_k is the overall input-oriented CCR efficiency measure of the DMU k, ω_k is the pure output-oriented BCC efficiency measure of the DMU k , φ_k is the overall input-oriented CCR efficiency measure of the DMU k , and ψ_k is the pure output-oriented BCC efficiency measure of the DMU k. k is a subscript to indicate the evaluated DMU by the model in set of $r = 1, \dots, s$ DMUs. x_{ik} is the quantity of the input i of the DMU k ; x_{ir} is the quantity of the i^{th} input variable for the r^{th} DMU; y_{jk} is the quantity of j^{th} output variable that is produced by the DMU k; y_{jr} is the quantity of j^{th} output variable that is produced by r^{th} DMU; λ_r is a structural variable assigned to all inputs and outputs of DMU “r”; s_{ik}^{-} and s_{jk}^{+} are the non-negative slack variables for input and output constraints respectively.

Returns to Scale (RTS) status of the DMUs is another information provided by the input- and output-oriented CCR models. This index suggests whether a given DMU should decrease, increase, or sustain its current operational level. According to DEA equations for a given wind farm the status for RTS are identified with the following conditions;

- If $\sum \lambda_r^* = 1$ then, Constant Returns to Scale (CRS) prevail.
- If $\sum \lambda_r^* > 1$ then, Decreasing Returns to Scale (DRS) prevail.
- If $\sum \lambda_r^* < 1$ then, Increasing Returns to Scale (IRS) prevail.

Where λ is the dual weight obtained from the CCR models. DMUs with CRS status should maintain their current operational level because they are operating at the optimal efficiency level. On the other hand, DMUs with IRS and DRS status should respectively increase and decrease their inputs to become efficient.

3.3. Tobit model

Tobit model, developed by Tobin (1958), is a regression model for the cases when the range of the dependent variable is censored or truncated. The DEA model in the first stage provides efficiency scores range from 0.0 to 1.0, indicating that the dependent variable could be left-censored or right-censored. Tobit regression model is useful to investigate the impact of exogenous factors on the efficiency of the DMUs. The formulation of the Tobit model has been described in equation (5)

$$\theta_{it}^{*} = z_{it}'\beta + \varepsilon_{it} \text{ with } \varepsilon_{it} \approx N(0, \sigma^2) \tag{5}$$

$$\theta_{it} = \begin{cases} \theta_{it}^{*} \text{ if } 0 < \theta_{it}^{*} < 1 \\ 0 \text{ for other values of } \theta_{it}^{*} \end{cases}$$

Where β is a vector of coefficient to be estimated, Z_{it} is the vector of independent variables, θ_{it} denotes the relative efficiency obtained from the DEA models, θ_{it}^{*} is a latent random variable, and ε_{it} is the error term with normal distribution.

3.4. Sensitivity Analysis

Sensitivity analysis explores the effects of specific variations in the inputs and/or parameters of a mathematical model on the outputs of the system. In other terms, sensitivity analysis examines the robustness and reliability of the model results exposed to uncertainties which arise from the inputs of the model. There are a variety of methods to conduct sensitivity analysis. One-[factor]-At-a-Time (OAT) method is the most common method in sensitivity analysis literature (Federico Ferrettia, Andrea Saltelli, Stefano Tarantolac, 2016). In OAT approach, output variations of a model are examined by fluctuating or eliminating one input factor at a time, while fixing all other factors (Pianosi et al., 2016). Due to the orientation of DEA to relative efficiency, it is exposed to degrees of freedom problems which increases with the number of DMUs and decrease with the number of input and outputs (Cooper, Seiford, Tone, 2007).

Considering that the efficiency scores of the DEA models are highly dependent on the number of DMUs and input and output variables, conducting sensitivity analysis is indispensable to assess the robustness and stability of the DEA results. Hence, after the initial computations, we extended the efficiency computations where each output and input is eliminated from the model. The comparison of these efficiency scores under alternative input/output mixes are examined in the results.

3.5. Data Description and Sources

In this empirical application, we choose a sample of Turkish wind farms connected to the Turkish Electricity Transmission Corporation's network, the sole owner of the electricity transmission system in Turkey, as DUMs to be evaluated regarding their efficiency of energy production. Turkish Energy Market Regulatory Authority (EMRA), on its annual report, has published the list of the operating wind farms during 2017 (EMRA, 2019). According to this report, 146 wind farms with the total installed capacity of 6,559.4 MW have generated 16,667,918.65 MWh of electricity in 2017, licensed by the Renewable Energy Resources Support Mechanism (RERSM). Using the available data for the operating wind farms, this study benchmarks 73 large-scale wind farms with the installed capacity of greater than 10 MW which includes total 3,293.20 MW of power and 8,601,421.05 MWh of energy. This accounts for 51.6% of total licensed wind energy generation of Turkey in 2017. The evaluated wind farms are located at 5 different regions predominately wind-rich regions of Ege and Marmara. Table 4. represents the distribution of the regions for the evaluated wind farms.

Table 4. Distribution of the evaluated wind farms' regions

Regions	Number of Wind Farms	Percent
Ege	31	42.74
Marmara	28	38.36
Akdeniz	9	12.33
İç Anadolu	3	4.11
Karadeniz	2	2.74
Total	73	100

The DEA method estimates the relative productive efficiency of DMUs based on chosen input and output variables. So, the results of the approach are intensely sensitive to the specifications of input and output variables and the errors in the data set. Therefore, the selection of inputs and outputs as well as the collection process of the required data set ought to be carried out meticulously. In this regard, we considered availability and validity of sources as two principal criteria for the data set of input/output variables.

Similar to other electricity-generating technologies, the ultimate output of wind farms is electrical energy transferred to the distribution grid, while, capital, labor, and fuel would be the typical inputs of the process. If one defines, a general microeconomic production function can be formulated based on the aforementioned inputs and output for a given wind farm;

$$E = f(L, K, F)$$

Where E is the electrical energy, L the labor, K the capital, and F the fuel.

However, in wind farm operations, inputs of the electricity generation process are slightly different than a standard production function. The labor factor performs an insignificant role in efficiency levels of wind farms (Iglesias et al., 2010). Because it presents the highest slack values in the DEA results, which means any change in the labor factor would result in a negligible change in the efficiency of the wind farms. Thus, beside the unavailability of labor data, in this study, we eliminated the labor factor from the input data set.

In this study we define 3 input variables and 2 output variables for conducting input- and output-oriented CCR and BCC models in order to evaluate the productive efficiency of the selected wind farms using data envelopment analysis. The summary statistics of the inputs, outputs, and other key variables affecting the performance of the wind farms are shown in Table 5. The first input is installed power capacity of a wind farm, which provides a rational economic indication for the capital invested in the project. Undoubtedly, the amount of generated electricity is directly dependent on the installed capacity of the power plants and wind power plants are not the exception. Hence, the installed capacity is a prevailing input variable in DEA models regarding benchmarking the performance of wind farms as well as the other electricity-generating technologies e.g.[(Iglesias, Castellanos, Seijas, 2010); (Wu, Hu, Xiao, Mao, 2016); and (Sağlam, 2017)]. Therefore, denoted by X_1, we selected the installed capacity measured in megawatts (MW) as the first input variable.

Table 5. Statistical summary of input and output variables; and exogenous variables.

Variable	Description	Unit	Mean	Minimum	Median	Maximum	S.D.
X_1	Installed capacity	MW	45.11	10	32	200.25	35.87
X_2	Number of wind turbines	#	18.21	4	15	81	14.29
X_3	Wind power density	W/m2	166.6	5.19	78.13	1389.96	239.2
Y_1	Electricity Generated	MWh	117827.69	17672.11	88648.00	453356.00	90946.28
Y_2	Availability	%	30.55	6.23	31.02	45.93	6.1
Z_1	Age		5.0	1.0	4.0	18.0	3.3
Z_2	Site elevation	m	660	8	515	1909	525

The installed power capacity of the evaluated wind farms varies from 10 MW to 200.25 MW, and the average installed capacity in the data set is 45.11 MW.

