



MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES



DEVELOPING OPTIMIZATION MODELS FOR WIND ENERGY USING DESIGN OF EXPERIMENT

YASEMİN AYAZ ATALAN

Ph.D. THESIS

Department of Environmental Engineering

Thesis Supervisor

Prof. Dr. Mete TAYANÇ

ISTANBUL, 2020



MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES



DEVELOPING OPTIMIZATION MODELS FOR WIND ENERGY USING DESIGN OF EXPERIMENT

YASEMİN AYAZ ATALAN

(724315821)

Ph.D. THESIS

Department of Environmental Engineering

Thesis Supervisor

Prof. Dr. Mete TAYANÇ

ISTANBUL, 2020

MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES IN
PURE AND APPLIED SCIENCES

Yasemin AYAZ ATALAN, a Doctor of Philosophy student of Marmara University Institute for Graduate Studies in Pure and Applied Sciences, defended her thesis entitled “**Developing Optimization Models for Wind Energy Using Design of Experiment**”, on October 5, 2020 and has been found to be satisfactory by the jury members.



ACKNOWLEDGEMENTS

This thesis was written to be a step towards a more livable environment, as well as to meet the energy needs of humanity at the maximum level with a sustainable way. I have presented a new approach in this thesis study in order to provide maximum benefit from wind energy by combining the potential of the nature with today's technology. I would be happy to use my knowledge for environmentally sustainable energy.

I would like to express my deepest appreciation to my thesis supervisor, Prof. Dr. Mete TAYANÇ, who guided me in the preparation of this thesis, shared his deep knowledge with me and provided his support during the thesis period.

I am very grateful to Assoc. Dr. Kamil ERKAN, who is the member of thesis committee, for his contributions in the emergence of a different perspective in the formation of my thesis. In addition, I would like to thank Prof. Dr. Ali DENİZ, who is the member of thesis committee, from Istanbul Technical University for his valuable contribution.

Last but not the least, I wish to emphasize my heartfelt gratitude to my family, my husband and my daughters for all kinds of their support, time, opportunity and patience during my doctoral study.

October 2020

Yasemin AYAZ ATALAN

ACKNOWLEDGEMENTS	IV
CONTENTS.....	I
ABSTRACT.....	IV
ÖZET	V
CLAIM OF ORIGINALITY	VI
SYMBOLS	VII
ABBREVIATIONS	IX
LIST OF FIGURES	XI
LIST OF TABLES	XIII
1. INTRODUCTION.....	1
1.1. Overview of Energy	1
1.2. Classification of Energy.....	3
1.2.1. Fossil Fuels	3
1.2.2. Nuclear Power.....	5
1.2.3. Renewable Energy	7
1.3. Objective and Scope of the Study	9
2. WIND ENERGY	11
3. DESIGN OF EXPERIMENT (DOE)	14
3.1. Background Information.....	14
3.2. The Types of Design of Experiment Applications	19
3.2.1. Full Factorial Design (FFD).....	19
3.2.2. Fractional Factorial Design (fFD).....	24
3.2.3. Multi-level Factorial Design (MFD).....	26
3.2.4. Screening Experiments Design (SED).....	26
3.2.5. Response Surface Design (RSD)	27
3.2.5.1. Central Composite Design (CCD)	27
3.2.5.2. Box-Behnken Design (BBD)	28
4. OPTIMIZATION.....	30
4.1. Background Information	30
4.2. Applications of Optimization Approaches for Renewable Energy.....	31
4.3. Applications of Optimization Approaches for Wind Energy	32
4.4. Structure of Optimization Model.....	32
5. DATA AND FORMULATION OF THE METHODOLOGY.....	35
5.1. Data of the Research	35
5.1.1. Marmara Region	38
5.1.2. Mediterranean Region.....	38

5.1.3.	Aegean Region.....	39
5.1.4.	Central Anatolia Region	40
5.1.5.	Black Sea Region.....	40
5.1.6.	Southeast Anatolia Region.....	41
5.1.7.	Eastern Anatolia Region	41
5.2.	The Formulation of the Factors for WPPs	41
6.	APPLICATION OF THE METHODOLOGY	44
6.1.	Statistical Analysis.....	45
6.2.	Application of the Design of Experiments.....	48
6.3.	Implementation of Optimization.....	51
7.	RESULTS AND DISCUSSION	55
8.	CONCLUSIONS	65
	REFERENCES.....	66
	APPENDIX.....	74
A.1.	Some of the data collected for this study (representation).....	74
A.2.	Locations information of WPPs used for developed method	75
	RESUME	76

dedicated to my husband and daughters



Clean Energy for Humanity!

ABSTRACT

DEVELOPING OPTIMIZATION MODELS FOR WIND ENERGY USING DESIGN OF EXPERIMENT

This study aims to develop an optimization model for obtaining the maximum benefit from wind energy and to help reduce external dependence. In this sense, design of experiment and optimization method were comprehensively combined together in wind energy field for the first time. Existing data of installed wind power plants operating in Turkey were analyzed in this work. Initially, both the individual and interactive effects of controllable and uncontrollable factors on wind power generation were investigated with the help of Box-Behnken design. Secondly, an optimization technique was utilized to estimate optimum values for each decision variable in order to maximize the amount of energy to be produced for the future. The results showed that the overall model and all the input factors were significant for wind energy production. Based on the established nonlinear optimization model, the optimum results with high desirability value (0.9587) for turbine power, hub height, rotor diameter and wind speed were calculated as 3.0670 MW, 108.8424 m, 106.7597 m, 6.1684 m/sec, respectively, for the maximized energy output which was 9952000 kWh per unit turbine, annually. This study represents a guideline for governments and entrepreneurs with respect to the design of new power plants to produce maximum amount of energy from wind.

Keywords: Wind energy; Design of experiment; Box-Behnken design; Optimization; Decision variables

Yasemin Ayaz Atalan

2020

ÖZET

DENEY TASARIMINI KULLANARAK RÜZGÂR ENERJİSİ İÇİN OPTİMİZASYON MODELLERİ GELİŞTİRME

Bu çalışma, rüzgâr enerjisinden maksimum faydayı elde etmek ve dışa bağımlılığın azaltılmasına yardımcı olmak için bir optimizasyon modeli geliştirmeyi amaçlamaktadır. Bu anlamda, deneme tasarımı ve optimizasyon yöntemi ilk kez rüzgâr enerjisi alanında kapsamlı bir şekilde bir araya getirildi. Bu çalışmada, Türkiye'de faaliyet gösteren kurulu rüzgâr santrallerinin mevcut verileri analiz edildi. İlk olarak, kontrol edilebilir ve kontrol edilemeyen faktörlerin rüzgâr enerjisi üretimi üzerindeki bireysel ve etkileşimli etkileri Box-Behnken tasarımının yardımıyla araştırıldı. İkinci olarak, gelecek için üretilecek enerji miktarını en üst düzeye çıkarmak amacıyla her karar değişkeni için optimum değerleri tahmin etmek için bir optimizasyon tekniği kullanılmıştır. Sonuçlar, genel modelin ve tüm girdi faktörlerinin rüzgâr enerjisi üretimi için önemli olduğunu göstermiştir. Oluşturulan doğrusal olmayan optimizasyon modeline dayanarak, türbin gücü, göbek yüksekliği, rotor çapı ve rüzgâr hızı için yüksek arzu edilebilirlik değeri (0.9587) olan optimum sonuçlar sırasıyla, sırasıyla 3.0670 MW, 108.8424 m, 106.7597 m, 6.1684 m/sn olarak hesaplandı. Birim türbin başına yıllık 9952000 kWh olan maksimum enerji çıkışı. Bu çalışma, hükümetler ve girişimciler için, rüzgârdan maksimum miktarda enerji üretecek yeni enerji santrallerinin tasarımına ilişkin bir rehber niteliğindedir.

Anahtar Kelimeler: Rüzgâr Enerjisi; Deney tasarımı, Box-Behnken Tasarımı; Optimizasyon, Karar Değişkenleri

Yasemin Ayaz Atalan

2020

CLAIM OF ORIGINALITY

Energy is the key factor indicating not only the level of social and economic development of countries but also reflecting improvement of life standards people have. In writing this thesis, the most important element that triggers me is the increasing energy demand of people. Unfortunately, the energy demand is exponentially growing as the population of the world ascends and living standards of people rises, most of which, however, has been supplied by nonrenewable energy resources. For this reason, I did this work to meet the energy needs of people as much as possible with clean or renewable energy without harming our planet by a more sustainable way. In this study, wind energy, which is one of the renewable energy types, has been discussed deeply.

The primary aim of this study is to gain maximum benefit from wind energy that has the potential to meet increasing energy demands in a cost effective and environmentally friendly way without depending on foreign fossil fuel sources.

This work represents the first application of the design of experiment (DOE) method and optimization technique combined together to the field of wind energy, having such a comprehensive and descriptive nature. Firstly, the approach of design of experiment was used to determine and analyze the factors considered to be effective for wind power generation. Secondly, optimization technique was employed to calculate the optimum values of the factors in order to maximize the amount of energy to be produced for the future. Existing data of installed wind power plants operating in Turkey were analyzed in this work. This study represents a guideline for governments and entrepreneurs with respect to the design of new power plants to produce maximum amount of energy from wind for the future.

October 5, 2020

Prof. Dr. Mete TAYANÇ

Yasemin Ayaz Atalan

SYMBOLS

a	the distance from the central point to the points at the end of the arrows
α	wind speed power law coefficient
A	swept area
b_1	the right-hand side for the first constraint
β_2	regression coefficient
b_2	the right-hand side for the second constraint
β_i	main effects for each factor
β_{ij}	two-way interaction between i^{th} and j^{th} factors
β_{ijk}	three-way interaction between i^{th} , j^{th} , and k^{th} factors
β_k	regression coefficient
b_n	the right-hand side for the n^{th} constraint
β_o	overall mean response
$\widehat{\beta}_o$	regression coefficient
c_p	power coefficient, referred to as the Betz limit
ε	random error
$E(y)$	expected response value
ε_σ	random error of the standard deviation
ε_μ	random error of the mean
f	function
h_o	initial hub height
k	the number of levels for each factor
l	radius of rotor
$l/2$	rotor diameter
l_l	lower limit
p	fraction of factorial design
ρ	air density
$Q1$	the first quartile
$Q2$	the second quartile (median)
$Q3$	the third quartile
R_1	the first run

R_2	the second run
R^n	real number
R_n	the n^{th} run
s_1	the first constraint
s_2	the second constraint
s_n	the n^{th} constraint
τ_σ	target value of the standard deviation
τ_μ	target value of the mean
u_l	upper limit
v	wind speed
v_0	wind speed at the initial hub height h_0
v_{pd}	intensity wind energy
w_σ	standard deviation for the target value
w_μ	the mean for the target value
x	input variable
X	axial induction factor
x_{AJ}	the value of the factor A for the j^{th} WPP
x_{BJ}	the value of the factor B for the j^{th} WPP
x_{CJ}	the value of the factor C for the j^{th} WPP
x_{DJ}	the value of the factor D for the j^{th} WPP
x_{ij}	the value of the factor i for the j^{th} WPP
y	response or output variable
y_1	regression coefficient for the polynomial models
y_2	regression coefficient for the polynomial models
y_3	regression coefficient for the polynomial models
y_σ	output of the target standard deviation
y_k	regression coefficient for the polynomial models
y_0	regression coefficient for the polynomial models
y_μ	output of the target mean

ABBREVIATIONS

ANOVA	Analysis of Variance
BBD	Box-Behnken Design
Btu	British Thermal Units
CCD	Central Composite Design
CO₂	Carbondioxide
DOE	Design of Experiment
EIA	International Energy Administration
EU	European Union
F	F-test
FFD	Full Factorial Design
fFD	Fractional Factorial Design
GW	Gigawatt
GW_e	Gigawatt Electrical
HH	Hub Height
IEO	International Energy Outlook
IPCC	International Panel on Climate Change
kWh	kilowatt hour
m	meter
m/sec	meter per second
MFD	Multi-Level Factorial Design
MW	Megawatt
NOAA	National Oceanic & Atmospheric Administration
NO_x	Nitrous Oxides
OECD	Organization for Economic Cooperation and Development
ppm	part per million
prob	Probability
RD	Rotor Diameter
RE	Renewable Energy
RSD	Response Surface Design
SED	Screening Experiments Design
SO₂	Sulfur Dioxide

StDev	Standard Deviation
t	t-test
TP	Turbine Power
TWh	Terawatt hour
WPP	Wind Power Plant
WS	Wind Speed



LIST OF FIGURES

Figure 1: Links between energy and human, economic and social development.....	1
Figure 2: World energy consumption through 2018-2050.....	2
Figure 3: Energy consumption by sector for OECD and non-OECD countries	3
Figure 4: CO ₂ concentration between 1980 and 2017	4
Figure 5: Global nuclear electricity production between 1970 and 2017.....	6
Figure 6: Renewable energy resources of the world.....	7
Figure 7: World energy consumption by energy source between 2018 and 2050.....	9
Figure 8: Global benefits of renewable energies production.....	9
Figure 9: Conversion from wind power to electrical power in a wind turbine.....	11
Figure 10: Global onshore and offshore wind installations	12
Figure 11: Procedure for designing an experiment.....	15
Figure 12: The combination of the runs in the 2 ² design.....	20
Figure 13: The combination of the runs in the 2 ³ design.....	21
Figure 14: The combination of the runs in the 3 ³ design.....	23
Figure 15: Fractional Factorial Design	25
Figure 16: CCD of 3 factors with 3 Levels (a=1.682).....	28
Figure 17: BBD of 3 factors with 3 Levels.....	29
Figure 18: The map of the wind power plants' locations in Turkey.....	35
Figure 19: WPP production rates of Regions for 2017.....	36
Figure 20: WPP production rates of Regions for 2018.....	36
Figure 21: Annual amount of wind energy produced in 2017 from the 112 installed facilities in Turkey	37
Figure 22: Annual amount of wind energy produced in 2018 from the 112 installed facilities in Turkey	38
Figure 23: Marmara Region.....	38
Figure 24: Mediterranean Region	39
Figure 25: Aegean Region	39
Figure 26: Central Anatolia Region.....	40
Figure 27: Black Sea Region	40
Figure 28: Southeast Anatolia Region	41
Figure 29: Parameters used for wind turbine structure	42
Figure 30: Flow chart of the proposed methodology.....	44

Figure 31: Average annual energy production of 112 WPPs in 2017 and 2018	45
Figure 32: Box plots showing data distribution of factors.....	48
Figure 33: The data of response selected for DOE	50
Figure 34: Normal Probability Plot	50
Figure 35: Normal distribution and histogram plot of response	51
Figure 36: Pareto chart of the standardized effects.....	56
Figure 37: Main effects of factors on response variable.....	56
Figure 38: Contour and surface plots showing interactive effects of factors	59
Figure 39: Optimization Results according to Desirability Function	59
Figure 40: Optimization results for Target ₁ (maximize y subject to constant σ).....	60
Figure 41: Optimization results for Target ₂ (minimize σ subject to constant y)	61
Figure 42: Optimization results for Target ₁ and Target ₁ (maximize y and minimize σ).....	62

LIST OF TABLES

Table 1: Different Fields of DOE Applied.....	17
Table 2: Design of 2 factors with 2 levels	20
Table 3: Design of 3 factors with 2 levels	21
Table 4: Design of 3 factors with 3 levels	22
Table 5: Design of 2 factors with 2 levels	24
Table 6: The number of runs for fFD based on the number of factors and levels	26
Table 7: The number of runs for MFD based on the number of factors and levels	26
Table 8: The number of runs for SED based on the number of factors and levels	27
Table 9: The number of runs for CCD based on the number of factors with 3 levels	27
Table 10: The numbers of runs for BBD depends on the number of factors with 3 levels	28
Table 11: Descriptive Statistical Data of Factors and Responses	46
Table 12: Level and limit values of factors.....	48
Table 13: Box-Behnken Design of Experiment According to Factor Levels	49
Table 14: Analysis of variance.....	55
Table 15: Best 10 solutions based on desirability value	60
Table 16: The results of all optimization models.....	62
Table 17: The comparison of the decision variables' results.....	63

1. INTRODUCTION

1.1. Overview of Energy

Energy is the key factor indicating not only the level of social and economic development of countries but also reflecting improvement of life standards people have (Khare, Nema, & Baredar, 2016; Toklu, 2013). In order to sustain improvement, satisfactory amount of energy has always to be supplied to public in a cost-efficient way (**Figure 1**). However, billions of people face shortage of energy today which is associated with poverty. As a crucial necessity, energy is needed for a variety of daily human activities such as lighting, cooking, heating, cooling, pumping of water, transportation, communication, etc. (Kaygusuz, 2007).