The number of wind turbines is the second input variable that reflects the production level of wind farms. Single modern onshore wind turbine whose power capacity can reach 7 MW requires significantly less area compared to the group of old turbines with 700 kW. Thus, installing brand new powerful turbines can reduce land lease expenditures of the companies involved in wind farm projects. Indeed, the installed power capacity and the number of turbines have a direct correlation with the capital factor of the production function. Therefore, the number of wind turbines, denoted by X_2, is chosen as the second input variable of the DEA analysis. The number of the turbines range from 4 to 81, and the average number of turbines on the wind farms are 18.

The fuel propelling turbines of the wind power plants is provided by the kinetic energy of wind. When air stream crosses blades of the turbines, some portion of this kinetic energy is transformed into electricity. The kinetic energy of the air parcel moving towards the wind turbine can be formulated as

$$P = \frac{1}{2}\rho_a A_T V^3$$

Where P is the wind power density, ρ_a is the density of air on the site, A_T is the swept area by the turbine, and V is the wind velocity.

In the formula above, wind velocity has a more influential effect due to its cubic meter correlation with the power. Regarding previous formula, if we know the elevation and temperature at a given wind farm's site, then the air density can be calculated by the following formula (Mathew, 2006);

$$\rho_a = \frac{353.049}{T} e^{\left(-0.034\frac{Z}{T}\right)}$$

Where Z is the elevation of the site measured in meters, and T is the average temperature in degrees of kelvin. After the calculation of wind power density for each wind farm, denoted by X_3, the third input variable of the DEA models in W/m^2 unit is included in the data set.

The primary objective of wind farms is to generate electricity. The net electricity generated by not only wind farms but by plants powered by the other sources of energy e.g. thermal, hydraulic, solar, etc. is a crucial output for the assessment of their productive efficiency. Therefore, denoted by Y_1, we selected the annual net electricity generation of the selected operating wind farms in Turkey measured in megawatt-hour (MWh) as the first output variable of the DEA models. Electricity generated by the evaluated wind farms range from 17,672.11 MWh (Manastır-

Esenköy RES) to 453,356.00 MWh (Dinar RES) and the average electricity generation of the 73 wind farms is 117,827.69 MWh.

Availability is another common metric for evaluating the performance of operation and maintenance of wind power plants, giving an insight into the potential for generating electrical power (Ederer, 2015). Wind turbines can generate electricity at an average wind speed of 3-4 meters per second (cut-in speed) and at the speed of 15-16 meters per second (rated speed) the electricity generation is at the optimal level. However, at the speeds beyond 25 meters per second (cut-out speed) the turbines are shut down to prevent them from potential damages. Thus, wind power plant shutdowns due to maintenance, downtimes, or extreme wind speeds prevent wind power plants from generating electricity constantly so they are not always available for the production. That is why wind farms could only reach 40%-70% of their theoretical maximum power.

There are two common methods in order to calculate the availability of wind farms; time-based and production-based. While the former may be simply calculated using the operational time of the wind farms with the ratio of the available time to total time in consideration, the latter is an indication for the energy losses and it is the ratio of the net generated energy to potentially expected energy under the ideal wind speeds and site conditions. According to the unavailability of essential data to calculate the time-based availability, in this study, we opted production-based availability, denoted by Y_2, as the second output variable. (Sağlam, 2018) proposed the following formula for the production-based availability in a study to benchmark the performance of 95 wind farms in Texas;

$$\mathrm{Y}_2 = \frac{\text{Net generation (MWh)}}{365\ \text{(days)} \times 24 \left(\frac{\text{hours}}{\text{day}}\right) \times \text{InstalledCapacity (MW)}} \times 100$$

The availability of the wind farms ranges from 6.23% to 45.93%, and average availability of a wind farm is 30.55%.

The data of the input and output variables are acquired from various sources. The data on the amount of electricity generation, the number of turbines, and installed capacity are obtained from the annual electricity market reports of the Turkish electricity market regulatory authority (EMRA, 2019). The average wind speed and the average temperature of the nearest weather station to the wind farms are acquired upon a request form the Turkish State Meteorology Service Department. Google Earth software was utilized to find the elevation of each wind farm. Finally, the information on the turbine models in order to find the swept area of them is obtained from annual reports published by the Turkish Wind Energy Association (TÜREB, 2017).

3.6. Empirical Results

3.6.1. DEA Results

In this section, we attempt to appraise the relative productive efficiency of 73 Turkish wind farms operating during 2017 for the first time. The DEA models using equations (1)-(4) presented in section 3.2., calculates the efficiency scores of the wind farms as DMUs with predetermined three input variables and two output variables. The relative productive efficiency scores of the representative sample of Turkish wind farms are given in Table 6. The scores are computed by input- and output-oriented CCR and BCC models. Moreover, Table 6. presents the Scale Efficiency (SE) scores calculated by the ratio of the corresponding CCR and BCC scores and the Returns to Scale (RTS) status of the evaluated wind farms.

We realized that the input- and output-oriented CCR models under Constant Returns to Scale assumption present the same results for corresponding DMUs. The reason lies in the fact that the duality gap[2] between input- and output-oriented CCR models are equal to zero (Sağlam, 2017). Thus, in both of these models; overall efficiency scores range from 0.214 to 1.000, the average efficiency score is 0.770, and the median score is 0.757. The CCR models disclose that out of 73 wind farms, 8 wind farms achieve the maximum possible efficiency score of 1. Also, there are 28 wind farms with the CCR efficiency scores greater than 0.8 and 21 wind farms exceeding the score of 0.9 which means about 30% of the wind farms were operating at acceptable levels[3]. We noticed that the CCR efficiency scores of 28 wind farms are below 0.7 and the analogy between these wind farms is the availability of below 30% maintaining the significance of availability on the efficiency of wind farms. Moreover, we detected that among the 8 wind farms with the CCR scores below 0.6, 4 wind farms were using Chinese and Indian wind turbines. It also should be noted that the efficiency scores of wind farms which utilized Chinese and Indian wind turbines do not exceed 0.75. "WF46" (Manastır-Esenköy RES) is the most inefficient wind farm with the least generated electricity and availability in the data set. However, we observed that the wind farms with approximately the same installed capacity as

[2] The duality gap is the difference between the optimal values of the primal and dual problems.
[3] This standard comes from the empirical works done on the US, Spanish, and Chinese wind farms using a similar methodology in papers of (Sağlam, 2018), (Iglesias, Castellanos, Seijas, 2010), and (Wu, Hu, Xiao, Mao, 2016)

"WF46" generated about four times more electricity during the same period.