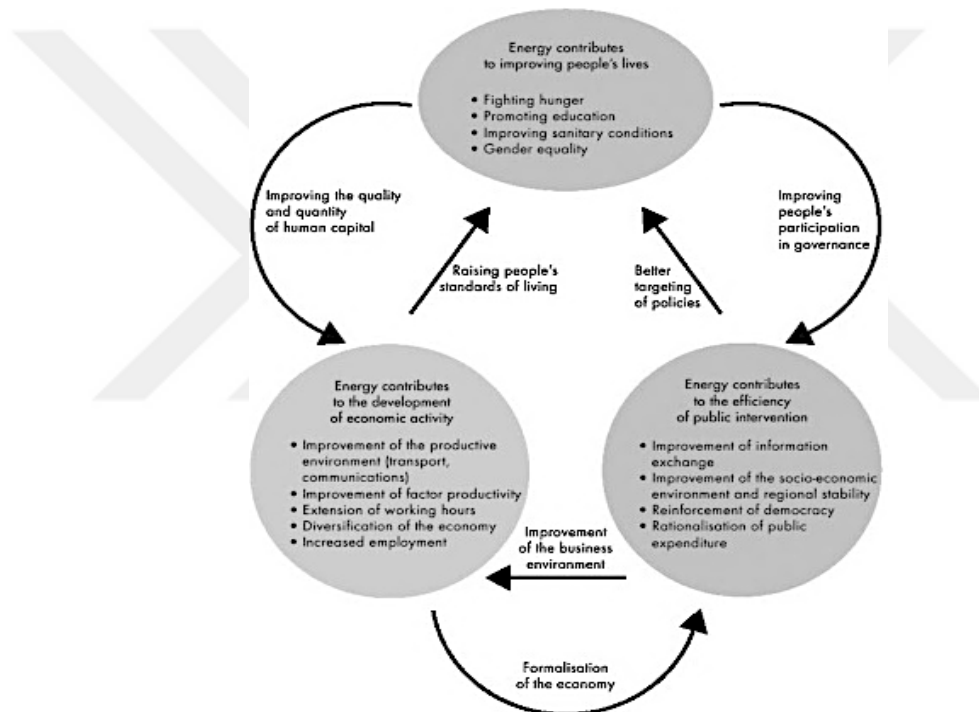


Figure 1: Links between energy and human, economic and social development (Kaygusuz, 2012)

The requirement of energy on a global scale has risen as a consequence of population growth, industrialization, and improvement in life quality (Asif & Muneer, 2007). The human population of world is 7 billion today and, expected to be 9 billion in 2050 and to 10 billion in 2100 , showing indications for need to provide more energy (Chu & Majumdar, 2012). Industrialization basically refers to technological improvements with the social and economic alteration of a community. It is a large-scale economical organization for the purpose of production, which requires a large amount of energy all the time (Mgbemene, 2011). Today's living conditions has also resulted in increasing use of energy.

The 2019 International Energy Outlook (IEO, 2019) by the U.S. Energy Information Administration (EIA) predicts approximately 50% growth for global energy consumption between 2018-2050, most of which comes from countries not belonging to the OECD (Organization for Economic Cooperation and Development) (U.S. Energy Information Administration, 2019). The greatest escalation in energy utilization is observed in Asia, which is not a member of the OECD, especially in China and India. The reason why most of the rises in energy use arise from non-OECD nations is that development of strong economy, enhancement in access to energy market and speedy growth of population cause energy usage to increase. On the contrary, slow growth of economy and population besides fewer inclination to facilities demanding excessive energy and lastly recent advances in energy performance, help the OECD countries consume less energy as compared to non-OECD partners. **Figure 2** shows the projections of world energy consumption of the OECD countries comparatively with non-OECD members through 2018-2050 (U.S. Energy Information Administration, 2019).

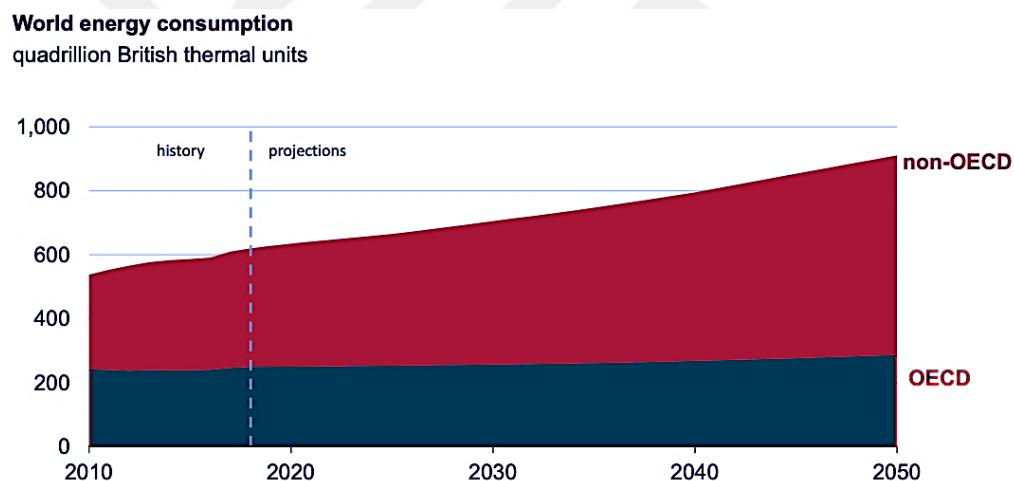


Figure 2: World energy consumption through 2018-2050

IEO states that the industry ranks first in terms of the sectoral distribution of energy consumption, accounting for more than 50% of energy use worldwide. The industrial activities, which have the greatest proportion with regard to energy demand for both OECD and non-OECD countries, involves agriculture, construction, mining, manufacturing, refining, etc. At the time of projection period between 2018 and 2050, the energy consumption of industrial sector rises by more than 30% that equals to 315 quadrillion British thermal units (Btu) by 2050. **Figure 3** represents the share of each sector in energy consumption for both OECD and non-OECD nations through 2018-2050 (U.S. Energy Information Administration, 2019).

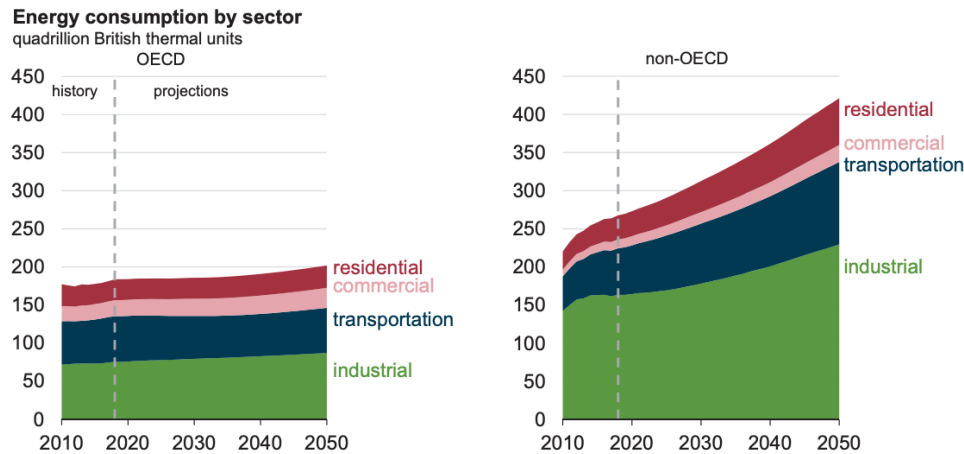


Figure 3: Energy consumption by sector for OECD and non-OECD countries
(U.S. Energy Information Administration, 2019)

Energy is perceived as a vital need, whether for developed or developing countries, in order to be able to carry out all activities. Most of the total energy consumption belongs to the industrial use, whose large-scale manufacturing and so energy demand leads to environmental degradation (Suganthi & Samuel, 2012). Energy is of great importance in determining economic competitiveness and employment too. Thus, policy-makers with international society and entrepreneurs have to figure out both effective ways for energy use and guarantee energy security to supply increasing energy demand while paying great attention to environmental concerns for the future (Abdelaziz, Saidur, & Mekhilef, 2011; Suganthi & Samuel, 2012).

1.2. Classification of Energy

Energy in different forms is utilized throughout the world as a complementary component for human needs. A rough separation of energy might include fossil fuels, nuclear and renewable energy (Asif & Muneer, 2007).

1.2.1. Fossil Fuels

The increasing demand for energy is mostly fulfilled with fossil fuels, for instance coal, oil and gas, which leads to exhaustion of those sources (Asif & Muneer, 2007). It is projected in the IEO, 2017 (EIA, 2017) that %77 of total energy usage is met by fossil fuels in 2040.

Fossil fuels are non-renewable energy sources meaning that they do not have the capacity to replenish themselves and so they are exposed to depletion eventually (Ulutaş, 2005). Besides

being not capable of dealing with future's energy needs, fossil fuels damage environment extremely (Asif & Muneer, 2007).

The concerns for the relationship between fossil fuels and production of both carbon dioxide and other greenhouse gases emissions arose in the mid-1990s. The burning of fossil fuels is accused of about 65% of total greenhouse gas emissions worldwide; 45% of these emissions are originated from coal, whereas 35% and 20% come from oil and natural gas, respectively. There have been some policies applied in the sense of limitation for fossil fuel use, such as adjustments in taxes and expenses of carbon emissions (in the European Union, some US states, Japan, Canada, and Australia), subventions for conserving energy (the United States and elsewhere), and improvements of energy sources releasing low- or zero-carbon (the United States and elsewhere), in some of the developed nations (Covert, Greenstone, & Knittel, 2016).

The fossil fuels are responsible for being the main cause of carbon dioxide (CO₂) emissions produced by human activities. The global level of CO₂ concentration in the atmosphere escalated to 385 parts per million (ppm) in 2007 that had been 280 ppm before industrial revolution (Erdem, 2010). According to U.S. National Oceanic & Atmospheric Administration (NOAA), the atmospheric CO₂ concentration was monitored as 405.58 ppm in November 2017, globally. **Figure 4** shows that CO₂ emissions have increased from 1980 to 2017 with growing usage of fossil fuels.

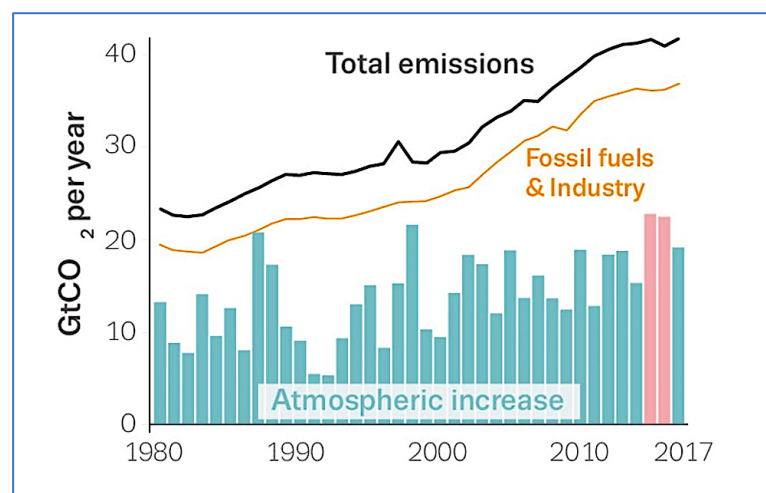


Figure 4: CO₂ concentration between 1980 and 2017
(Canadell et al., 2017)

Global warming poses a threat to whole world, which is a result of building up of greenhouse gas emissions, in particular CO₂ (Toklu, 2013). Actually, it is supposed that climate change is inevitable if there is no significant decline in greenhouse gases emitted as a result of combustion process of fossil fuels (Covert et al., 2016). In addition, air pollution, acid precipitation, ozone depletion, forest destruction, and radioactive emissions are the other environmental concerns related to the usage of fossil fuels (Toklu, 2013).

The issues with regard to fossil fuels, including rise of oil prices, limitedness in quantity, and interest in protecting the environment and the need for security and health of society, have revealed a perception for seeking new and renewable energy technologies (Erdem, 2010).

1.2.2. Nuclear Power

The first consideration of nuclear energy as a potential energy source by scientists and writers' dates back to the 1930s and early 1940s, due to its charming promise to provide a large quantity of energy utilizing relatively few feedstocks. It was believed that nuclear energy could be used for commercial purposes after the 2nd World War, where the humanity witnessed the first atomic bombs as nuclear weapons (Bodansky, 2005).

The popularity of nuclear energy began towards the end of 1960s. The share of nuclear power was 9% in total electricity production when the oil crisis broke out and then reached up to 20% in 1990 (Bilgen, 2014). It was stated in World Nuclear Performance Report 2018 that the total nuclear energy capacity reached to 392 (Gigawatt electrical) GW_e and the net capacity of operating nuclear reactors was 352 GW_e in 2017, excluding those did not produce electricity. As of the end of 2017, 2506 TWh of electricity was generated using nuclear power from operational 448 reactors as worldwide with an increase of 29 TWh in the previous year.

Figure 5 demonstrates the global nuclear electricity production from 1970 to 2017, also indicating regional status independently (World Nuclear Association, 2018). Many investments have been made worldwide in nuclear energy with the intention of both reducing emissions and providing energy demand. The employment of nuclear power plants helps to mitigate 10% of global CO₂ emissions recently. The positive effect of nuclear energy is also observed in OECD countries, especially in the way of decreasing emissions of greenhouse gases originated from electricity production (Apergis, Payne, Menyah, & Wolde-Rufael, 2010).

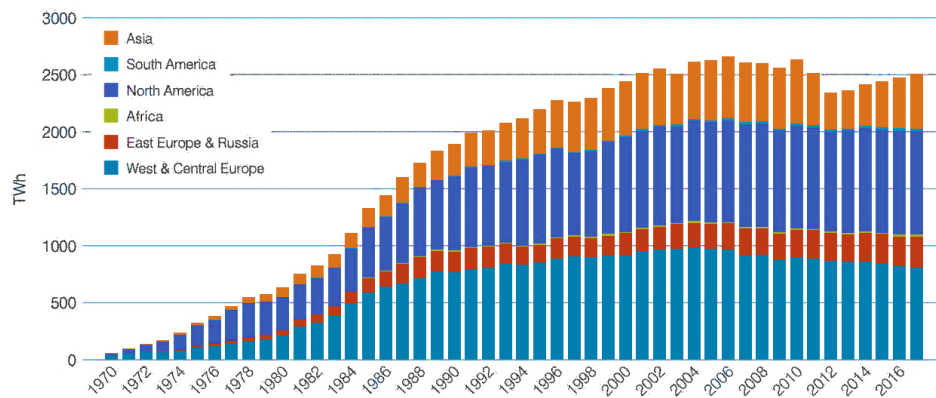


Figure 5: Global nuclear electricity production between 1970 and 2017
(World Nuclear Association, 2018)

The recent percentage of nuclear power in electrical energy mix of the world is limited to only 14%. Nuclear power is struggling with too many issues that have not been solved yet. The challenges that the community is less familiar with nuclear power plants are their inability to produce energy based on demand and the need to run at full capacity even in low requirement periods and the necessity to build reservative hydropower storage systems in regions that provide nuclear power (Dittmar, 2012).

The difficulties which are needed to be overcome about nuclear energy are cost, radioactive waste, safety, and enlargement of weapons material. Nuclear power plants are planned distinctively necessitating different precautions for security, which in turn causes capital costs to be higher and so electricity cost to increase. The cost of producing electricity from nuclear power is twice of that from wind or gas. Another concern related to nuclear energy is radioactive gas formed when the plant operates. Possible emissions of these gases into the atmosphere are risky for health. Leakage of radiated uranium, employed as feedstock for gaining energy, poses hazard during mining and managing processes. The toxicity of nuclear power also brings an obligation to maintain proper places to store nuclear waste permanently since it continues to be perilous even after 240,000 years. Security measures for both new and old nuclear power plants must be discussed in a broad manner in order to prevent undesirable incidents as in Chernobyl nuclear accident. Lastly, the enlargement of nuclear power industry should not give rise to changing of the material into nuclear weapons, other than nuclear energy (Asif & Muneer, 2007).

The entire world has painfully experienced three major nuclear disasters, named as the Three Mile Island accident, Chernobyl and Fukushima accidents, that have had very serious consequences, seriously undermining the reliability of nuclear power technology in the majority of the nations (Gu, 2018). The consideration of nuclear fission energy to commercially generate electricity brings the dependency on uranium which is a finite and nonrenewable source. The required annual amount is 68,000 tons of natural uranium per equivalent to supply recent 14% of global electricity demand by nuclear power. It is a matter of doubt whether the uranium mines will be sufficient in the coming years (Dittmar, 2012). In addition, nuclear power plants operate with an excessive volume of water, both to cool the instruments and suck up waste heat, causing the reactors needed to be built in places close to water bodies such as lakes, rivers and oceans. The returning of warmer water produced finally to the local environment negatively impact the aquatic habitat and life due to thermal contamination (Pearce, 2012).

1.2.3. Renewable Energy

It is a fact that the world is inevitable to face declining growth and, more significantly, environmental tragedy, without implementing severe measures to diminish global warming. In terms of economy, global warming is predicted to cause a 25% reduction in global GDP, whereas the cost of lessening greenhouse gases is anticipated to be only 1% of GDP worldwide (Menyah & Wolde-Rufael, 2010). Renewable energy can mitigate the greenhouse gas emissions for the limitation of the average global surface temperature rise below 2 °C to be achieved by 2050 (Gielen et al., 2019). In addition, renewable energy sources are sufficient to supply more than 3000 times the current global energy demand. **Figure 6** depicts the potential of renewable energy resources of the world (Ellabban, Abu-Rub, & Blaabjerg, 2014).

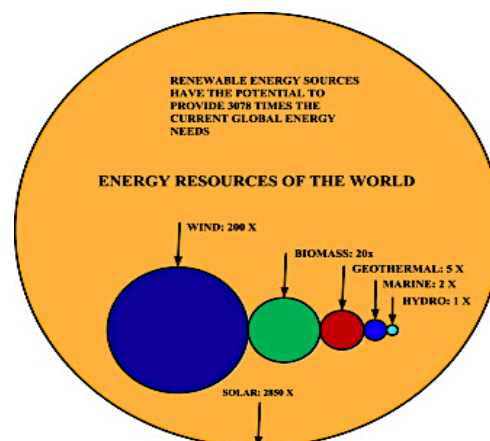


Figure 6: Renewable energy resources of the world

Renewable energy sources, such as wind, solar, hydropower, biomass, and geothermal, have been extensively used throughout the history as in the examples of biomass for cooking, heating and wind to drive mills for grinding grains, etc. (Asif & Muneer, 2007). Considering the negative effects of conventional sources of energy, the importance of renewable energy in terms of decreasing polluting emissions and also diminishing the impact on human health, environment and climate change is undeniable (Markarian, Fazelpour, & Markarian, 2019).