Table 6 Efficiency Scores of 73 Wind Farms in Turkey

DMUs	Input-oriented models				Output-oriented models			
	CCR	BCC	SE	RTS	CCR	BCC	SE	RTS
WF 1	0.9870 (3)	1.0000 (1)	0.9870 (20)	IRS	0.9870 (3)	1.0000 (1)	0.9870 (24)	IRS
WF 2	0.5490 (62)	0.6126 (55)	0.8963 (51)	IRS	0.5490 (62)	0.5552 (56)	0.9890 (20)	IRS
WF 3	0.7491 (31)	0.7619 (33)	0.9832 (24)	DRS	0.7491 (31)	0.7795 (28)	0.9610 (39)	DRS
WF 4	0.6316 (55)	0.7314 (41)	0.8635 (58)	IRS	0.6316 (55)	0.6487 (50)	0.9736 (33)	IRS
WF 5	0.9157 (9)	0.9334 (9)	0.9810 (26)	IRS	0.9157 (9)	0.9246 (10)	0.9904 (18)	IRS
WF 6	0.7753 (25)	0.8372 (21)	0.9261 (46)	IRS	0.7753 (25)	0.7779 (29)	0.9967 (8)	IRS
WF 7	0.8648 (17)	1.0000 (1)	0.8648 (57)	DRS	0.8648 (17)	1.0000 (1)	0.8648 (58)	DRS
WF 8	0.7173 (37)	0.7585 (34)	0.9457 (37)	IRS	0.7173 (37)	0.7212 (38)	0.9946 (16)	IRS
WF 9	0.7341 (35)	0.7408 (39)	0.9910 (14)	IRS	0.7341 (35)	0.7370 (35)	0.9961 (12)	IRS
WF 10	0.7734 (26)	0.8274 (22)	0.9346 (44)	DRS	0.7734 (26)	0.8451 (20)	0.9151 (49)	DRS
WF 11	0.6988 (39)	0.7098 (45)	0.9845 (23)	DRS	0.6988 (39)	0.7226 (37)	0.9670 (36)	DRS
WF 12	0.8974 (15)	1.0000 (1)	0.8974 (50)	DRS	0.8974 (15)	1.0000 (1)	0.8974 (54)	DRS
WF 13	0.7022 (38)	1.0000 (1)	0.7022 (63)	IRS	0.7022 (38)	0.7132 (40)	0.9845 (27)	IRS
WF 14	0.6790 (46)	0.6830 (49)	0.9941 (9)	IRS	0.6790 (46)	0.7175 (39)	0.9463 (45)	IRS
WF 15	0.7721 (28)	0.7771 (30)	0.9935 (12)	IRS	0.7721 (28)	0.7811 (27)	0.9884 (21)	IRS
WF 16	0.6876 (44)	0.6944 (48)	0.9903 (15)	DRS	0.6876 (44)	0.7047 (42)	0.9758 (32)	DRS
WF 17	0.7880 (22)	0.8822 (16)	0.8932 (52)	DRS	0.7880 (22)	0.9106 (13)	0.8654 (57)	DRS
WF 18	0.6626 (49)	0.7674 (32)	0.8634 (59)	IRS	0.6626 (49)	0.6648 (46)	0.9966 (9)	IRS
WF 19	0.9104 (11)	0.9688 (6)	0.9397 (40)	DRS	0.9104 (11)	0.9722 (6)	0.9364 (47)	DRS
WF 20	0.7601 (29)	0.8132 (25)	0.9348 (43)	IRS	0.7601 (29)	0.7601 (33)	1.0000 (1)	IRS
WF 21	0.7345 (34)	0.7816 (27)	0.9397 (41)	IRS	0.7345 (34)	0.7433 (34)	0.9881 (22)	IRS
WF 22	0.6006 (58)	0.6140 (54)	0.9782 (29)	DRS	0.6006 (58)	0.6554 (49)	0.9163 (48)	DRS
WF 23	0.6442 (53)	1.0000 (1)	0.6442 (64)	DRS	0.6442 (53)	1.0000 (1)	0.6442 (64)	DRS
WF 24	0.7382 (33)	0.7455 (37)	0.9902 (16)	DRS	0.7382 (33)	0.7704 (30)	0.9583 (41)	DRS
WF 25	0.7859 (23)	0.8589 (18)	0.9150 (48)	DRS	0.7859 (23)	0.8778 (16)	0.8953 (55)	DRS
WF 26	0.7783 (24)	0.8393 (20)	0.9274 (45)	IRS	0.7783 (24)	0.7879 (26)	0.9878 (23)	IRS
WF 27	0.6911 (42)	0.7139 (44)	0.9681 (32)	DRS	0.6911 (42)	0.8137 (23)	0.8494 (60)	DRS
WF 28	0.9962 (2)	1.0000 (1)	0.9962 (5)	IRS	0.9962 (2)	1.0000 (1)	0.9962 (11)	IRS
WF 29	0.5602 (61)	0.7492 (36)	0.7478 (62)	DRS	0.5602 (61)	0.8168 (22)	0.6859 (63)	DRS
WF 30	0.6902 (43)	0.7340 (40)	0.9403 (39)	IRS	0.6902 (43)	0.6904 (43)	0.9997 (3)	IRS
WF 31	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 32	0.6525 (51)	0.6572 (51)	0.9928 (13)	DRS	0.6525 (51)	0.6824 (44)	0.9562 (43)	DRS
WF 33	0.6542 (50)	0.6800 (50)	0.9621 (33)	IRS	0.6542 (50)	0.6576 (48)	0.9949 (15)	IRS
WF 34	0.8330 (19)	0.8455 (19)	0.9852 (21)	DRS	0.8330 (19)	0.8745 (17)	0.9526 (44)	DRS
WF 35	0.6161 (56)	0.6525 (53)	0.9443 (38)	IRS	0.6161 (56)	0.6191 (54)	0.9952 (14)	IRS
WF 36	0.7729 (27)	0.9439 (8)	0.8188 (60)	DRS	0.7729 (27)	0.9539 (9)	0.8102 (62)	DRS
WF 37	0.8143 (20)	0.8245 (23)	0.9876 (19)	DRS	0.8143 (20)	0.8305 (21)	0.9805 (31)	DRS
WF 38	0.8478 (18)	0.9064 (14)	0.9354 (42)	IRS	0.8478 (18)	0.8533 (19)	0.9935 (17)	IRS
WF 39	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 40	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS

Table 6 (cont'd)

WF 41	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 42	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 43	0.7579 (30)	0.7773 (29)	0.9751 (31)	DRS	0.7579 (30)	0.8010 (24)	0.9462 (46)	DRS
WF 44	0.9694 (7)	0.9870 (2)	0.9822 (25)	IRS	0.9694 (7)	0.9827 (4)	0.9865 (26)	IRS
WF 45	0.6335 (54)	0.7309 (42)	0.8668 (56)	IRS	0.6335 (54)	0.6341 (52)	0.9990 (6)	IRS
WF 46	0.2144 (66)	0.7802 (28)	0.2749 (66)	IRS	0.2144 (66)	0.2179 (60)	0.9842 (28)	IRS
WF 47	0.9707 (6)	0.9854 (4)	0.9851 (22)	IRS	0.9707 (6)	0.9838 (2)	0.9867 (25)	IRS
WF 48	0.6776 (47)	0.7767 (31)	0.8724 (54)	IRS	0.6776 (47)	0.6783 (45)	0.9990 (7)	IRS
WF 49	0.9144 (10)	0.9334 (10)	0.9796 (28)	IRS	0.9144 (10)	0.9233 (11)	0.9904 (19)	IRS
WF 50	0.5875 (60)	0.5905 (57)	0.9949 (7)	DRS	0.5875 (60)	0.6113 (55)	0.9610 (40)	DRS
WF 51	0.9770 (5)	0.9789 (5)	0.9980 (3)	IRS	0.9770 (5)	0.9770 (5)	1.0000 (1)	CRS
WF 52	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 53	0.5456 (63)	0.8722 (17)	0.6256 (65)	IRS	0.5456 (63)	0.5480 (58)	0.9957 (13)	IRS
WF 54	0.4342 (65)	0.4558 (59)	0.9525 (35)	IRS	0.4342 (65)	0.4415 (59)	0.9833 (30)	IRS
WF 55	0.8933 (16)	0.8969 (15)	0.9960 (6)	IRS	0.8933 (16)	0.8937 (15)	0.9995 (4)	IRS
WF 56	0.7400 (32)	0.7448 (38)	0.9936 (10)	DRS	0.7400 (32)	0.7684 (31)	0.9631 (38)	DRS
WF 57	0.9063 (13)	0.9173 (12)	0.9880 (18)	DRS	0.9063 (13)	0.9212 (12)	0.9838 (29)	DRS
WF 58	0.6627 (48)	0.6949 (47)	0.9536 (34)	DRS	0.6627 (48)	0.7267 (36)	0.9118 (51)	DRS
WF 59	0.9801 (4)	0.9864 (3)	0.9936 (11)	IRS	0.9801 (4)	0.9836 (3)	0.9965 (10)	IRS
WF 60	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 61	0.6462 (52)	0.6530 (52)	0.9895 (17)	IRS	0.6462 (52)	0.6637 (47)	0.9735 (34)	IRS
WF 62	0.9596 (8)	0.9605 (7)	0.9990 (2)	IRS	0.9596 (8)	0.9597 (7)	0.9999 (2)	IRS
WF 63	0.5945 (59)	0.5966 (56)	0.9965 (4)	DRS	0.5945 (59)	0.6210 (53)	0.9574 (42)	DRS
WF 64	0.6924 (41)	0.7301 (43)	0.9484 (36)	DRS	0.6924 (41)	0.7669 (32)	0.9029 (53)	DRS
WF 65	0.8113 (21)	0.9299 (11)	0.8724 (55)	DRS	0.8113 (21)	0.9548 (8)	0.8496 (59)	DRS
WF 66	0.7190 (36)	0.8175 (24)	0.8796 (53)	DRS	0.7190 (36)	0.8539 (18)	0.8420 (61)	DRS
WF 67	0.6824 (45)	0.6964 (46)	0.9799 (27)	DRS	0.6824 (45)	0.7076 (41)	0.9644 (37)	DRS
WF 68	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS	1.0000 (1)	1.0000 (1)	1.0000 (1)	CRS
WF 69	0.6930 (40)	0.7573 (35)	0.9151 (47)	DRS	0.6930 (40)	0.7986 (25)	0.8678 (69)	DRS
WF 70	0.6146 (57)	0.8034 (26)	0.7651 (61)	IRS	0.6146 (57)	0.6345 (51)	0.9688 (35)	IRS
WF 71	0.5064 (64)	0.5179 (58)	0.9778 (30)	IRS	0.5064 (64)	0.5534 (57)	0.9150 (50)	IRS
WF 72	0.9017 (14)	0.9065 (13)	0.9947 (8)	IRS	0.9017 (14)	0.9030 (14)	0.9987 (7)	IRS
WF 73	0.9099 (12)	1.0000 (1)	0.9099 (49)	DRS	0.9099 (12)	1.0000 (1)	0.9099 (52)	DRS
Mean	0.770705	0.829084	0.930128	-	0.770705	0.809212	0.954345	-
Min	0.214428	0.455817	0.274855	-	0.214428	0.217879	0.644234	-
Median	0.757918	0.824475	0.977751	-	0.757918	0.800986	0.984162	-
Max	1	1	1	-	1	1	1	-
S.D.	0.161004	0.139567	0.11225	-	0.161004	0.162352	0.06786	-

Note: Numbers in the parentheses represents rankings of the DMUs

The BCC model, under the VRS assumption, is more flexible and inclusive than the CCR model, thereby the former model's efficiency scores are higher than the latter for the same DMUs. Confirming this fact, the results in Table 6 indicate that the average input- and output-oriented BCC scores are 8% and 5% higher than the average of the corresponding CCR scores. Regarding BCC models, Table 6 reveals that the scores of the input-oriented model with the average of 0.8291, range from 0.455 to 1, while the output-oriented model's scores vary from 0.2179 to 1 presenting the mean of 0.8092. 15 wind farms reach the maximum relative efficiency score in the input-oriented BCC model and 14 in the output-oriented model. Moreover, for the input-oriented BCC model, 38% of the wind farms exceed the efficiency score of 0.9 while, 55% of the wind farms attain the scores greater than 0.8. Regarding the output-oriented BCC model, the efficiency scores of 37% of the wind farms exceed 0.9 and 50% of them exceed the score of 0.8.

Table 6 also provides the scale efficiency scores for the input- and output-oriented models. The scale efficiency scores of the DMUs are calculated by the ratio of the efficiency scores obtained from the corresponding CCR and BCC models. 8 wind farms reach the maximum scale efficiency scores, indicating that any change in their current operating characteristics would decrease their efficiency levels. The scale efficiency results are relatively high presenting the average of 0.930 for input-oriented model and 0.954 for the output-oriented model. Moreover, there are 56 wind farms with the scale efficiency higher than 0.9 in input-oriented models and 62 wind farms in the output-oriented model which all together confirm the compatibility of the efficiency scores obtained from four different models.

The RTS results of the input- and output-oriented CCR models shown in Figure 11 indicate 8 wind farms reach maximum efficiency for the input-oriented model and 9 wind farm for the output-oriented model. However, WF51 (Mut RES) reaches maximum scale efficiency in the output-oriented model, because its CCR and BCC scores are both equal to 0.971.

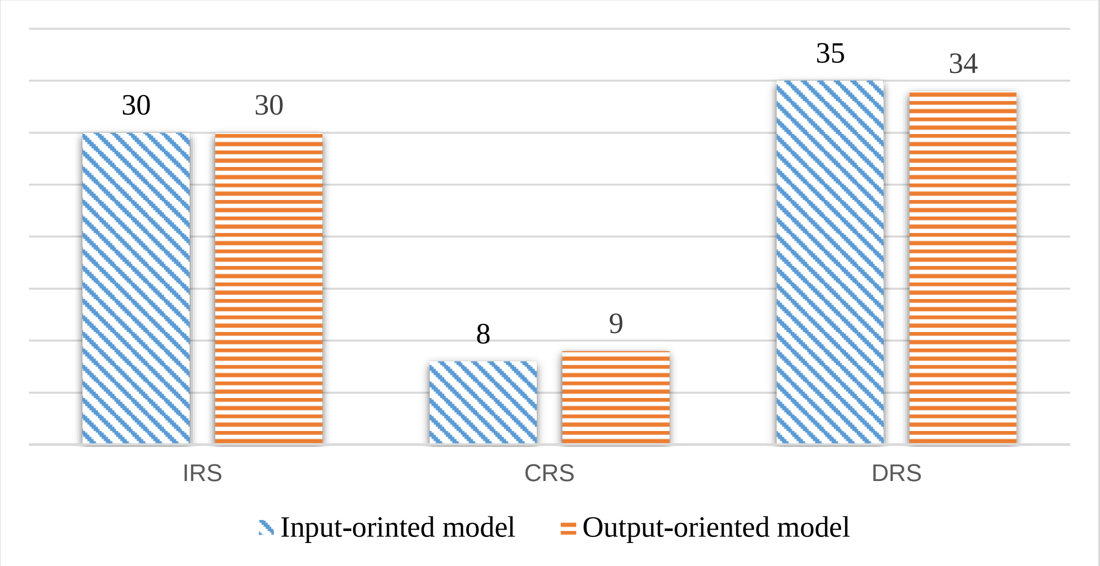

Figure 11. Returns to Scale (RTS) results of the 73 Turkish wind farms

The RTS results also indicate 30 wind farms should increase their operational level by installing new wind turbines in order to improve their efficiency level according to both input- and output-oriented models. However, 35 wind farms have decreasing returns to scale situation which means managerial decision ought to be taken to decrease the operational levels of those wind farms in order to drive the wind farms toward efficiency frontiers.