It was estimated by the World Energy Forum that the time remaining for depletion of fossil-based oil, coal and gas reserves is no more than 100 years. Due to the fact that alternative energy is able to reproduce itself, exhaustion is no longer a worry for policy makers in response to ascending energy need (Toklu, 2013). The other reasons behind the inclination for renewable energies can be listed as fluctuations in oil prices, desire to eliminate the imperativeness to buy energy from the other countries, and environmental impacts resulted from emissions of carbon dioxide (Bilgen, 2014). The technical improvement in the field of alternative energy may offer a solution to environmental issues, such as acid rain, stratospheric ozone depletion, and greenhouse effect, caused by conventional energy resources, with relatively less expenditure (Dincer, 2000).

The U.S. EIA states that renewables that involve wind, solar and hydroelectric power are the fastest growing resources of energy by 2050 as compared to the other forms containing coal, natural gas, nuclear, etc. (U.S. Energy Information Administration, 2019). **Figure 7** is the illustration of the global energy consumption estimate of energy sources by 2050 and the percentage shares of each resource in 2018 and the predictions in 2050. The portion of alternative energy resources in the total energy requirement on a global scale was 15 % in 2018, which is anticipated to rise to 28 % in 2050 (Inzlicht, Schmeichel, & Macrae, 2014).

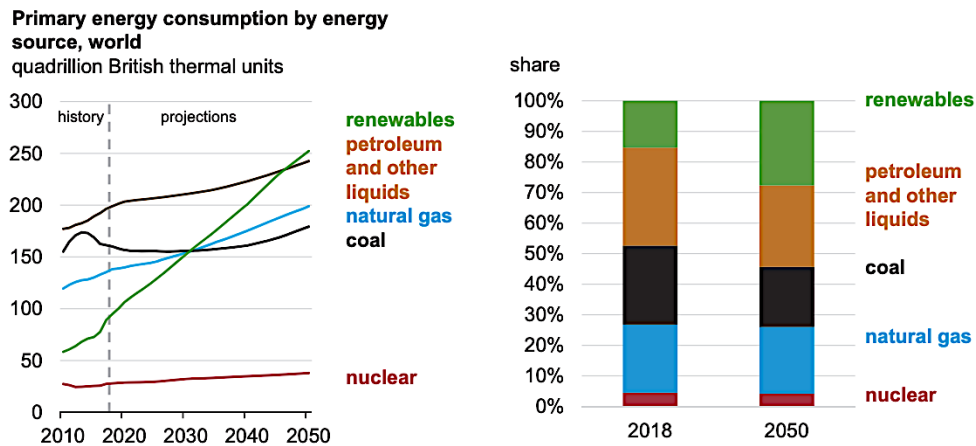


Figure 7: World energy consumption by energy source between 2018 and 2050
(U.S. Energy Information Administration, 2019)

Figure 8 shows the crucial influences of renewable energies for the public from different standpoints. Policy makers try to carry out different legislations about renewable energy (RE) for the purposes of making access to energy easier especially for non-urban areas, improving energy safety with the help of combining various energy sources with separate technologies, increasing employment which is associated with the social and economic progress (Ellabban et al., 2014).

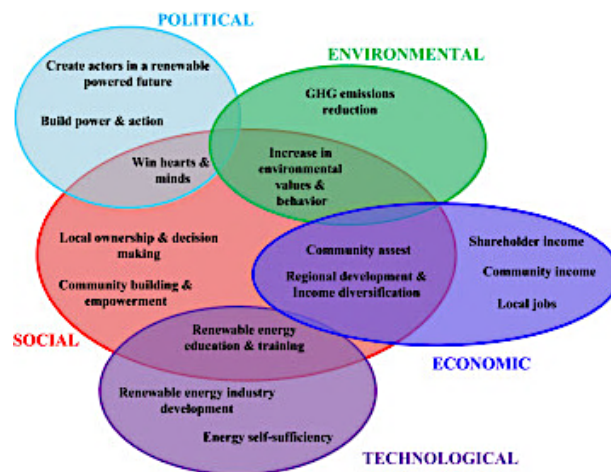


Figure 8: Global benefits of renewable energies production

1.3. Objective and Scope of the Study

The primary aim of this thesis study is to obtain maximum benefit from the wind energy potential to help minimize the dependence on foreign fossil fuel sources besides dealing with the other environmental issues. This work represents the first application of the design of

experiment (DOE) method and optimization technique combined together to the field of wind energy, having such a comprehensive and descriptive nature. Firstly, the approach of design of experiment was used to determine and analyze the factors considered to be effective for wind power generation. Secondly, optimization technique was employed to calculate the optimum values of the factors in order to maximize the amount of energy to be produced for the future.

In the literature, different optimization models were developed to get maximum energy sometimes with minimizing cost, while however considering only one factor. Negm and Maalawi (2000) compared five separate optimization models for wind turbine tower design to achieve optimum solutions for the productivity of the system generally (Negm & Maalawi, 2000). Gao et al. (2015) investigated wind turbine layout optimization in order to maximize energy output and minimize the capital cost, for which three different conditions related to the wind speed and wind direction were implemented to a 2km×2km wind farm (Gao, Yang, Lin, & Koo, 2015). Chan et al. (2018) studied blade shape optimization of Savonius wind turbine to enhance its power coefficient, in which three models were developed to figure out the optimum blade shape of this specific turbine (Chan, Bai, & He, 2018). Differently from such examples mentioned, in this research optimization technique was applied considering four factors, namely turbine hub height, rotor diameter, turbine power and wind speed, for the maximum capture of the wind power, right after the determination of how these variables individually and interactively have influenced the amount of energy produced by the design of experiment method. In the scope of this work, the existing data belonging to the wind power plants installed and in operation in Turkey were analyzed so as to reach optimum values of the decision variables for the maximized energy output.

2. WIND ENERGY

Renewable sources of energy will be profoundly significant for the future of the world. The portion of alternative energy resources in the total energy requirement on a global scale is anticipated to rise to 30-80 % in 2100 (Panwar, Kaushik, & Kothari, 2011). Of the renewables, wind energy is predicted to be the biggest contributor in this increase (Kaygusuz, 2010).

The employment of wind energy by mankind began many centuries ago, the aim of which was firstly to produce mechanical energy but recently to get electricity. Wind is an accessible and a readily obtainable energy source all over the world. Wind energy is gained through wind turbines by converting kinetic energy of wind to mechanical energy and then electrical energy, respectively (Çapik, Yilmaz, & Çavuşoğlu, 2012). Power is transferred from wind with the aid of aerodynamically planned blades to rotational energy in order to operate a generator which then converts motion into electricity (see **Figure 9**) (Panwar et al., 2011).

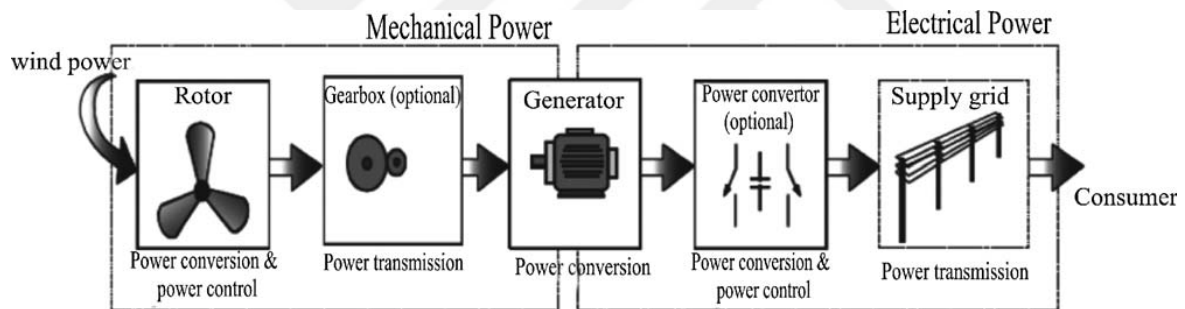


Figure 9: Conversion from wind power to electrical power in a wind turbine
(Panwar et al., 2011)

It was emphasized in the 4th Assessment Report of the International Panel on Climate Change (IPCC) that it is necessary to start reducing emissions throughout the world by 2020 to prevent the impacts of climate change. Wind energy is extremely essential for controlling emissions on a global scale at the targeted time and so for the energy sector which is responsible for almost 40% of CO₂ emissions, globally. It was also estimated in the report that the capacity of wind energy will escalate to 1000 GW by 2020, which equals to 2600 TWh of electricity and avoids 1500 million tons of carbon dioxide annually (Kaygusuz, 2010).

The top five countries in onshore wind market were China, USA, Germany, India and Brazil with installations of 21.2 GW, 7.6 GW, 2.4 GW, 2.2 GW and 1.9 GW in 2018,

respectively, which corresponds to 75% of total capacity. China, as the leading market since 2008, is also the primary nation exceeding 200 GW of total installed capacity, achieving 206 GW of installment by the end of 2018. The global offshore wind capacity has ascended reaching to 23.1 GW in 2018 that equals to 8% for new installments and 4% for the total capacity of the year. **Figure 10** shows the total onshore and offshore wind capacities of the world, giving details about the percentages of the countries (Ohlenfrorst, 2019). Approximately 1.25% of total annual energy production from wind was supplied by 155 WPPs installed in Turkey approaching 7.4 GW by the end of 2018 (REN21, 2018).

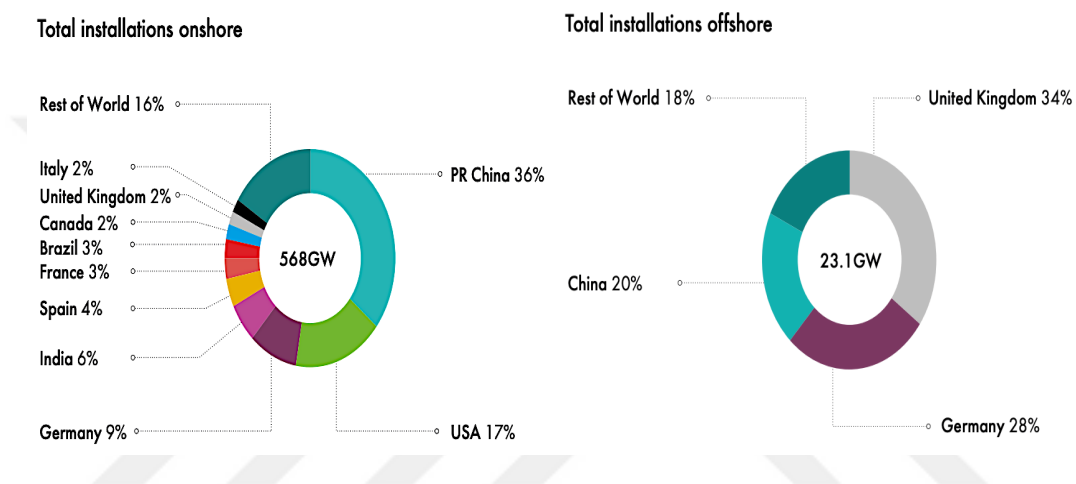


Figure 10: Global onshore and offshore wind installations

With the spread of wind power, its share in electricity production is also increasing. Approximately 14% of European Union's (EU's) consumed energy per annum was supplied by wind energy in 2018. Wind energy has become the most suitable choice for a wide range of places all over the world, owing to its quickly decreasing costs for both onshore and also offshore (REN21, 2018). Being an eco-friendly energy source, wind energy does not cause any emissions of nitrous oxides (NO_x) and sulfur dioxide (SO_2) that is relevant to conventional energy sources (Cullen, 2013). Additionally, unlike fossil fuels, wind energy does not release any CO_2 leading to climate change during its operation (Hossain, Hasanuzzaman, Rahim, & Ping, 2015).

Air pollution, caused by those pollutants mentioned above, is not only a concern for our climate but also it is stated as the most serious threat for human health. Indeed, pollution of air is reported to be responsible for one out of every nine deaths in 2012 (World Health Organization, 2016). Pollution in China, which supplies about 80% of its electricity needs from

coal-fired power plants, has reached such serious dimensions that the World Health Organization estimates that over 650,000 people die each year for this reason. Thus, the air quality is also positively influenced by wind energy (Kaygusuz, 2010).

Wind energy, which is both easy and fast to set up and operate, even in areas that is rugged and difficult to reach, is a feasible electricity source for developing countries. The electricity from the wind neither is exhausted nor the price rises. Generating electricity with this technology may contribute to the prohibition of millions of tons of carbon and other emissions while saving several billion barrels of oil (Panwar et al., 2011). Wind is present both at night and day with high conversion performance to electrical energy (Santhakumar, Palanivel, & Venkatasubramanian, 2019).



3. DESIGN OF EXPERIMENT (DOE)

3.1. Background Information

The first use of the Design of Experiment (DOE) dates back to the early 1920s (Craig & Fisher, 1936). As the father of DOE, Ronald Fisher previously tried to observe the impact of different fertilizer species on different parts of the land. With the help of DOE technique, he was able to distinguish the impact of each factor, such as the amount of moisture in the soil and the condition of underground besides fertilizer variety, on the final state of the crop. Afterwards, DOE became a very beneficial tool used in agricultural and biological areas (Antony, 2014). However, the application of this method in different fields has become increasingly widespread (Hatami, Cuijpers, & Boot, 2015b; Palkar & Shilapuram, 2017; Yu, Varavei, & Sepehrnoori, 2015).

Design of experiment (DOE) is a very influential statistical and mathematical method improving the performance of a system or process that is defined as the conversion of inputs into outputs. The components of design of experiment approach are composed of factors or variables, levels and responses. Factors, as controllable and uncontrollable, are the input variables of the process (Antony, 2014). Levels are the settings related with each factor of the system. Outputs or responses are the constituents that determine the process performance (Sundararajan, 2018).

Designed experiments are useful to ascertain cause-and-effect relationships for the process of interest, which in turn help on the optimization of the response variable. DOE assists in maximizing the correctness of the result or response of a process conversely with minimizing the quantity of experiments, to escalate the system performance. DOE not only helps to specify the most important factors that influence the output but also points out the interactions among them (Wahdame, Candusso, Franc, & Harel, 2009). The components of the design of experiment approach are composed of factors or variables, levels and responses (D. C. Montgomery, 2012; Panda, Satapathy, & Sarangi, 2019). Factors, as controllable and uncontrollable, are the input variables of the process (Antony, 2014). Levels are the settings related to each factor of the system. Outputs or responses are the constituents that determine the process performance.

Experimental design is a very effective method in terms of increasing the performance of a system. In order to accomplish an experiment successfully, there are several steps should be followed in a systematic manner. The procedure for designing an experiment is given in **Figure 11** (D. C. Montgomery, 2012).

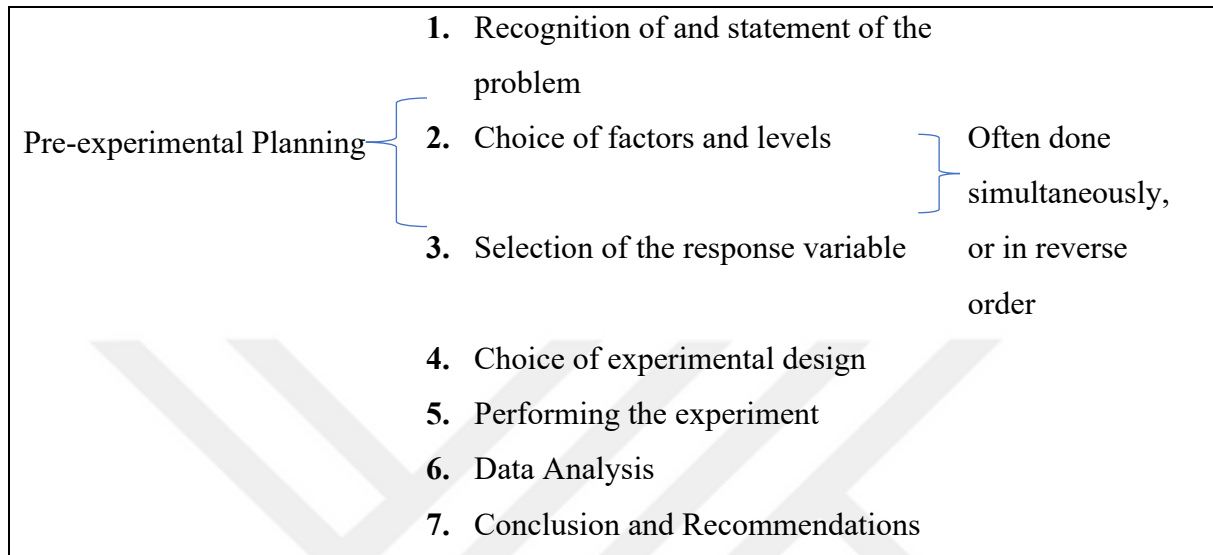


Figure 11: Procedure for designing an experiment

(D. C. Montgomery, 2012)

1. Recognition of and statement of the problem. The problem needs to be defined briefly in sense of giving a better idea of what to do. The purpose of the expression should be distinct and quantifiable so as to be meaningful in practice (Antony, 2014).
2. Choice of factors and levels. The selection of input factors that affect the output or response is vital due to the fact that eliminating an important factor or including an irrelevant variable may change the outcome substantially. Levels of the process variables should be determined cautiously after arranging design parameters (Rekab & Shaikh, 2005).
3. Selection of the response variable. The decision of the response variable for the experiment properly is one of the most important factors affecting the achievement of the experimental design. The response or quality characteristic might be described as either variable or attribute. In general, variable outputs (e.g.: diameter, viscosity, etc.)

give further information but need less samples as compared to attribute outputs (e.g.: yes/no, good/bad, pass/fail, etc.) (Antony, 2014).

4. Choice of experimental design. This step includes sample size determination (i.e.: the number of runs or tests), choice for the adequate sequence of each test, deciding if blocking or any randomization limitations are used (D. C. Montgomery, 2012).
5. Performing the experiment. It is recommended to do a few runs before starting the experiment so as to make practice entirely, control the measurement system, give an idea about the consistency of the material used besides possible errors regarding with the experiment. Observing the whole system with great caution is necessary to see whether or not the plan is followed, which maintains the accuracy of the experiment (D. C. Montgomery, 2012).
6. Data analysis. In order to obtain impartial and unbiased results, the data should be analyzed with the aid of statistical methods. There are lots of software packages and graphical tools existing that are helpful in terms of both analysis and evaluation of the data (D. Montgomery, 2009).
7. Conclusions and recommendations. Some outcomes should be derived about the results after the analysis of the data and an action plan should be proposed. Especially in relation to explaining the results, it is so beneficial to employ graphical tools (D. C. Montgomery, 2012).

There are three principles of DOE, which are replication, randomization and blocking, that help to eliminate any bias arising from the experiment to prevent the results from being impacted negatively. Replication is defined as repeating the whole experiment or part of it more than once. It enables to predict experimental error approximately and also helps to forecast the impact of variables or interactions (Antony, 2014). Randomization allows to select the material to be used in the experiment besides the sequence of each test haphazardly. With the help of randomization of the experiment in an appropriate manner, it is ensured that the influence of any potential external factor is averaged out. As one of the design methods, blocking is employed for improving the comparison of the variables precisely. In other words, it aids to decrease the instability originated from nuisance factors, which affect the output of any system

but are out interest (D. C. Montgomery, 2012). A block is described as the adjustment of experimental conditions homogenously. In order to raise the experiment accuracy, variability among blocks must be removed (Antony, 2014). The implementations of DOE might be classified, depending on the purpose to achieve, as smallest-is-the-best (e.g., cost), largest-is-the-best (e.g., profit) or nominal-is-the-best (e.g., room temperature at 72 °F) (Rekab & Shaikh, 2005). **Table 1** represents some of the different fields in which DOE method was applied in the literature.

Table 1: Different Fields of DOE Applied

Title	Field	Source
The use of Design of Experiment and sensory analysis as tools for the evaluation of production methods for milk	Chemometrics and Intelligent Laboratory Systems	(Wormbs et al., 2004)
A technical note on the role of process parameters in predicting flow behavior of plasticine using design of experiment	Materials Processing Technology	(Sofuoglu, 2006)
Numerical Design of Experiment for Sensitivity Analysis- Application to Skin Burn Injury Prediction	Biomedical Engineering	(Autrique & Lormel, 2008)
Screening of factors influencing the performance of manipulator using combined array design of experiment approach	Robotics and Computer-Integrated Manufacturing	(Rout & Mittal, 2009)
Application of statistical design of experiment with desirability function for theremoval of organophosphorus pesticide from aqueous solution by low-cost material	Hazardous Materials	(Islam, Sakkas, & Albanis, 2009)
Design of experiment study of the parameters that affect performance of three flow plate configurations of a proton exchange membrane fuel cell	Energy	(Carton & Olabi, 2010)
CO ₂ modeling in a deep saline aquifer: A predictive uncertainty analysis using DOE	Environmental Science & Technology	(Liu & Zhang, 2011)
Sensitivity analysis of efficiency thermal energy storage on selected rock mass and grout parameters using design of experiment method	Energy Conversion and Management	(Wołoszyn & Gołaś, 2014)
Optimization of Shale Gas Production Using Design of Experiment and Response Surface Methodology	Energy	(Yu et al., 2015)
Experimental optimization of the vanes geometry for a variable geometry turbocharger (VGT) using a Design of Experiment (DoE) approach	Energy Conversion and Management	(Hatami, Cuijpers, & Boot, 2015a)
Detailed parametric design methodology for hydrodynamics of liquid–solid circulating fluidized bed using design of experiments	Particuology	(Ramesh Palkar & Shilapuram, 2017)

Models are frequently utilized in the engineering field to formulate and solve any kind of problem. The model employed for DOE to show the relationship between the response (y) (i.e., produced energy annually) and the input variables (x 's) (i.e., hub height, turbine power, rotor diameter and wind speed) is expressed as:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^p \sum_{j=1}^p \beta_{ij} x_i x_j + \sum_{i=1}^p \sum_{j=1}^p \sum_{k=1}^p \beta_{ijk} x_i x_j x_k \quad (i \neq j \neq k) \quad (1)$$

where β_0 is the overall mean response, β_i is the main effects for each factor ($i = 1, 2, 3, \dots, p$), β_{ij} is the two-way interaction between i^{th} and j^{th} factors, β_{ijk} is the three-way interaction between i^{th} , j^{th} and k^{th} factors (Uy & Telford, 2009).

Regression models are harnessed to describe the relationship between factors (independent variables) and responses (dependent variables) mathematically. Designed experiments involve first-order and multiple linear regression models, when there are two or more independent variables exist, in general. Multiple linear regression model with k regressor variables (input factors) might be explained as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon \quad (2)$$

where $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ are the regression coefficients and ϵ is random error (D. C. Montgomery, 2012).

Box-Behnken design (BBD), one of the subsets of DOE methodology, helps to develop higher-order models that need fewer runs as compared to other factorial designs. Thus, application of BBD not only saves time but also reduces cost with the help of decreasing the number of experiments. BBD aims to optimize the output of a system with fewest runs by combining the mathematical and statistical methods necessary for the optimization modeling and analysis of experiments where output is affected by multiple factors (Panda et al., 2019).

In this study, the BBD tool was applied to improve wind energy production process and point out the interactions among considered parameters. This design type was chosen because of the fact that it requires less design studies. More specifically, in the full-factorial

experimental design with four factors having three levels of each factor, the number of designs is 162 (81×2) with two replicates, while the number of required designs is only 54 (27×2) in BBD tool. Based on BBD method, the process yield (y) is given as:

$$y = f(x_1, x_2, x_3, \dots, x_n) + \epsilon \quad (3)$$

where x_i denotes the numbers of factors maximizing the yield, y , of a process and ϵ symbolizes the noise or error observed in the response y . If the expected response is expressed by $E(y)$, then the surface denoted by:

$$E(y) = f(x_1, x_2) \quad (4)$$

is termed as response surface (D. C. Montgomery, 2012).

3.2. The Types of Design of Experiment Applications

3.2.1. Full Factorial Design (FFD)

Full factorial design (FFD) method is used generally in which the number of experiments with 2 levels is calculated by:

$$2^k \quad (5)$$

where; k is the number of levels (D. C. Montgomery, 2012). Data that are analysed by design of experiment gives a result in the first order regression equation generally as shown below (Castillo, 2007):

$$\hat{y} = \hat{\beta}_0 + \sum \hat{\beta}_i x_i + \epsilon \quad (6)$$

where β_0 is the regression coefficient, x_i represents the input factors, and ϵ is random error.

FFD is a kind of designed experiment allowing to indicate the impacts of each factor on a response with all possible combinations (Minitab, 2020a). **Table 2** shows the FFD of 2 factors with 2 levels that requires a total of 4 runs. **Figure 12** is the representation of the FFD of 2 factors having 2 levels with a total of 4 runs schematically.

Table 2: Design of 2 factors with 2 levels

Run	Pattern	Inputs		Output
		Factor 1 (x_1)	Factor 2 (x_2)	Response (y)
1.00	11	1.00 (Low)	1.00 (Low)	y_1
2.00	12	1.00 (Low)	2.00 (High)	y_2
3.00	21	2.00 (High)	1.00 (Low)	y_3
4.00	22	2.00 (High)	2.00 (High)	y_4

Note: x_1 and x_2 denote the input factors and y_1, y_2, y_3 , and y_4 symbolize the result of responses.

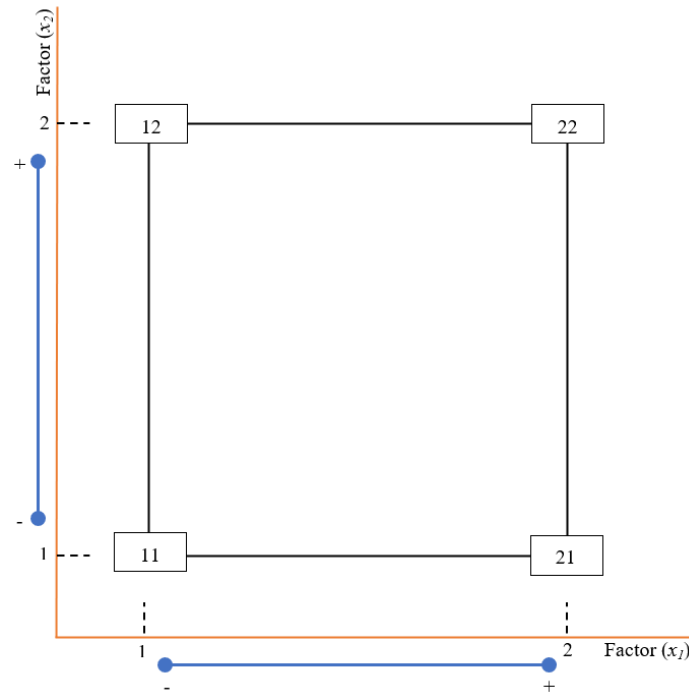
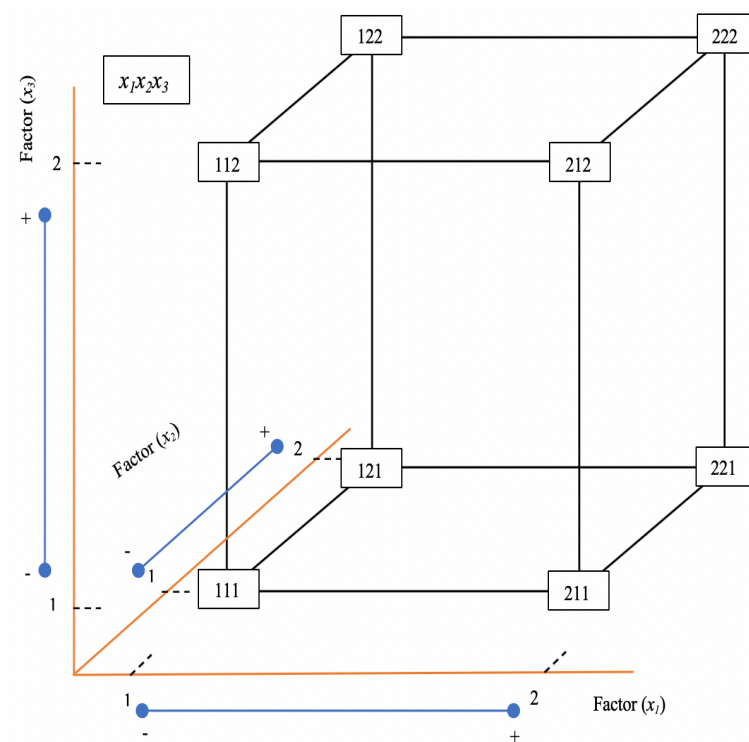
**Figure 12:** The combination of the runs in the 2^2 design

Table 3 demonstrates the FFD of 3 factors with 2 levels that requires a total of 8 runs. **Figure 13** visually illustrates the FFD of 3 factors having 2 levels with a total of 8 runs.

Table 3: Design of 3 factors with 2 levels

Run	Pattern	Inputs			Output
		Factor 1 (x_1)	Factor 2 (x_2)	Factor 3 (x_3)	Response (y)
1.00	111	1.00 (Low)	1.00 (Low)	1.00 (Low)	y_1
2.00	112	1.00 (Low)	1.00 (Low)	2.00 (High)	y_2
3.00	121	1.00 (Low)	2.00 (High)	1.00 (Low)	y_3
4.00	122	1.00 (Low)	2.00 (High)	2.00 (High)	y_4
5.00	211	2.00 (High)	1.00 (Low)	1.00 (Low)	y_5
6.00	212	2.00 (High)	1.00 (Low)	2.00 (High)	y_6
7.00	221	2.00 (High)	2.00 (High)	1.00 (Low)	y_7
8.00	222	2.00 (High)	2.00 (High)	2.00 (High)	y_8

Note: x_1 , x_2 , and x_3 denote the input factors and y_1 , y_2 , y_3 , y_4 , y_5 , y_6 , y_7 , and y_8 , symbolize the result of responses.

**Figure 13:** The combination of the runs in the 2^3 design

The formulation of the number of experiments in FFD having 3 levels for each factor is given by:

$$3^k \quad (7)$$

The display of the FFD of 3 factors with 3 levels which involves a total of 27 runs is given in **Table 4**. The combination of the runs in the FFD of 3 factors having 3 levels is presented in **Figure 14**.

Table 4: Design of 3 factors with 3 levels

Run	Pattern	Inputs			Output
		Factor 1 (x_1)	Factor 2 (x_2)	Factor 3 (x_3)	Response
1.00	111	1.00 (Low)	1.00 (Low)	1.00 (Low)	y_1
2.00	112	1.00 (Low)	1.00 (Low)	2.00 (High)	y_2
3.00	121	1.00 (Low)	2.00 (High)	1.00 (Low)	y_3
4.00	122	1.00 (Low)	2.00 (High)	2.00 (High)	y_4
5.00	211	2.00 (High)	1.00 (Low)	1.00 (Low)	y_5
6.00	212	2.00 (High)	1.00 (Low)	2.00 (High)	y_6
7.00	221	2.00 (High)	2.00 (High)	1.00 (Low)	y_7
8.00	222	2.00 (High)	2.00 (High)	2.00 (High)	y_8
9.00	111	1.00 (Low)	1.00 (Low)	1.00 (Low)	y_9
10.00	112	1.00 (Low)	1.00 (Low)	2.00 (High)	y_{10}
11.00	121	1.00 (Low)	2.00 (High)	1.00 (Low)	y_{11}
12.00	122	1.00 (Low)	2.00 (High)	2.00 (High)	y_{12}
13.00	211	2.00 (High)	1.00 (Low)	1.00 (Low)	y_{13}
14.00	212	2.00 (High)	1.00 (Low)	2.00 (High)	y_{14}
15.00	221	2.00 (High)	2.00 (High)	1.00 (Low)	y_{15}

16.00	222	2.00 (High)	2.00 (High)	2.00 (High)	y_{16}
17.00	111	1.00 (Low)	1.00 (Low)	1.00 (Low)	y_{17}
18.00	112	1.00 (Low)	1.00 (Low)	2.00 (High)	y_{18}
19.00	121	1.00 (Low)	2.00 (High)	1.00 (Low)	y_{19}
20.00	122	1.00 (Low)	2.00 (High)	2.00 (High)	y_{20}
21.00	211	2.00 (High)	1.00 (Low)	1.00 (Low)	y_{21}
22.00	212	2.00 (High)	1.00 (Low)	2.00 (High)	y_{22}
23.00	221	2.00 (High)	2.00 (High)	1.00 (Low)	y_{23}
24.00	222	2.00 (High)	2.00 (High)	2.00 (High)	y_{24}
25.00	111	1.00 (Low)	1.00 (Low)	1.00 (Low)	y_{25}
26.00	112	1.00 (Low)	1.00 (Low)	2.00 (High)	y_{26}
27.00	121	1.00 (Low)	2.00 (High)	1.00 (Low)	y_{27}

Note: x_1 , x_2 , and x_3 denote the input factors and $y_1, y_2, \dots, y_{27}$, symbolize the result of responses.