Table 7 presents slack values of the inputs and the outputs obtained from the input-oriented CCR and the output-oriented CCR models respectively. The slacks emerge when the piecewise linear DEA frontier run parallel to the axes (Coelli, 1996). The slack values imply that inefficient units in order to be located on the allocative efficiency frontier should decrease their inputs by the amount presented by the corresponding slacks (Omid, Ghojabeige, Delshad, Ahmadi, 2011). However, since wind power density as the fuel of wind power plants is provided by nature and does not impose any cost on DMUs, non-zero slacks related to third input variable could be neglected. The slack results, regarding inputs, indicate 63 (86%) wind farms for the installed capacity variable, 69 (94%) wind farms for the number of turbines variable, and 52 (71%) wind farms for the wind power density variable, show the slack value of zero which mean efficiency level of the corresponding wind farms are strongly dependent on any changes in the amount these inputs (Wu, Hu, Xiao, Mao, 2016). The slack values of the first input variable (installed capacity) display the highest amount for WF27 (Fatma RES) which generated 149,324 MWh of electricity with 80 MW of installed capacity. However, due to its low availability (21%), this wind farm could have generated the same amount of electricity with total 67 MW of installed capacity. WF22 (Datça RES) has the highest slack value for the second input variable (number of turbines). This wind farm utilizes a combination of 36 units of 800 kW and 900 kW turbines which have been operating for ten years. However, the slack value suggests that the same level of production can be obtained by installing 25 modern turbines with larger capacity. WF71 (Uşak RES) which has the second-highest slack value for the second input variable (number of turbines) also experiences the same problem. This wind farm which obtained a low DEA score of 0.5 includes 36 Chinese turbines with 1.5 MW capacity can generate the same amount of electricity with 29 large-capacity western turbines and also operate more efficiently. Regarding the slack values of output variables, we observed that almost all DMUs presented zero slacks for electricity generation. This outcome confirm that efficiency level of Turkish wind farms is extremely dependent on the amount of the electricity generation which also affect the availability

Table 7. Slack of input and output variables in CCR models

DMUs	Input-oriented CCR model			Output-oriented CCR model	
	Installed capacity	Number of turbines	Wind power density	Electricity generated	Availability
WF01	0.20	0.00	0.00	10960.70	0.00
WF02	0.00	0.00	54.01	0.00	10.53
WF03	0.00	0.00	38.42	0.00	37.56
WF04	0.00	0.00	0.00	0.00	5.82
WF05	0.00	0.00	0.00	0.00	0.00
WF06	0.00	0.00	0.00	0.00	0.00
WF07	2.19	0.00	0.00	0.00	77.32
WF08	0.00	0.00	47.71	0.00	4.58
WF09	0.00	0.00	551.99	0.00	3.98
WF10	0.00	0.00	380.72	0.00	107.17
WF11	0.00	0.00	0.00	0.00	44.86
WF12	0.00	0.00	0.00	0.00	64.54
WF13	0.32	0.00	36.18	0.00	0.00
WF14	6.72	0.00	0.00	0.00	20.91
WF15	0.00	0.00	196.86	0.00	11.34
WF16	0.00	0.00	369.45	0.00	31.63
WF17	0.00	0.00	70.28	0.00	121.16
WF18	0.00	0.00	0.00	0.00	0.00
WF19	0.00	0.00	317.70	0.00	89.24
WF20	0.00	0.00	0.00	0.00	0.00
WF21	3.21	0.00	0.00	0.00	0.00
WF22	0.00	10.51	5.34	0.00	39.03
WF23	0.60	0.00	0.00	0.00	167.37
WF24	0.00	0.00	0.00	0.00	32.17
WF25	0.00	0.00	0.00	0.00	54.41
WF26	0.00	2.26	0.00	0.00	0.00
WF27	12.89	0.00	0.00	0.00	33.22
WF28	0.00	0.00	0.00	4780.86	0.00
WF29	0.00	0.00	0.00	0.00	154.13
WF30	0.00	0.00	0.00	0.00	0.00

Table 7 (cont'd)

WF31	0.00	0.00	0.00	0.00	0.00
WF32	0.00	0.00	56.90	0.00	34.63
WF33	0.00	0.00	0.00	0.00	6.56
WF34	0.00	0.00	0.00	0.00	26.23
WF35	0.00	0.00	0.00	0.00	6.22
WF36	0.00	0.00	94.15	0.00	252.02
WF37	0.00	0.00	0.00	0.00	24.78
WF38	0.00	0.00	0.00	0.00	0.00
WF39	0.00	0.00	0.00	0.00	0.00
WF40	0.00	0.00	0.00	0.00	0.00
WF41	0.00	0.00	0.00	0.00	0.00
WF42	0.00	0.00	0.00	0.00	0.00
WF43	0.00	0.00	0.00	0.00	24.88
WF44	0.82	0.00	0.00	0.00	0.00
WF45	0.00	0.00	0.00	0.00	2.09
WF46	1.90	0.00	0.00	0.00	0.00
WF47	5.10	0.00	0.00	0.00	0.08
WF48	0.00	0.00	0.00	0.00	1.69
WF49	0.00	0.00	470.21	0.00	0.00
WF50	0.00	0.00	332.00	0.00	37.56
WF51	9.60	0.00	0.00	0.00	7.61
WF52	0.00	0.00	98.29	0.00	0.00
WF53	1.29	0.00	0.00	0.00	0.00
WF54	0.00	0.00	0.00	0.00	17.28
WF55	0.03	0.00	33.04	0.00	0.00
WF56	0.00	0.00	0.00	0.00	27.17
WF57	0.00	0.00	0.00	0.00	16.73
WF58	0.00	0.00	0.00	0.00	96.08
WF59	1.10	0.00	0.00	0.00	0.00
WF60	0.00	0.00	0.00	0.00	0.00
WF61	0.00	0.00	0.00	0.00	17.89
WF62	0.15	0.00	6.02	0.00	0.00

Table 7 (cont'd)

WF63	0.00	0.00	10.01	0.00	34.73
WF64	0.00	0.00	0.00	0.00	67.03
WF65	0.00	0.00	0.00	0.00	56.88
WF66	2.93	0.00	0.00	0.00	70.33
WF67	0.00	0.00	29.75	0.00	41.19
WF68	0.00	0.00	0.00	0.00	0.00
WF69	0.00	2.85	0.00	0.00	79.80
WF70	2.13	0.00	0.00	0.00	0.00
WF71	0.00	5.85	0.00	0.00	36.49
WF72	0.49	0.00	99.49	0.00	0.00
WF73	0.00	0.00	0.00	0.00	110.99
Mean	0.71	0.29	45.19	215.63	22.12
Min	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	5.78
Max	12.89	10.51	551.99	10960.70	194.78
S.D.	2.14	1.45	115.16	1392.43	34.69

3.6.2. Sensitivity Analysis Results

The relative productive efficiency scores obtained by the data envelopment analysis are determined by the number of DMUs, inputs, and outputs. Thus, any alteration in the data set, or any error can affect the scores significantly. One method to overcome this defect of the DEA approach is to assess the sensitivity of the results to specific inputs or outputs by discarding them from the original model. This study proposes 5 new models to examine the sensitivity and stability of both input- and output-oriented CCR models results. Table 8 presents the characteristics of new models regarding their combination of input and output variables and Table 9 repeats the CCR efficiency scores of the six alternative models.

Table 8 Specification of the Six Models for Sensitivity Analysis.

Variables	Denotation	M1	M2	M3	M4	M5	M6
Installed capacity	X_1	✓		✓	✓	✓	✓
Number of wind turbines	X_2	✓	✓			✓	✓
Wind power density	X_3	✓	✓	✓		✓	✓
Electricity generated	Y_1	✓	✓	✓	✓		✓
Availability	Y_2	✓	✓	✓	✓	✓	

Note: The inputs and outputs included in the models are marked with ✓.