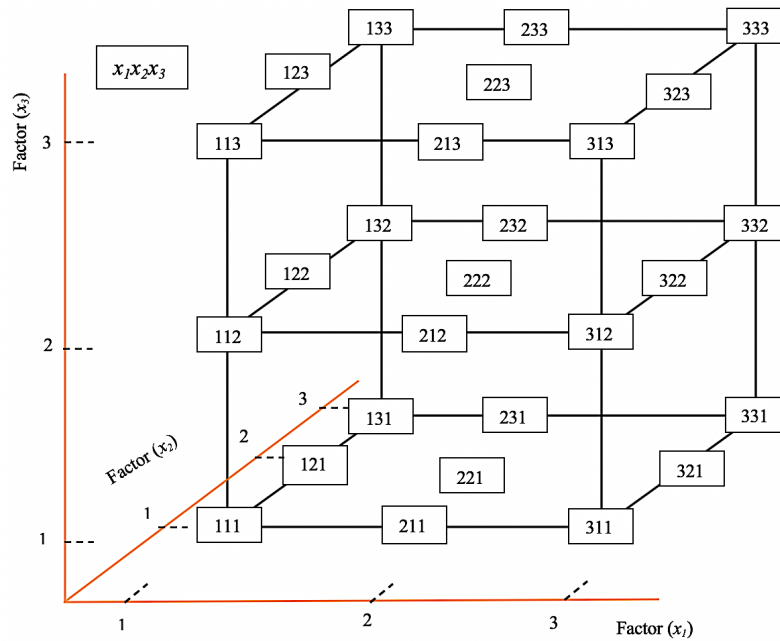


Figure 14: The combination of the runs in the 3^3 design

3.2.2. Fractional Factorial Design (fFD)

As a different sort of factorial design, fractional factorial design deals with only some part of the experiment (D. C. Montgomery, 2012). When there are some constraints to run the full factorial experiment, such as budget, time and resource, fractional factorial designs are employed, which permit to search essential impacts with interactions using limited number of tests or runs. The total number of experiments with each factor having 2 levels is given as:

$$2^{k-p} \quad (8)$$

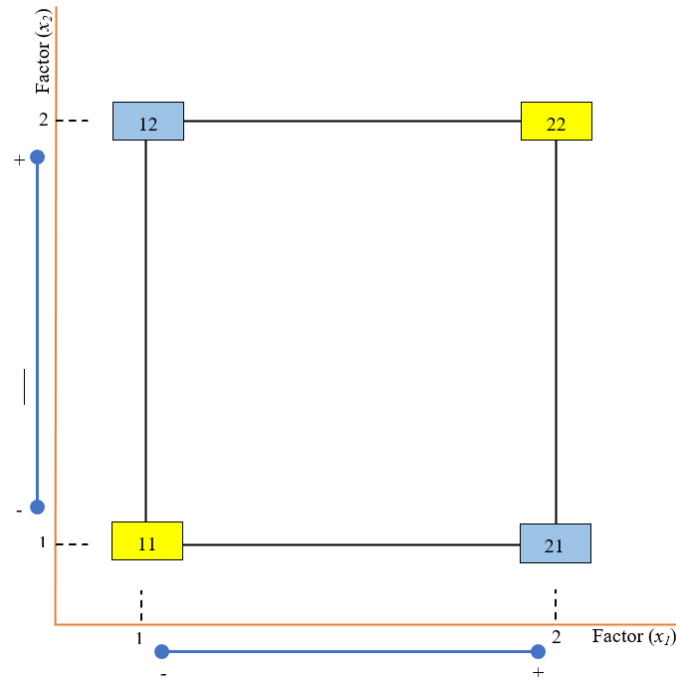
where k is the number of factors, and p is the fraction of the full factorial experimental design (Antony, 2014). **Table 5** exhibits the 1/2 fFD of 2 factors with 2 levels including a total of 4 runs which is half of the total runs required in FFD.

Table 5: Design of 2 factors with 2 levels

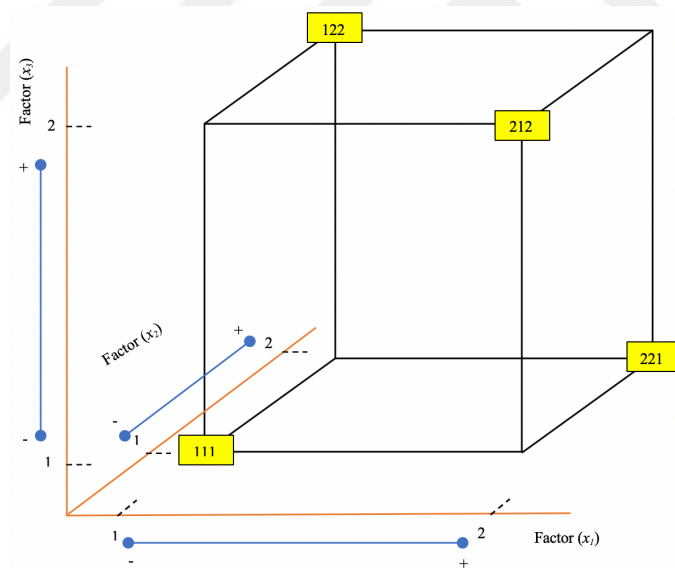
Run	Pattern	Inputs		Output
		Factor 1 (x_1)	Factor 2 (x_2)	Response
1.00	11	1.00 (Low)	1.00 (Low)	y_1
2.00	12	1.00 (Low)	2.00 (High)	y_2
3.00	21	2.00 (High)	1.00 (Low)	y_3
4.00	22	2.00 (High)	2.00 (High)	y_4

Note: x_1 and x_2 denote the input factors and y_1, y_2, y_3 , and y_4 symbolize the result of responses.

Figure 15 shows the illustrative fFD of 2 factors with 2 levels in part a and fFD of 3 factors with 2 levels in part b. The 2 yellow runs or 2 blue runs can be selected for the measurement of the response of the factor levels.



(a) 2 factors with 2 levels



(b) 3 factors with 2 levels

Figure 15: Fractional Factorial Design

Table 6 gives general information about the number of runs for the fractional factorial experimental design for different number of factors and levels.

Table 6: The number of runs for fFD based on the number of factors and levels

Number of Factors	Number of Levels	Number of (1/2) Runs	Number of (1/4) Runs	Number of (1/8) Runs	Number of (1/16) Runs
2	2	2	-	-	-
3	2	4	-	-	-
4	2	8	-	-	-
5	2	16	8	-	-
6	2	32	16	8	-
7	2	64	32	16	8
8	2	128	64	32	16

3.2.3. Multi-level Factorial Design (MFD)

The multi-level factorial design (MFD) takes into consideration different levels of the variables affecting the output. The cornerstone of multi-level factorial designs is the excess of scenario variation of simulation studies (Dziak, Nahum-Shani, & Collins, 2012). **Table 7** demonstrates the quantity of the runs of multi-level factorial experimental design on the basis of the number of factors and their levels.

Table 7: The number of runs for MFD based on the number of factors and levels

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Runs
Levels	2	3	-	-	-	6
Levels	2	4	-	-	-	8
Levels	3	4	-	-	-	12
Levels	2	2	3	3	-	36
Levels	2	3	2	3	2	72
Levels	3	3	3	2	2	108
Levels	4	3	4	3	4	576

3.2.4. Screening Experiments Design (SED)

Screening is a very advantageous tool that ensures to distinguish which design parameters are more important for the response, especially when there are too many factors to deal with. Screening designs allow a large number of factors to be examined with very few experiments. With the help of this technique, the process parameters requiring more investigation are designated and kept apart that ensures to minimize both resources and budget (Antony, 2014). The total number of experimental runs in SED based upon the number of factors and levels is represented in **Table 8**.

Table 8: The number of runs for SED based on the number of factors and levels

Number of factors	Number of Runs	Number of factors	Number of Runs	Number of factors	Number of Runs
2-6	13	17-18	37	33-38	77
7-8	17	19-20	41	39-42	85
9-10	21	21-24	49	43-44	89
11-12	25	25-26	53	45-48	97
13-14	29	27-30	61	-	-
15-16	333	31-32	65	-	-

3.2.5. Response Surface Design (RSD)

The response surface analysis, which is almost certainly the most commonly utilized and successful technique, is an optimization approach based on design of experiment. Response surface design (RSD) is employed for both modeling and analysis when several factors affect the response of a process, which is aimed to be optimized (D. Montgomery, 2009). RSD has two types that are termed as central composite design and box-behnken design.

3.2.5.1. Central Composite Design (CCD)

Central composite design comprises factorial or fractional factorial design. The generalized cases for the quantity of runs of CCD that depends on the number of factors each having 3 levels are displayed in **Table 9**.

Table 9: The number of runs for CCD based on the number of factors with 3 levels

Number of factors	Levels	α Level	Number of Runs
2	[-1,1]	1.414	13
3	[-1,1]	1.682	20
4	[-1,1]	2	31
5	[-1,1]	2.378	54
6	[-1,1]	2.828	90

It has central points that are extended by a set of points parallel to the axis helping to figure out curvature. This type of design enables to put in central and axial points to the preceding factorial experiments that makes it advantageous for the experiments in series (Minitab, 2020b). The value of α is the distance from the central point to the points at the end of the arrows. **Figure 16** shows the CCD of 3 factors each having 3 levels.

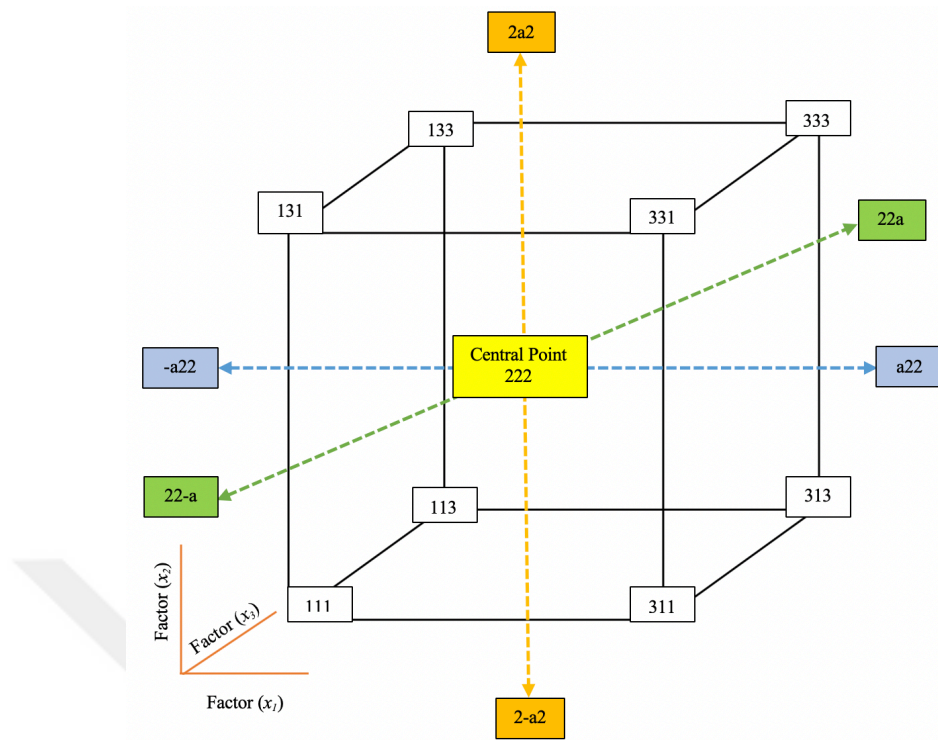


Figure 16: CCD of 3 factors with 3 Levels ($a=1.682$)

3.2.5.2. Box-Behnken Design (BBD)

The Box-Behnken design (BBD) is a three-level and a quadratic factorial design that does not necessitate all combinations of the experimental scenarios (Ferreira et al., 2007). BBD is utilized for the purpose of optimization of the quantity of the required tests to discover the interactions may probably occur among parameters with their influences on the response function. It is a rotational design equipped with a center point on the sphere and the midpoints of the sides of the cube (Kumar, Prasad, & Mishra, 2008). **Table 10** shows the number of runs needed for BBD based on the number of factors with 3 levels.

Table 10: The numbers of runs for BBD depends on the number of factors with 3 levels

Number of factors	Number of Runs	Number of factors	Number of Runs
3	15	7	62
4	27	8	---
5	46	9	130
6	54	10	170

The cost of BBD is lower than that of CCD each having the same quantity of factors, since BBD involves less design points as compared to CCD (Minitab, 2020b). BBD is also advantageous in terms of disregarding extreme cases where the factors entirely have their highest or lowest levels at the same time making the outcomes inadequate (Ferreira et al., 2007). The graphical representation of BBD including 3 factors with 3 levels is given in **Figure 17**.

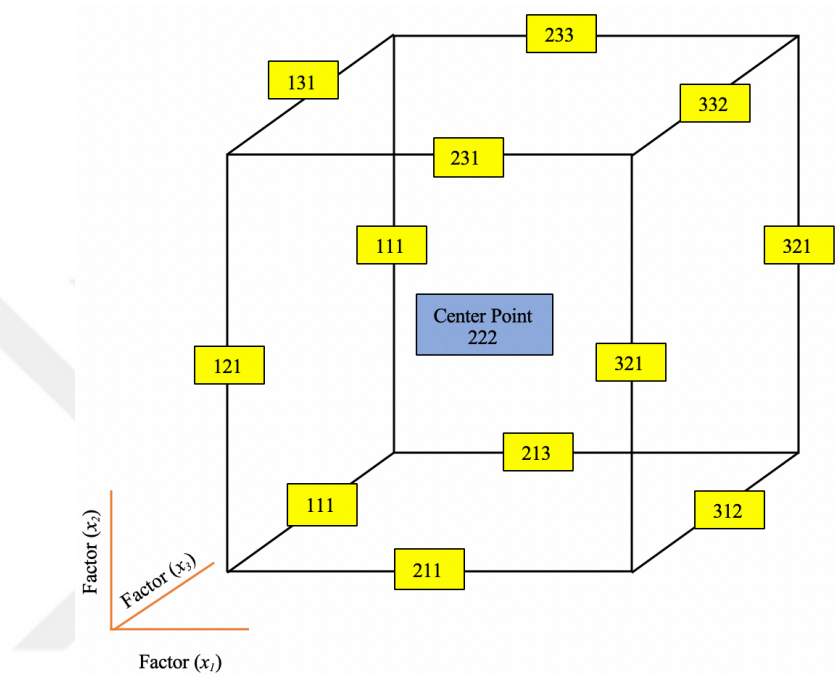


Figure 17: BBD of 3 factors with 3 Levels

BBD is utilized in this research in order to save both time and cost. The four factors determined for the study are turbine power, hub height, rotor diameter and wind speed. The impact of these parameters on the output of annual energy production is investigated and also optimum values of each factor are computed to achieve maximum amount of wind energy.

4. OPTIMIZATION

4.1. Background Information

The basic meaning of optimization is to reveal feasible solutions satisfying one or more objective functions of a problem. It is a scientific approach that enables real life complex problems to be transformed into a mathematical structure for analysis, employed especially in engineering field (Kusiak & Zheng, 2010). In this sense, optimization models are developed in order to determine the optimum decision variables that meet the objective function(s) (by maximizing and/or minimizing) of any problem to be examined. In many interesting maximization and minimization problems, the objective(s) or constraints may not follow linear trend, making them hard to solve. This type of optimization model is called nonlinear programming (Winston, 2004). It was observed that the optimization model obtained in this study fits into nonlinear mathematical modeling type. The reason for this situation is that the factors were taken into account both singularly and interactively in the optimization model. The nonlinear optimization model is formulated as following (Yurkiewicz, 2007):

$$\begin{aligned} & \max \text{ or } \min Z = f(x_1, x_2, x_3, \dots, x_n) \\ & \text{subject to} \\ & \quad s_1(x_1, x_2, x_3, \dots, x_n) \leq, =, \text{ or } \geq b_1 \\ & \quad s_2(x_1, x_2, x_3, \dots, x_n) \leq, =, \text{ or } \geq b_2 \\ & \quad \dots\dots\dots \\ & \quad s_n(x_1, x_2, x_3, \dots, x_n) \leq, =, \text{ or } \geq b_n \end{aligned} \tag{9}$$

The set of all points $(x_1, x_2, x_3, \dots, x_n)$ such that x_i is a real number is R^n . The following subsets of R^n (called intervals) will be of particular interest:

$$[l_i, u_i] = \text{all } x \text{ satisfying } l_i \leq x_i \leq u_i \tag{10}$$

where l_i, u_i represent lower limit and upper limit for the constraints, respectively.

4.2. Applications of Optimization Approaches for Renewable Energy

The aim of this research is to obtain the maximum benefit of the mathematical optimization model for renewable energy systems. Optimization models in the literature are usually designed to achieve maximum performance in energy systems or to provide minimum installation cost. There are also studies in which the objective function in both cases takes place. A linear programming model was developed by using the idea MARKAL model to apply energy to the optimization model which is one of the first studies. In this model, it is aimed to optimize useful energy demands (G. Fishbone & Abilock, 1981). In the first optimization model that was set up in renewable energy, it was aimed to provide fuel-saving and as a peak-shaving strategy. For this purpose, a planning model was established to determine which strategy would benefit in the long term (Farghal & Aziz, 1988).

Optimum or feasible results have been achieved with the help of computer programming in most of the optimization studies on renewable energy. The main reason for this is that the mathematical model takes a stochastic situation, which has too many factors affecting the renewable energy systems. The difficulty of resolving such a situation or requirement of a lot of time is seen as negative. In some cases, however, the presence of excessively variable factors reduced the baseline of a linear model and allowed optimal results to be obtained without statistical modeling. An example of this is the development of a model to create an optimal combination to minimize the cost of the life cycle of the system in which multiple and different components of the hybrid energy system are present (Ashok, 2007).

Sometimes the desired goals for renewable energy systems are more than one (Fadaee & Radzi, 2012). The most common goals are the excessive amount of energy produced and the low installation cost of the system. Where there are multiple objective functions, one objective function is selected, and the other objective function is added as a constraint. Or, if the aims of the objective functions are the same (min-min or max-max), both objective functions are expressed as a single objective function. This is an example of this work aiming to find the configurations of a suitable system in which the set-up cost and fuel emissions of the hybrid energy system are minimized (Ming, Wang, Zha, & Zhang, 2017).

The conversion of a model with more than one objective function into a single-purpose model is a nonlinear model. In the solution of a nonlinear model, it is difficult to obtain optimum

results. The results obtained are feasible results. If a multipurpose optimization model has different directions (max-min) and uses the same constraints for these purposes, it will cause a closed stochastic mathematical formula to be solved. The reason behind this is that the conflict of purpose arises.

4.3. Applications of Optimization Approaches for Wind Energy

Optimization models for wind energy have been the subject of study by many researchers from different disciplines. The goal of utilization of optimization approach for wind energy is to obtain maximum benefit, same as renewable energy. This method ensures to eliminate the ambiguity in the amount of energy produced due to the unpredictability of wind power in short or long run (Garcia-Gonzalez, Muela, Santos, & Gonzalez, 2008). The most important parameters to be considered in the wind energy system are wind direction and turbine location. By reaching optimum values of these factors, it is achieved that energy output is maximized (Kusiak & Song, 2010).

The formation of the physical structure of a wind energy system based on the maximum energy output is reflected in the installation fee. The optimization modeling approach is able to provide the physical structure of the system to be at the optimum level and minimize the installation cost, simultaneously (Zhao & Zeng, 2012). All the scenarios are taken into consideration in the optimization model to get maximum energy with minimum cost. In that case, it is necessary to distinguish two main factors in the wind energy system. The first factor is the physical structure of the wind energy and the other factor is the geographical structure for the establishment of the wind energy system. Researchers have generally created optimization models by evaluating these two factors separately. This study aimed to develop optimization model by using these factors separately first and then combine them altogether.

4.4. Structure of Optimization Model

The aim of this experiment is to get maximum amount of energy produced in the wind power plants. Therefore, the objective of the proposed nonlinear programming model is to maximize the estimated objective function subject to the boundary constraints over the experimental region. The proposed optimization model is expressed as following:

$$\begin{aligned}
& \text{Maximize } y = f(x_1, x_2, x_3, \dots, x_n) + \epsilon \\
& \text{s. t. } -1 \leq x_i \leq +1 \text{ and } i = \{1, 2, \dots, n\} \\
& \quad x_i \in R^n
\end{aligned} \tag{11}$$

Furthermore, development of additional optimization models for the mean and standard deviation of response variable are required simultaneously so as to improve the optimization process. The idea behind this concept is to maximize the mean value and minimize the standard deviation of outputs symbolized by y (Ding, Lin, & Wei, 2004). The use of RSD method necessitates to minimize the standard deviation to reach target value for industrial problems. Thus, we have extended the developed optimization models with this approach due to the fact that wind power generation is a real industrial issue as worldwide.

The polynomial models for the mean ($\hat{w}_\mu$) and standard deviation ($\hat{w}_\sigma$) of the response were formed by Vining and Myers as following (Vining & Myers, 1990):

$$w_\mu = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^k \sum_{j=1}^k \beta_{ij} x_i x_j + \epsilon_\mu \quad i < j \tag{12}$$

$$w_\sigma = \gamma_0 + \sum_{i=1}^k \gamma_i x_i + \sum_{i=1}^k \gamma_{ii} x_i^2 + \sum_{i=1}^k \sum_{j=1}^k \gamma_{ij} x_i x_j + \epsilon_\sigma \quad i < j \tag{13}$$

where $\beta_0, \beta_1, \beta_2, \dots, \beta_k$, and $\gamma_0, \gamma_1, \gamma_2, \dots, \gamma_k$ are regression coefficients, x_i is the numbers of the factors, and ϵ_μ and ϵ_σ are the random errors of the mean and standard deviation of the response variable, respectively. Determining the optimum values which minimizes performance deviation from the target value is preferable. The additional optimization models were introduced as below:

$$\begin{aligned}
& \text{Minimize } \hat{y}_\sigma \\
& \text{Subject to } \hat{y}_\mu = \tau_\mu,
\end{aligned} \tag{14}$$

and;

$$\text{Maximize } \hat{y}_\mu \tag{15}$$

$$\text{Subject to } \hat{y}_\sigma = \tau_\sigma$$

where τ_μ and τ_σ are the target values of the mean and standard deviation of output. $\hat{y}_\mu$ and $\hat{y}_\sigma$ represent the functions of regressions.

Determining the optimum values which minimizes performance deviation from the target value is preferable. The additional optimization models were introduced as below:

$$\begin{aligned} &\text{Minimize } \hat{y}_\sigma = f(x_1, x_2, x_3, \dots, x_n)_\sigma \\ &\text{Subject to } f(x_1, x_2, x_3, \dots, x_n)_\mu = \tau_\mu \end{aligned} \tag{16}$$

$$\tau_\sigma, x_i, \text{nonnegative}$$

$$x_i \in R^n$$

and;

$$\begin{aligned} &\text{Maximize } \hat{y}_\mu = f(x_1, x_2, x_3, \dots, x_n)_\mu \\ &\text{Subject to } f(x_1, x_2, x_3, \dots, x_n)_\sigma = \tau_\sigma \end{aligned} \tag{17}$$

$$\tau_\sigma, x_i, \text{nonnegative}$$

$$x_i \in R^n$$

where τ_μ and τ_σ are the target values of the mean and standard deviation of output. $\hat{y}_\mu$ and $\hat{y}_\sigma$ represent the functions of regressions.

5. DATA AND FORMULATION OF THE METHODOLOGY

5.1.Data of the Research

The methodology of the study was developed to optimize the wind power plants (WPPs) in order to produce maximum energy output using the historical data of operational WPPs in Turkey. There are 155 WPPs located in Turkey from which the data belonging to 2017 and 2018 were collected (Ministry of Energy and Natural Resources, 2020). All the required data were taken from different sources to combine together for the analysis, including Turkish Wind Energy Association, General Directorate of Energy Affairs, Wind Energy Potential Atlas, Energy Market Regulatory Authority, and Environmental Impact Assessment Reports. The wind turbines of Turkey are installed in six of the seven physiographic regions of Turkey as depicted in **Figure 18**.

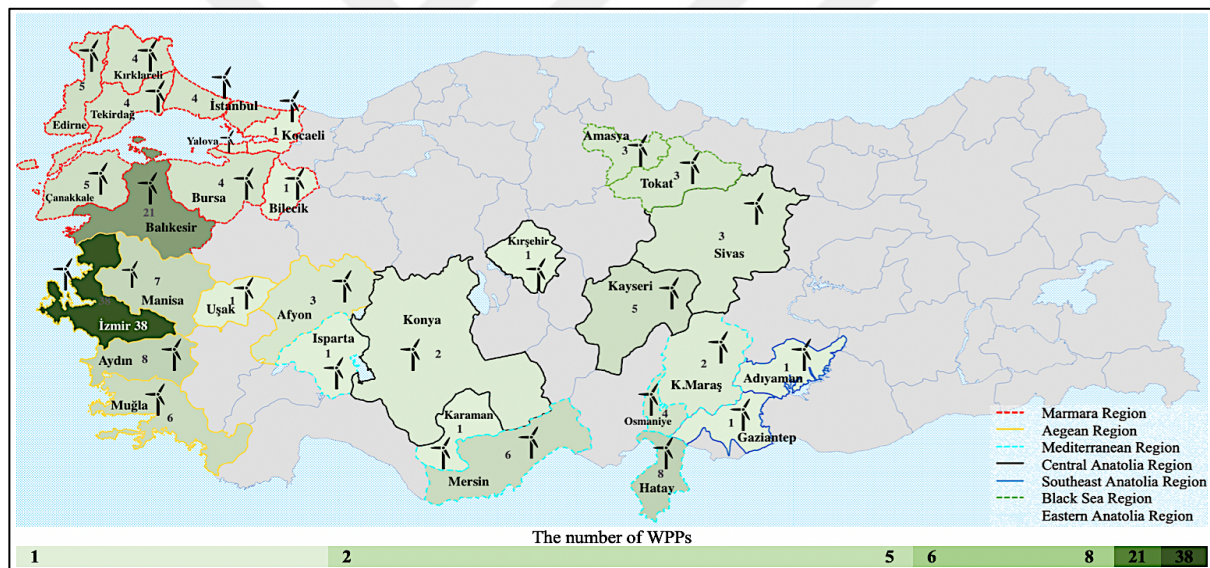


Figure 18: The map of the wind power plants' locations in Turkey

The WPPs in Turkey are more concentrated in the Aegean and Marmara regions as quantitatively displayed in **Figure 18**. The main reasons for the establishment of a large number of WPPs in these areas are the large population, heavy industry, high-altitude lands having the wind speed higher than the average of Turkey, etc. The total number of operational WPPs is 63 in Aegean Region, 51 in Marmara region, 21 in Mediterranean region, 12 in Central Anatolian region, 6 in Black Sea region, and 2 in Southeast Anatolian region. There have been no WPPs installed in Eastern Anatolian region so far.

Located in the Aegean region, İzmir is the city with the highest number of wind farms with 38 WPPs. Balıkesir, in the Marmara Region, ranks the second with 21 WPPs. According to the annual amount of energy generated for the years of 2017 and 2018, the ranking is as follows: Marmara, Aegean, Mediterranean, Central Anatolian, Black Sea and Southeast region. The percentages of energy produced yearly are 40.82%, 27.15%, 23.16%, 6.69%, 1.45% and 0.72% in 2017 and 36.75%, 31%, 18.8%, 9.5%, 3.01% (see **Figure 19**) and 0,94% in 2018 for Marmara, Aegean, Mediterranean, Central Anatolian, Black Sea and Southeast region, respectively (see **Figure 20**).

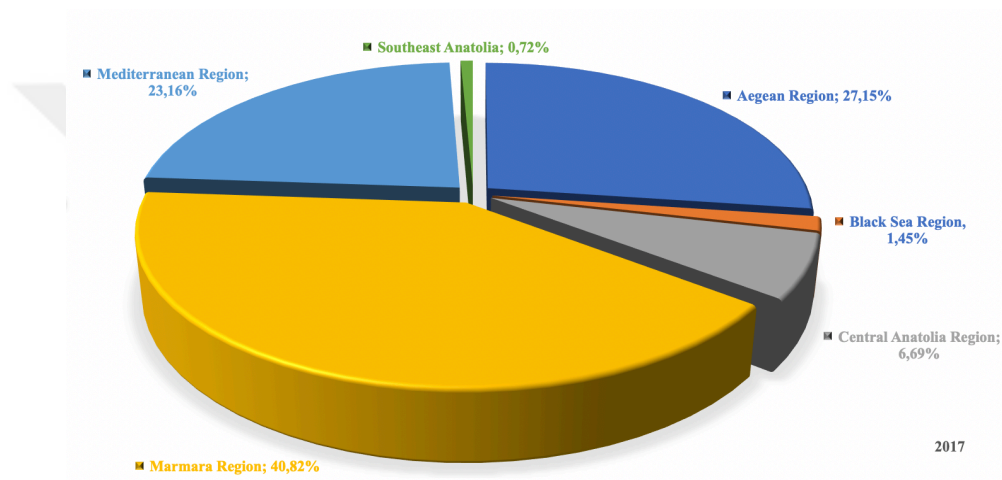


Figure 19: WPP production rates of Regions for 2017

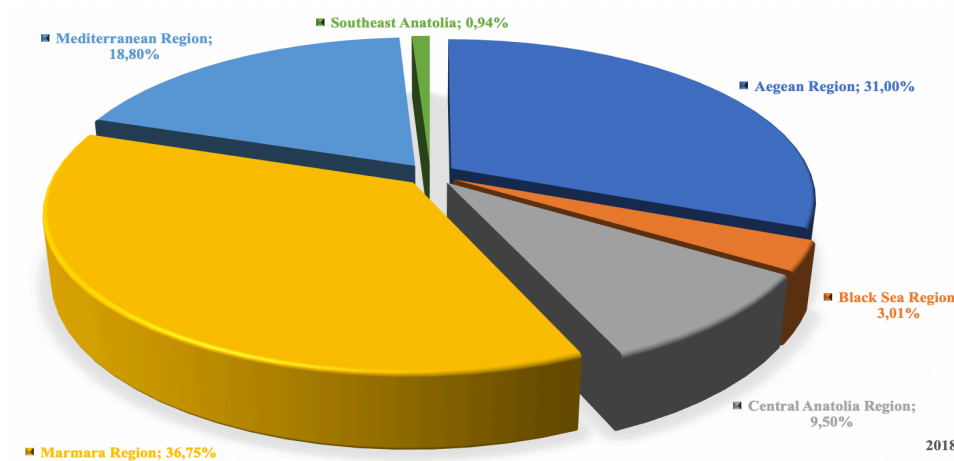


Figure 20: WPP production rates of Regions for 2018

The data of 43 WPPs out of 155 were ignored due to lack or contradictory data and the fact that some wind farms have not started production yet. The contradictory data, especially for the hub height and the amount of annual produced energy, were encountered in different sources, so these WPPs were left out of the scope of this study. Additionally, some WPPs have different types of turbines (i.e., distinct turbine power, hub height and rotor diameter). Nevertheless, the data of the energy generation amount is available for the entire facility in total. Thus, these were not taken into account in order to avoid confusion in the calculations.

In general, the areas with high wind speed are preferred to gain energy from wind effectively, but this is not the only factor to consider. We used hub height, rotor diameter, turbine power, and wind speed at 50 m as factors or input variables and we obtained the annual energy production amount for the years of 2017 and 2018 of the installed 112 facilities as a response or output variable (see **Figure 21** and **Figure 22**). Due to the fact that the number of turbines varies between the years in some WPPs, the average annual energy production per unit turbine was taken into consideration in each phase of the study.

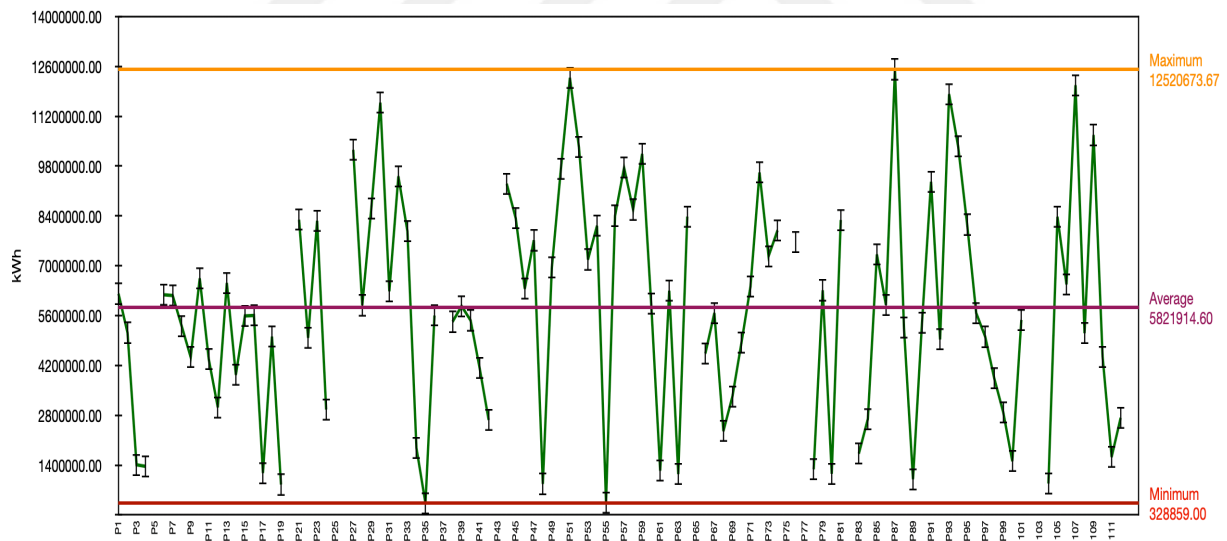


Figure 21: Annual amount of wind energy produced in 2017 from the 112 installed facilities in Turkey

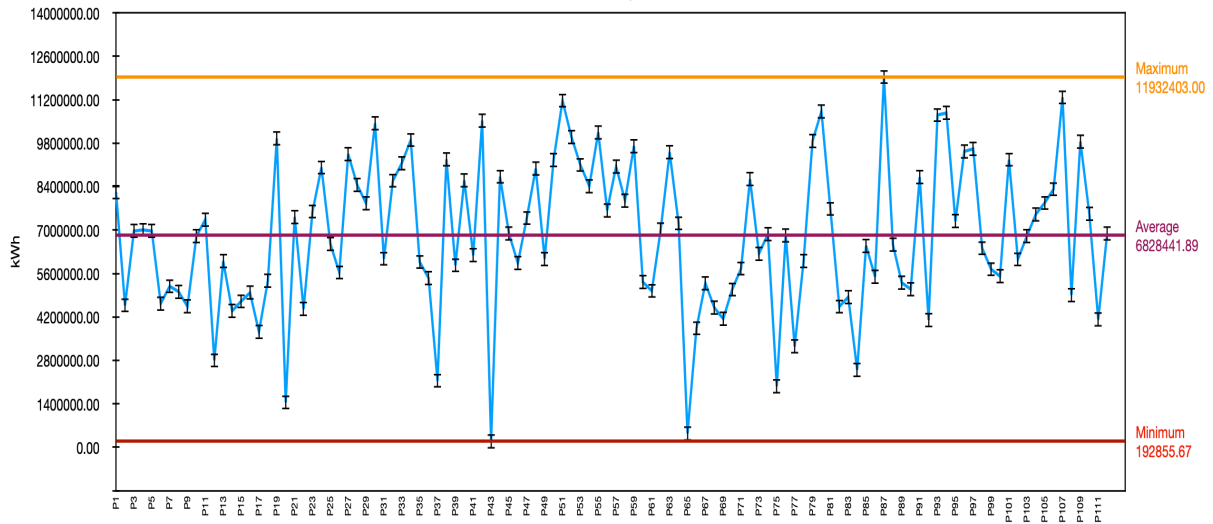


Figure 22: Annual amount of wind energy produced in 2018 from the 112 installed facilities in Turkey

5.1.1. Marmara Region

Marmara region ranks first in terms of annually generated amount of energy in 2017 and 2018. While almost all of the cities have WPPs in this region, most of the wind farms are located in Balıkesir as shown in **Figure 23**.