Table 9 CCR efficiency scores of six model proposed for sensitivity analysis

DMUs	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Mean	Min	Max	S.D.
WF01	0.987	0.987	0.964	0.804	0.987	0.642	0.895	0.642	0.987	0.143
WF02	0.549	0.403	0.520	0.549	0.368	0.549	0.490	0.368	0.549	0.082
WF03	0.749	0.548	0.710	0.749	0.345	0.749	0.642	0.345	0.749	0.165
WF04	0.632	0.630	0.628	0.611	0.462	0.632	0.599	0.462	0.632	0.068
WF05	0.916	0.719	0.869	0.909	0.856	0.871	0.857	0.719	0.916	0.072
WF06	0.775	0.716	0.729	0.773	0.718	0.764	0.746	0.716	0.775	0.028
WF07	0.865	0.865	0.824	0.821	0.207	0.865	0.741	0.207	0.865	0.262
WF08	0.717	0.591	0.664	0.717	0.524	0.717	0.655	0.524	0.717	0.081
WF09	0.734	0.732	0.639	0.734	0.370	0.734	0.657	0.370	0.734	0.146
WF10	0.773	0.631	0.714	0.773	0.175	0.773	0.640	0.175	0.773	0.234
WF11	0.699	0.592	0.640	0.693	0.241	0.699	0.594	0.241	0.699	0.178
WF12	0.897	0.861	0.773	0.880	0.157	0.897	0.744	0.157	0.897	0.292
WF13	0.702	0.702	0.621	0.702	0.688	0.604	0.670	0.604	0.702	0.045
WF14	0.679	0.679	0.530	0.591	0.212	0.679	0.562	0.212	0.679	0.182
WF15	0.772	0.521	0.746	0.772	0.520	0.772	0.684	0.520	0.772	0.127
WF16	0.688	0.538	0.641	0.688	0.318	0.688	0.593	0.318	0.688	0.147
WF17	0.788	0.772	0.691	0.788	0.120	0.788	0.658	0.120	0.788	0.266
WF18	0.663	0.533	0.623	0.661	0.601	0.652	0.622	0.533	0.663	0.050
WF19	0.910	0.882	0.816	0.910	0.224	0.910	0.776	0.224	0.910	0.273
WF20	0.760	0.760	0.681	0.760	0.591	0.760	0.719	0.591	0.760	0.070
WF21	0.734	0.734	0.600	0.636	0.419	0.728	0.642	0.419	0.734	0.123
WF22	0.601	0.238	0.601	0.601	0.323	0.601	0.494	0.238	0.601	0.167
WF23	0.644	0.644	0.644	0.610	0.108	0.644	0.549	0.108	0.644	0.216
WF24	0.738	0.691	0.661	0.722	0.273	0.738	0.637	0.273	0.738	0.181
WF25	0.786	0.761	0.715	0.765	0.216	0.786	0.671	0.216	0.786	0.225
WF26	0.778	0.723	0.778	0.655	0.679	0.702	0.719	0.655	0.778	0.051
WF27	0.691	0.691	0.683	0.540	0.290	0.691	0.598	0.290	0.691	0.162
WF28	0.996	0.835	0.993	0.905	0.996	0.805	0.921	0.805	0.996	0.087
WF29	0.560	0.540	0.560	0.544	0.104	0.560	0.478	0.104	0.560	0.184
WF30	0.690	0.662	0.621	0.678	0.487	0.685	0.637	0.487	0.690	0.078
WF31	1.000	1.000	0.842	1.000	0.316	1.000	0.860	0.316	1.000	0.274

Table 9 (cont'd)

WF32	0.653	0.646	0.560	0.653	0.154	0.653	0.553	0.154	0.653	0.199
WF33	0.654	0.611	0.594	0.642	0.399	0.654	0.592	0.399	0.654	0.098
WF34	0.833	0.819	0.711	0.828	0.204	0.833	0.705	0.204	0.833	0.250
WF35	0.616	0.566	0.563	0.606	0.394	0.616	0.560	0.394	0.616	0.085
WF36	0.773	0.619	0.716	0.773	0.091	0.773	0.624	0.091	0.773	0.268
WF37	0.814	0.706	0.746	0.811	0.388	0.814	0.713	0.388	0.814	0.165
WF38	0.848	0.634	0.824	0.825	0.821	0.750	0.784	0.634	0.848	0.080
WF39	1.000	0.988	1.000	1.000	1.000	0.825	0.969	0.825	1.000	0.071
WF40	1.000	1.000	0.897	1.000	0.778	1.000	0.946	0.778	1.000	0.092
WF41	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000
WF42	1.000	1.000	1.000	0.968	0.859	1.000	0.971	0.859	1.000	0.056
WF43	0.758	0.400	0.758	0.733	0.462	0.758	0.645	0.400	0.758	0.167
WF44	0.969	0.969	0.893	0.914	0.963	0.883	0.932	0.883	0.969	0.040
WF45	0.633	0.604	0.610	0.622	0.491	0.633	0.599	0.491	0.633	0.054
WF46	0.214	0.214	0.145	0.178	0.145	0.208	0.184	0.145	0.214	0.033
WF47	0.971	0.971	0.805	0.834	0.551	0.971	0.850	0.551	0.971	0.164
WF48	0.678	0.673	0.669	0.656	0.520	0.678	0.646	0.520	0.678	0.062
WF49	0.914	0.914	0.796	0.914	0.800	0.857	0.866	0.796	0.914	0.057
WF50	0.587	0.426	0.557	0.587	0.258	0.587	0.500	0.258	0.587	0.134
WF51	0.977	0.977	0.739	0.828	0.415	0.977	0.819	0.415	0.977	0.221
WF52	1.000	0.588	1.000	0.971	1.000	0.791	0.892	0.588	1.000	0.169
WF53	0.546	0.546	0.502	0.484	0.534	0.491	0.517	0.484	0.546	0.028
WF54	0.434	0.417	0.376	0.419	0.142	0.434	0.370	0.142	0.434	0.114
WF55	0.893	0.893	0.767	0.893	0.399	0.893	0.790	0.399	0.893	0.198
WF56	0.740	0.658	0.682	0.725	0.331	0.740	0.646	0.331	0.740	0.158
WF57	0.906	0.833	0.818	0.901	0.462	0.906	0.805	0.462	0.906	0.172
WF58	0.663	0.526	0.615	0.660	0.161	0.663	0.548	0.161	0.663	0.197
WF59	0.980	0.980	0.768	0.856	0.764	0.893	0.874	0.764	0.980	0.096
WF60	1.000	1.000	0.992	1.000	1.000	0.873	0.977	0.873	1.000	0.051
WF61	0.646	0.588	0.620	0.631	0.342	0.646	0.579	0.342	0.646	0.118
WF62	0.960	0.960	0.807	0.960	0.310	0.959	0.826	0.310	0.960	0.260
WF63	0.594	0.451	0.568	0.594	0.295	0.594	0.516	0.295	0.594	0.122
WF64	0.692	0.646	0.620	0.677	0.173	0.692	0.584	0.173	0.692	0.203
WF65	0.811	0.801	0.697	0.778	0.140	0.811	0.673	0.140	0.811	0.265
WF66	0.719	0.719	0.679	0.674	0.189	0.719	0.616	0.189	0.719	0.211
WF67	0.682	0.666	0.612	0.682	0.265	0.682	0.598	0.265	0.682	0.165
WF68	1.000	1.000	1.000	0.715	1.000	1.000	0.953	0.715	1.000	0.116
WF69	0.693	0.492	0.693	0.667	0.225	0.693	0.577	0.225	0.693	0.190
WF70	0.615	0.615	0.541	0.543	0.476	0.607	0.566	0.476	0.615	0.056
WF71	0.506	0.312	0.506	0.464	0.225	0.506	0.420	0.225	0.506	0.122
WF72	0.902	0.902	0.769	0.902	0.500	0.895	0.812	0.500	0.902	0.161
WF73	0.910	0.770	0.828	0.901	0.174	0.910	0.749	0.174	0.910	0.287
Mean	0.771	0.702	0.709	0.740	0.448	0.747	0.686	0.416	0.771	0.143
Min	0.214	0.214	0.145	0.178	0.091	0.208	0.184	0.091	0.214	0.000
Median	0.758	0.691	0.693	0.733	0.388	0.740	0.655	0.388	0.758	0.146
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.292
S.D.	0.161	0.194	0.155	0.158	0.275	0.148	0.158	0.231	0.161	0.076

The relative productive efficiency scores of the six models calculated by the CCR efficiency equation are shown in Table 9. The results indicate scores of the Model 1 which is the original model with 3 input variables and 2 output variables are higher than the scores obtained from any of the proposed models. The first model is more comprehensive and the drop in the dimensionality in the proposed models is the reason behind that their scores are not higher than the original model.