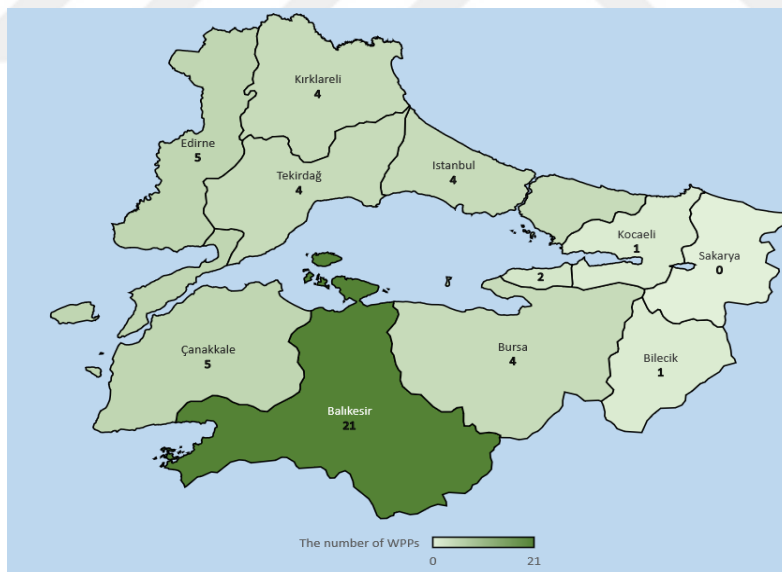


Figure 23: Marmara Region

5.1.2. Mediterranean Region

Mediterranean region ranks third in terms of both the number of installed WPPs and the annual energy production. The percentage of produced energy amount was 23.16% in 2017 and

18.8% in 2018 with 21 WPPs. The WPPs have been distributed in 5 of the cities in this region (see **Figure 24**)

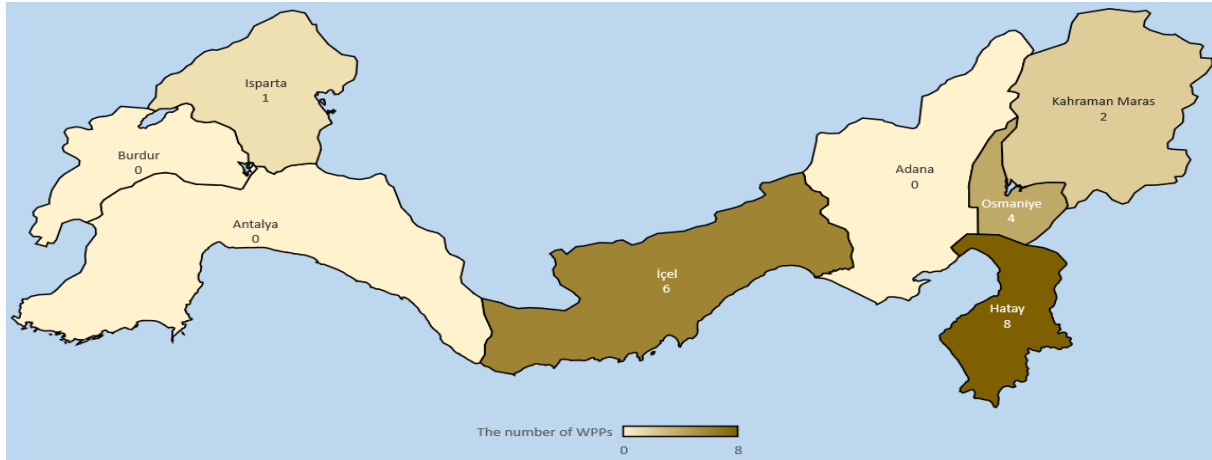


Figure 24: Mediterranean Region

5.1.3. Aegean Region

While the region with the highest number of 63 WPPs is the Aegean region, it is in the second place in terms of energy production amount. 27.15% of total generated energy in 2017 belonged to Aegean region that increased to 31.0% in 2018 possibly with new installations. **Figure 25** represents the locations of the WPPs in Aegean region with the numbers in each city.

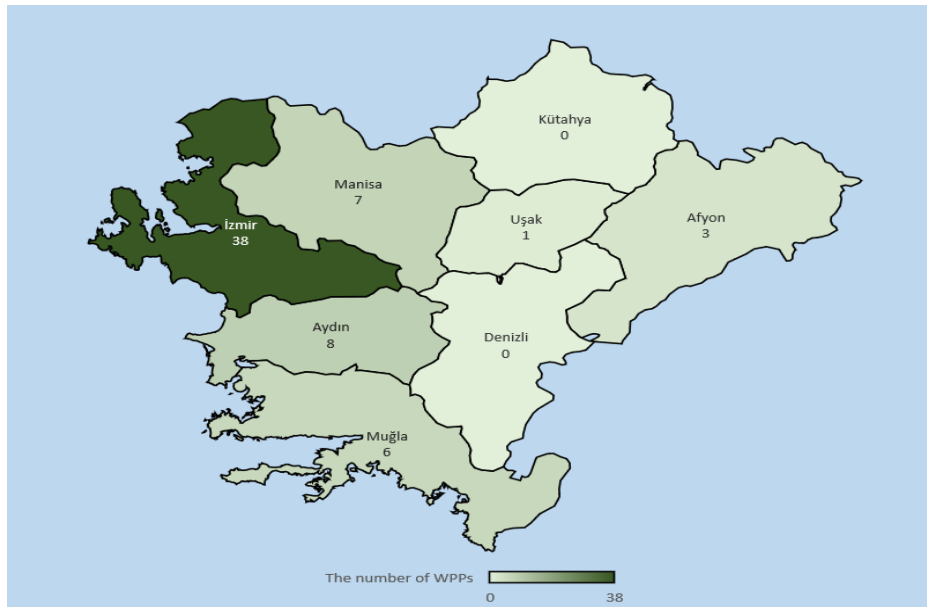


Figure 25: Aegean Region

5.1.4. Central Anatolia Region

There have been 12 WPPs established in Central Anatolia region, constituting 6.69% of total produced energy in 2017 that reached to 9.5% in 2018. There have been 5 cities in which WPPs are located in Central Anatolia region as shown in **Figure 26**.

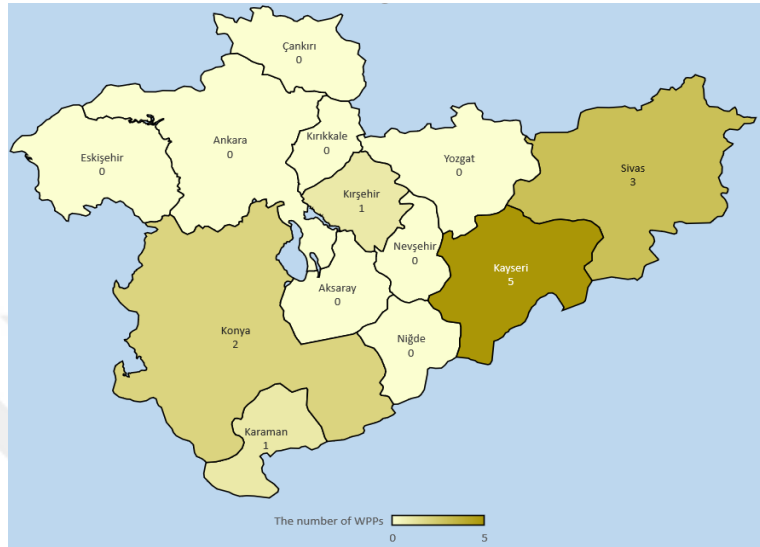


Figure 26: Central Anatolia Region

5.1.5. Black Sea Region

The total number of operational WPPs in Black Sea region is 6. The cities that have WPPs in this region are Amasya and Tokat (see **Figure 27**). The percentage of produced energy amount was 1.45% in 2017 and 3.01% in 2018 with 6 WPPs.

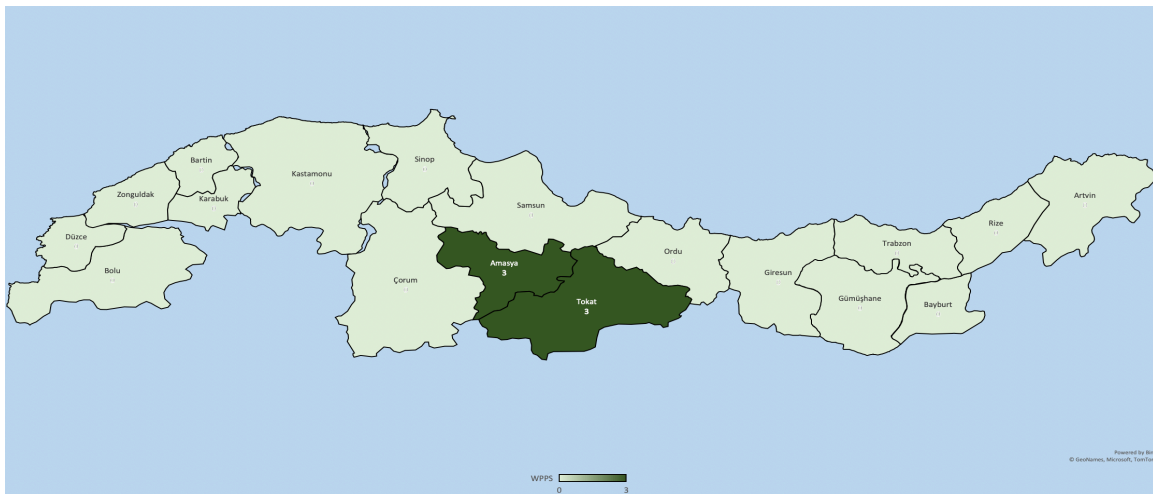


Figure 27: Black Sea Region

5.1.6. Southeast Anatolia Region

Southeast Anatolia region is the one with the minimum number of WPPs. At the same time, the least amount of energy is produced in this region. There has been a total of 2 WPPs in the region that are situated in Adiyaman and Gaziantep (see **Figure 28**). The percentage of produced energy amount was 0.72% in 2017 and 0.94% in 2018 with 2 WPPs.

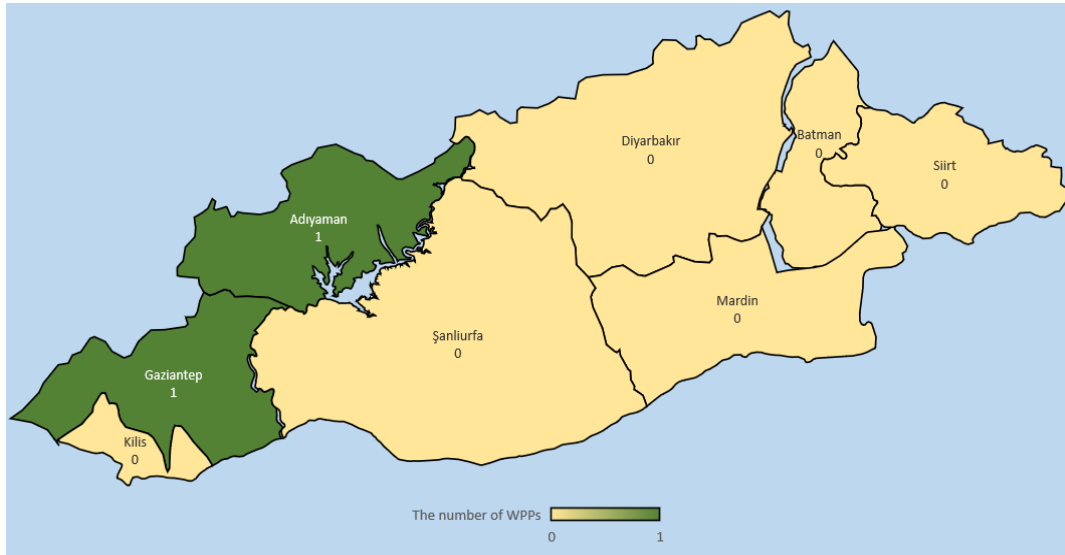


Figure 28: Southeast Anatolia Region

5.1.7. Eastern Anatolia Region

There has been no operated WPPs in Eastern Anatolia region of Turkey so far. Therefore, this region is not counted in this research.

5.2. The Formulation of the Factors for WPPs

There are many factors affecting the amount of electricity generation from wind energy (see **Figure 29**). The wind speed has an important effect on the power produced by the wind turbine. According to the study of wind speed variability and wind power potential over Turkey, Arslan et al. showed that the wind speed fitted the Weibull distribution based on hourly data of 335 stations covering 34 years (Arslan, Baltaci, Akkoyunlu, Karanfil, & Tayanc, 2020). Secondly, the hub height of the turbine should be taken into account concerning energy generation because of its impact on wind speed. The wind speed increases as hub height increases. The wind power-law helps to extrapolate wind speed data at different hub heights as a practical tool utilized in wind power applications. The wind profile power-law relationship is expressed as (Gul, Tai, Huang, Nadeem, & Yu, 2020; Song et al., 2020):

$$\frac{v}{v_0} = \left(\frac{h}{h_0}\right)^\alpha \quad (18)$$

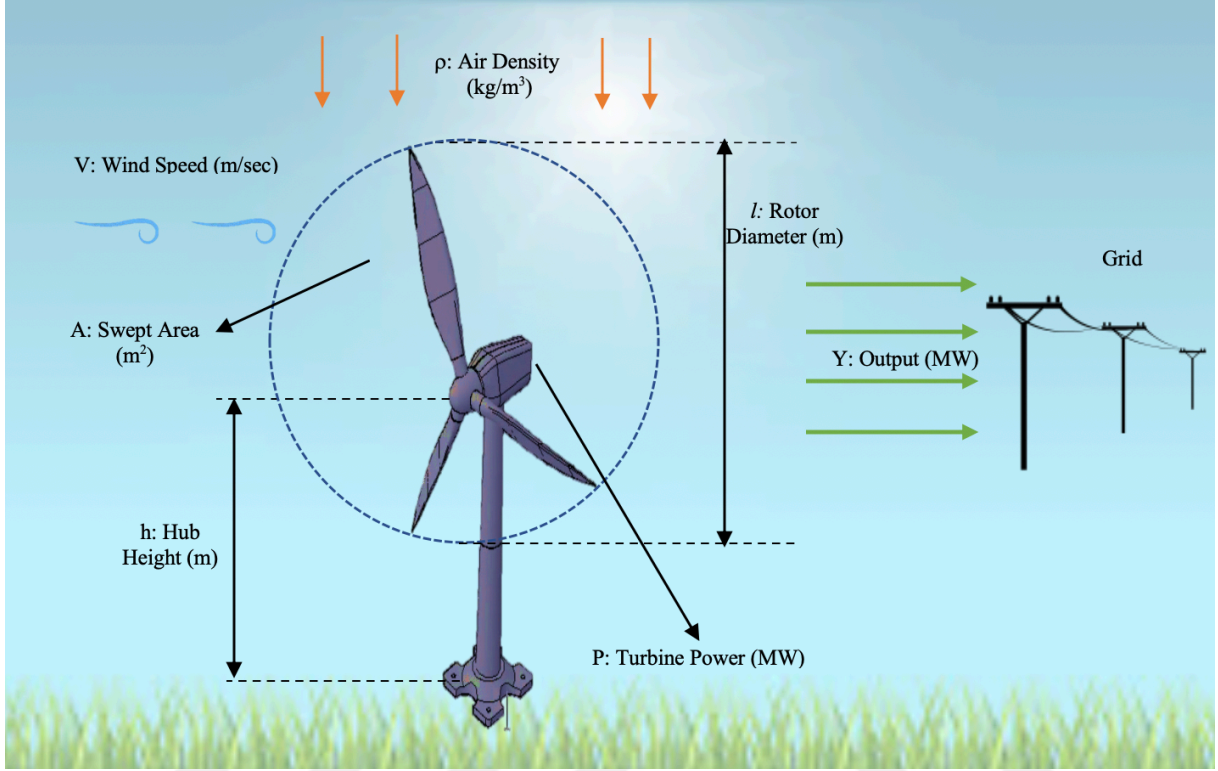


Figure 29. Parameters used for wind turbine structure

where v is the wind speed at hub height h , v_0 is the wind speed at the initial hub height, h_0 , and α is an empirically derived wind speed power-law coefficient depending on the stability of the air. The equation that shows the relationship between rotor diameter and wind speed is expressed as follows (Wang, Zuo, Xu, Zhou, & Tan, 2019):

$$v = v_0 \left[1 - 2\alpha \left(\frac{\frac{1}{2}}{\frac{1}{2} + \alpha x} \right) \right] \quad (19)$$

where $1/2$ is the radius of the rotor, and x is axial induction factor (Miao et al., 2020). With the aid of the combination of the equations explained above, the extractable wind power by the turbine rotor is given by:

$$P_{maxE} = \frac{1}{2} * \rho * A * v^3 * c_p \quad (20)$$

where A donates the swept area of the turbine, c_p symbolizes the power coefficient. The power coefficient is defined as the percent of the extraction of the energy by a wind turbine which is 59.3 % at the most, theoretically. The value of c_p is given as (Schubel & Crossley, 2012):

$$c_p = 0.593, \text{ referred to as the Betz limit} \quad (21)$$

The swept area of the turbine (A) in Equation (4) can be computed with the help of the equation for the area of a circle considering the length of the turbine blades as the radius of the circle during rotation (Y. Yang, Li, Yao, & Gao, 2019):

$$A = \pi * l^2 \quad (22)$$

where l represents the value for blade length as the radius of rotor.

6. APPLICATION OF THE METHODOLOGY

The flow chart in **Figure 30** illustrates the phases of the study in detail. There are three main phases to build the methodology of the study, which are statistical analysis, Box-Behnken design of experiment (DOE) and nonlinear optimization model. Each phase constitutes the infrastructure of the next phase.