Spearman's correlation analysis has been applied to the CCR scores obtained from 6 different models to examine the relationship between them. The analysis provides coefficient values ranging from +1 to -1 for the observations. Coefficients closer to +1 value indicate the stronger correlation between the observations vice versa. As shown in Table 10, the Spearman's correlation coefficients range from 0.2893 to 0.9522 which indicate positive interrelationship between the six models at 1% significance level confirming the stability of the proposed models. M5 has the least coefficient and correlation with the original models which means eliminating electricity generation variable affect the DEA scores significantly. As it also noticed in Spearman's analysis, omitting first output variable (electricity generation) results in a notable reduction of efficiency scores.

when a specific input or output is eliminated from the original model. The graph reveals when installed capacity and electricity generation is omitted from the original model efficiency scores drop considerably. Sensitivity analysis results in this section confirmed that installed capacity and electricity generation of wind farms are the indispensable factors of DEA models when evaluating the productive efficiency of wind farms. Figure 12 shows the illustration of the variations in the CCR efficiency scores.

Table 10 Spearman's correlation analysis results

	M1	M2	M3	M4	M5
M2	0.8464 (0.0000)				
M3	0.9522 (0.0000)	0.7427 (0.0000)			
M4	0.9410 (0.0000)	0.7654 (0.0000)	0.8997 (0.0000)		
M5	0.4800 (0.0000)	0.3703 (0.0000)	0.5016 (0.0000)	0.4084 (0.0003)	
M6	0.9214 (0.0000)	0.8077 (0.0000)	0.8634 (0.0000)	0.9022 (0.0000)	0.2893 (0.0131)

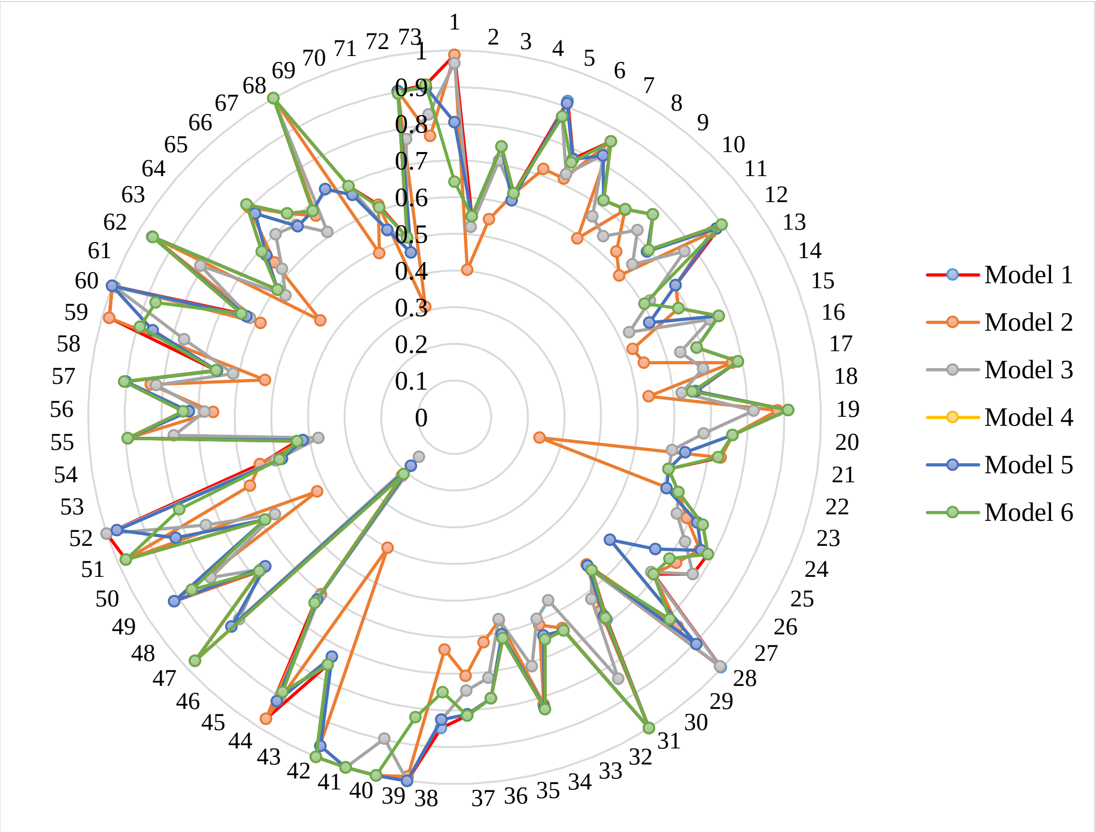

Figure 12. Sensitivity of six CCR models to specific input/output

3.6.3. Tobit Regression Results

In this section, by using an econometric analysis and with a Tobit estimation technique the determinants of the CCR efficiency scores are investigated. Here the objective is to examine the factors that contribute to the changes in the efficiency scores. The independent factors that may contribute to the variation in efficiency scores of different wind farms are chosen to be the age of the wind farms and elevation of the site that the farm is constructed. . Table 11 presents the Tobit results of the model. The coefficients for age and elevation variables are not statistically significant at even 15%, hence it is not clear whether these variables have any effect on the efficiency of the Turkish wind farms. This might be due to the fact that most of the wind farms are built recently and the average age for the wind farms in the data set is just 5 years and wear and tear of the turbines have not affected the performance of the wind farms yet. As for the elevation variable, most of the wind farms in Turkey are built on coastal areas (semi-offshore) of Ege and Marmara, with relatively high wind velocity despite the low elevation of the field. Thus, even at low elevation the wind farms are still efficient. It is possible that there is a positive correlation with wind velocity in the inner areas, however the number of wind farms from such areas are fewer in this study.

Second we examine the effect of the location on the performance level of the wind farms. In this regard, a dummy variable has been defined for five different regions in Turkey. The Akdeniz region is the one that is not explicitly included in the regression and hence all the comparisons are made according to this region. The Tobit results presented in Table 11 indicate in Karadeniz (Region_3) the wind farms have significantly higher efficiency values. The rest of the regions do not have statistically significantly different efficiency values when compared to the Akdeniz region. Even though the coefficient estimates are statistically significant for the Karadeniz region, in terms of the number of wind farms this is not a region which is highly populated with wind farms. Hence a more detailed study more wind farm projects could be initiated in this region after comprehensive topographic study to find the best locations for new wind farms across the regions.

Finally, Table 11 also presents the coefficients of the dummy variables for the brand of turbines. The results reveal that the contribution of the brands to efficiency are not uniform across different brands. The brand that does not have an explicit dummy variable included into the regression, is Enercon which is produced by Germany. When one examines the results of the Tobit estimation, we see that, using Brand 6 (Vestas) turbines provides higher efficiency in the wind farms with a 14% higher productive efficiency scores. This difference is statistically significant at 5% significance level. However, this result is not robust to different specifications. Another results that we see in the Tobit estimations, is that turbine Brand 7 (Sinovel) which includes Chinese and Indian turbines has statistically lower efficiency scores. We observe that wind farms which uses these Turbine brands show about 11 %-14 % less productive efficiency and furthermore this results are robust in all specifications. These illustrates that there may be several factors that influence the productive efficiency of wind farms. These may extend from the location to the chose brand of turbines, and these factors should be taken into consideration in energy investments in the wind farms.

Table 11. Tobit regression results

	(1)	(3)	(5)	(7)	(9)	(11)	(13)	(15)
VARIABLES	1	2	3	5	6	7	8	9
Age	-0.00541	-0.00616	-0.00600		-0.00690			-0.00977
	(0.0056)	(0.0061)	(0.0062)		(0.0062)			(0.0060)
Site Elevation		-0.00002	-0.00009		-0.00018			-0.00048
		(0.0000)	(0.0002)		(0.0003)			(0.0003)
Air Density			-0.58180		-0.84583			-3.04846
			(1.8820)		(2.8237)			(2.5610)
Region 2 (Ege)				-0.04979	-0.08606		-0.01990	-0.03873
				(0.0534)	(0.0652)		(0.0665)	(0.0747)
Region 3 (Karadeniz)				**0.21924***	**0.25603****		**0.22130***	**0.30307****
				(0.1128)	**(0.1186)**		**(0.1259)**	**(0.1325)**
Region 4 (Marmara)				-0.04412	-0.07156		-0.07087	-0.07230
				(0.0518)	(0.0867)		(0.0579)	(0.0865)
Region 5 (İç Anadolu)				-0.02071	0.03613		0.00193	0.13850
				(0.1077)	(0.1446)		(0.1276)	(0.1546)
Turbine Brand 2 (Gamesa)						0.06131	0.02016	0.05858
						(0.0685)	(0.0824)	(0.0803)
Turbine Brand 3 (GE)						0.07723	0.08588	0.11725
						(0.0652)	(0.0693)	(0.0711)
Turbine Brand 4 (Nordex)						0.04577	0.04273	0.06278
						(0.0714)	(0.0656)	(0.0699)
Turbine Brand 5 (Siemens)						0.03905	0.06393	0.08903
						(0.0495)	(0.0619)	(0.0629)
Turbine Brand (Vestas)						0.07826	0.08758	**0.14004****
						(0.0562)	(0.0622)	**(0.0659)**
Turbine Brand (Sinovel)						**-0.11375***	**-0.13064****	**-0.12626****
						(0.0623)	**(0.0610)**	**(0.0597)**
Constant	0.80691***	0.82283***	1.52713	0.81320***	1.94614	0.74531***	0.77712***	4.56457
	(0.0412)	(0.0582)	(2.2811)	(0.0407)	(3.3691)	(0.0373)	(0.0687)	(3.0388)
Observations	73	73	73	73	73	73	73	73
F test	0.333	0.605	0.764	0.166	0.0966	0.0918	0.0198	0.00518
Pseudo R-squared	-0.0324	-0.0414	-0.0444	-0.192	-0.331	-0.376	-0.620	-0.951

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.7. Explanation of Limitations

This study encounters two major limitations; First, limitation of the DEA methodology including its deterministic character, sensitivity to output and input specifications, and its limited possibilities for contrasting hypotheses. Outlier(s) and/or measurement error(s) may cause critical changes in the relative efficiency scores of DMU(s). The second restraint challenges the credibility of data collection of average wind speed to data in the calculation of wind power density of the wind farms. Since average wind speeds in the exact location of the wind farms were not available the data has been obtained from the nearest meteorological station which may be located in a considerable distance from the wind farms. This may also cause miscalculations in computing efficiency score of the wind farms. Third, due to data limitation we could only include 73 wind farms out of 140 in the analysis. This study will be extended to include more wind farms.

CHAPTER IV

CONCLUSIONS AND POLICY RECOMMENDETIONS

Turkey’s total installed wind power capacity of 6,516.2 MW generated 17903.8 GWh of electricity in 2017 which accounted for 6% of the country’s total electricity generation. The capacity factor of wind energy in Turkey was 31% which is preferable. however, since the country is over-dependent on natural gas and coal for generating electricity, it is vital to drive the electricity generation specifically with renewable sources of energy to the optimum points. Regarding the development of new onshore and offshore Turkish wind farms in upcoming years, this study attempted to evaluate the performance of a representative sample of these wind farms. Thus, for the first time, this study conducts a quantitative assessment to evaluate the productive efficiency of 73 Turkish wind farms in two stages.

Data envelopment analysis in the first stage relatively evaluates the performance of the wind farms regarding their performance in electricity generation and following the efficiency results Tobit regression examines the effect of distinct variables on the efficiency level of those wind farms. Input- and output-oriented CCR and BCC models as the most prominent DEA models in the literature has been applied to three input variables and two output variables. These variables as the vital elements of this study include installed power capacity, number of wind turbines, and wind power density for input variables while, output variables consist of generated electricity and availability. The DEA results explain that approximately 40% of the wind farms generated electricity at a sufficient level since 30 wind farms obtained the scores above 0.8 in CCR models. Regarding both the input- and output-oriented CCR models 8 wind farms operated at maximum efficiency level while in input- and output-oriented BCC models 15 and 14 wind farms obtained the highest efficiency scores.

Moreover, results of the input- and output-oriented models unanimously reveal that 42% of the wind farms have the potential to enhance their efficiency by expanding their operational level, However, DEA results detected overinvestment in 46% of the wind farms which can be interpreted as the result of inappropriate use of government incentives for the sector. Since the average slacks of three input variables and first output variable (electricity generation) is approximately, one can conclude that high significance of these variables which any variations in them would directly reflect on the performance level of the wind farms.

The sensitivity analysis is utilized to confirm the robustness level of DEA results and to examine the impacts of different input and output variables on the results. Thus, we introduced 5 new models by omitting each of input and output variables from the original model and acquired CCR efficiency score for the new models. Moreover, we used Spearman's rank-order correlation to measure the strength of association between new models which confirmed the stability and positive correlation between the proposed new models. As a result, not surprisingly, installed capacity and generated electricity proved to be the most significant factors to affect the efficiency of Turkish wind farms. In the second stage of this study, we utilized different Tobit regression models to investigate the impact of specific characteristics of the wind farms on their relative productive efficiency levels. First Tobit model revealed that age and elevation do not have any significant role in the efficiency of Turkish wind farms. To justify these results, first Turkish wind farms are relatively new and the effect of depreciation might occur later, secondly, the atlas of Turkish wind farms demonstrate that most of the wind power plants are built on the coastal plains of Marmara and Ege which are wind-rich and while have low elevations. Finally, the third Tobit model discloses that the Danish and the American turbines made the most contribution to the performance of the Turkish wind farms.

Based on the above outcomes, some policy recommendations to the Turkish wind power sector are given as follows;

First, the evaluated wind farms should adjust their installed capacity based on the results obtained from this study and the capacity of their local power grid. Wind farms classified as IRS should increase their number of the turbines to harness wind power more efficiently. On the other hand, DRS labeled wind farms should modify their capacity regarding the actual intensity of wind power density in their locations. Second, those wind farms with outdated and low capacity turbines should replace them with modern and modern and larger turbines. Moreover, although installing Chinese and Indian wind turbines requires lower investment, in the long-term due to inefficient electricity generation, it would lead to a lower return on investment. Third, it is necessary that private or governmental entities like Turkish Wind Energy Association (TWEA) evaluate the performance of Turkey’s wind farms annually or even monthly utilizing DEA method or other benchmarking methods like SFA or combination of two methods to give a precise insight for companies operating in the sector as well as for the future investment in the Turkish wind energy sector.

Finally, enhanced governmental incentives should be introduced in order to not only contribute to the sustainable development of Turkish wind power sector but also to prevent the project from overinvestment, and productive use of this renewable energy in electricity generation in Turkey.

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