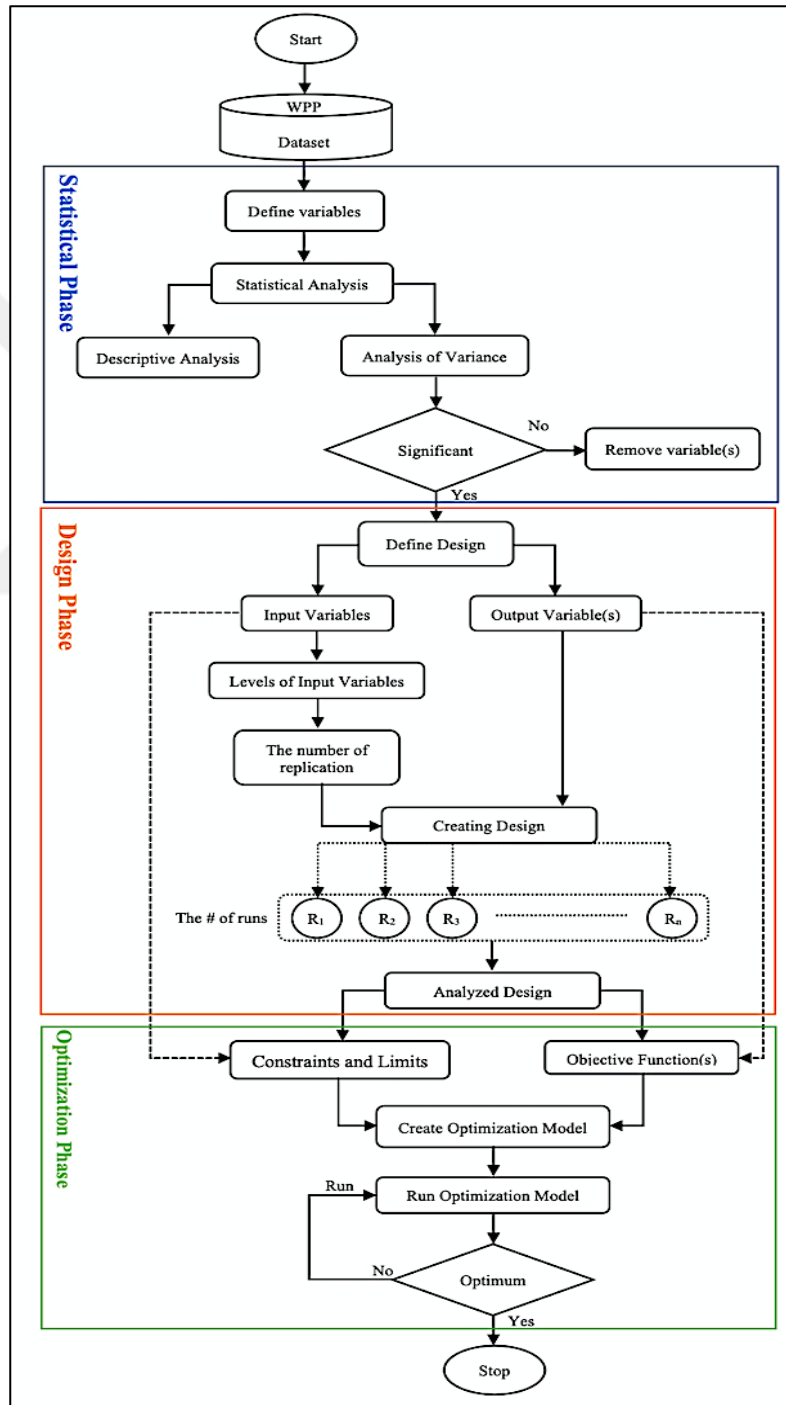


Figure 30: Flow chart of the proposed methodology

There are 155 WPPs installed in Turkey from which the data of turbine power, hub height, rotor diameter, average wind speed of the positions at 50 m and total annual average energy production were collected. However, only 112 of them is useful, owing to missing or contradictory data and the fact that some wind farms have not started production yet and additionally, some have different types of turbines (i.e., distinct turbine power, hub height and rotor diameter) and the available data about energy production we have is for the entire plant which makes the calculations very complicated. In this study, hub height, rotor diameter, turbine power, and wind speed were used as factors or input variables and the annual energy production amount for the years of 2017 and 2018 of the installed facilities were obtained as response or output variable, which are shown in **Figure 31**. Since the number of turbines varies between the years in some wind power plants, the average annual energy production per unit turbine was taken into consideration in statistical analysis, design of experiment and optimization phases.

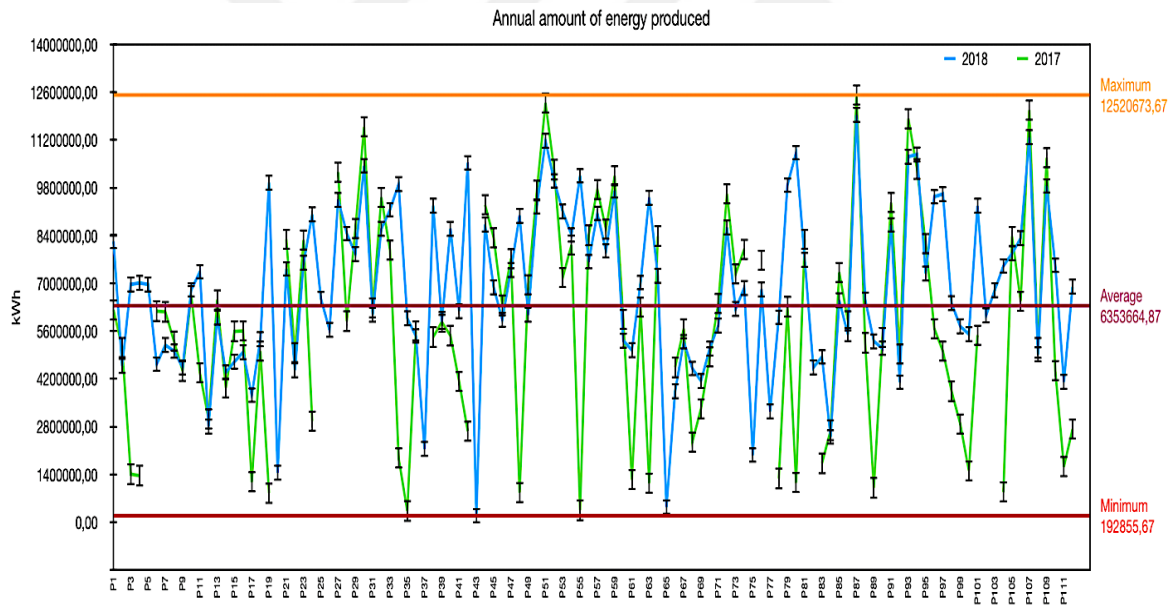


Figure 31: Average annual energy production of 112 WPPs in 2017 and 2018

6.1. Statistical Analysis

The production of energy amount by the WPPs operated in the provinces of Turkey was organized for the analysis. Statistical analysis is the basis for constructing the next steps of the methodology of this study. The first phase before applying the DOE with the optimization method is to arrange the statistical data descriptively. Quartiles (denoted as q_1 , q_2 and q_3) were used in order to separate the whole data set, belonging to 112 WPPs operating in Turkey, into

three parts that help to have an idea about the distribution of the data. **Table 11** shows the descriptive statistics of the factors and responses.

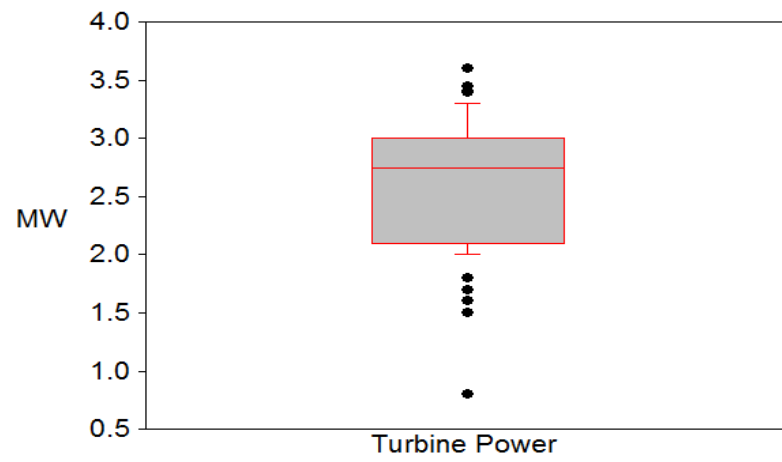
Table 11: Descriptive Statistical Data of Factors and Responses

	Variables	Unit	N	Mean	SD	Min	q1	q2 (median)	q3	Max
Factors	Turbine Power	MW	112	2.6277	0.5525	0.8000	2.1000	2.7500	3.0000	3.6000
	Hub Height	m	112	86.294	9.520	64.000	80.000	85.000	91.000	117.000
	Rotor Diameter	m	112	101.97	13.93	52.900	90.00	103.00	113.00	126.00
	Wind speed	m/sec	112	6.8000	0.5075	5.4000	6.5000	6.8000	7.0000	7.7500
Response	Annual energy production in 2018	million kWh	112	6.8284	2.4234	0.1928	5.1172	6.8462	8.7195	11.9324
	Annual energy production in 2017	million kWh	112	5.8219	3.0918	0.3288	3.4548	5.7695	8.2366	12.5206

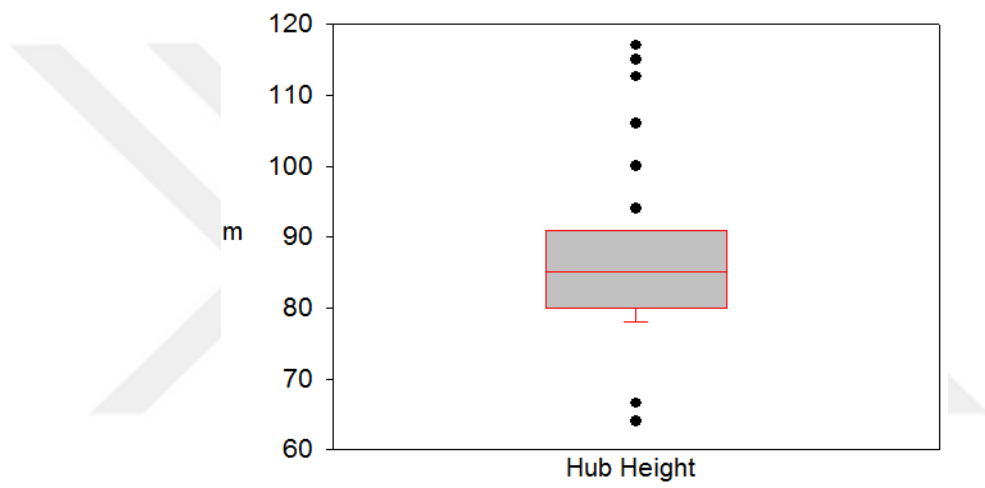
Note 1: Unit: the measurement unit; MW: megawatts; m: meters; m/sec: meter per second; kWh: kilowatt-hour.

Note 2: N: the number of WPPs (wind power plants) operated; Mean: the average value, Min: the minimum value, Max: the maximum value; SD (standard deviation) is a criterion to calculate the dispersion or variation quantity belonging to a data set. In statistics, data are divided into three parts to form quartiles in order to understand the distribution of the data set; q₁: 25% of the data set is less than or equal to this value; q₂ (median): 50% of the data set is less than or equal to this value; q₃: 75% of the data set is less than or equal to this value.

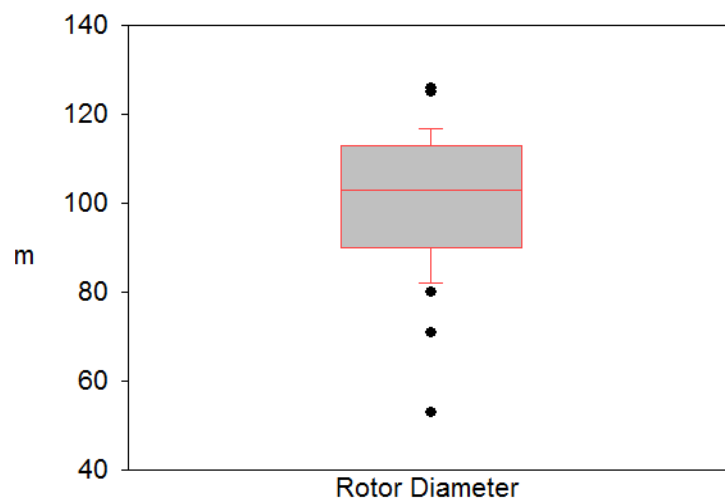
The Box plots of the four factors, namely turbine power, hub height, rotor diameter and wind speed, were generated to visually show the spread of the data set by making use of minimum value, q₁ (first quartile), q₂ (second quartile or median), q₃ (third quartile) and maximum value of each variable. As seen from **Figure 32**, the data of turbine power are mostly centered in the 1st quartile (2.1 MW–2.75 MW). Similarly, the data of rotor diameter and wind speed are almost concentrated in the q₁. However, hub height values are distributed more intensely in the 3rd quartile ranging from 92 m to 117 m. The intervals of quartiles for each factor are tabulated in the design part in detail.



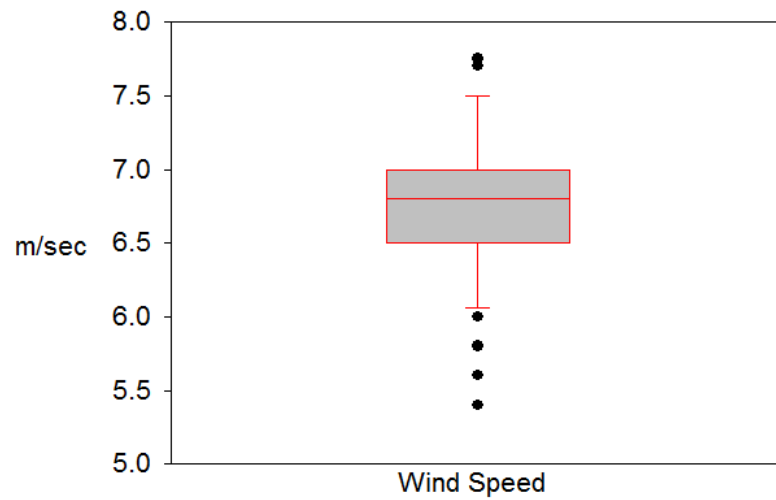
(a)



(b)



(c)



(d)

Figure 32: Box plots showing data distribution of factors
(a) Turbine Power; (b) Hub Height; (c) Rotor Diameter; (d) Wind Speed

6.2. Application of the Design of Experiments

The Box Plot method was used to show the distribution of variables' data. Box plots of each factor were formed to determine the limits for the levels of variables required for the design. The number of levels for each factor was chosen as 3. The levels and limit values of factors are depicted in **Table 12**.

Table 12: Level and limit values of factors

Factors	Notations	Level 1		Level 2		Level 3	
		Coded Level -1		Coded Level 0		Coded Level 1	
		Value	Limit	Value	Limit	Value	Limit
Turbine Power	A	0.800	0.80-2.10	2.2	2.11-3.0	3.6	3.1-3.6
Hub Height	B	64.00	64.00-80	90.5	81-91	117	92-117
Rotor Diameter	C	52.90	52.90-90	89.45	91-113	126	92-126
Wind Speed	D	5.400	5.40-6.50	6.575	6.6-7	7.75	7.1-7.75

In this research, four different factors, each having three levels, were considered with regard to their effects on wind energy production. While the number of basic designs is 27 in Box-Behnken design, the total number of data used is 54 by replicating the study twice. **Table 13** represents all possible combinations of factors according to the Box-Behnken design of experiment both with coded levels and actual levels of each variable. Factor 1, factor 2, factor 3 and factor 4 terms are the basic names used in Box-Behnken design of experiment, and their

values are denoted as -1.0 , 0 and 1.0 for level 1, level 2 and level 3, respectively. The factors used for this study were replaced by actual values corresponding to these notations.

Table 13: Box-Behnken Design of Experiment According to Factor Levels

Proposed Types of WPP	The features of WPPs							
	Coded Levels				Actual Levels			
	Factor 1 Unit 1	Factor 2 Unit 2	Factor 3 Unit 3	Factor 4 Unit 4	A (MW)	B (m)	C (m)	D (m/sec)
WPP 1.0	-1.00	-1.00	0.00	0.00	0.8	64.0	89.45	6.575
WPP 2.0	1.00	-1.00	0.00	0.00	3.6	64.0	89.45	6.575
WPP 3.0	-1.00	1.00	0.00	0.00	0.8	117.0	89.45	6.575
WPP 4.0	1.00	1.00	0.00	0.00	3.6	117.0	89.45	6.575
WPP 5.0	0.00	0.00	-1.00	-1.00	2.2	90.5	52.90	5.400
WPP 6.0	0.00	0.00	1.00	-1.00	2.2	90.5	126.0	5.400
WPP 7.0	0.00	0.00	-1.00	1.00	2.2	90.5	52.90	7.750
WPP 8.0	0.00	0.00	1.00	1.00	2.2	90.5	126.0	7.750
WPP 9.0	-1.00	0.00	0.00	-1.00	0.8	90.5	89.45	5.400
WPP 10.0	1.00	0.00	0.00	-1.00	3.6	90.5	89.45	5.400
WPP 11.0	-1.00	0.00	0.00	1.00	0.8	90.5	89.45	7.750
WPP 12.0	1.00	0.00	0.00	1.00	3.6	90.5	89.45	7.750
WPP 13.0	0.00	-1.00	-1.00	0.00	2.2	64.0	52.90	6.575
WPP 14.0	0.00	1.00	-1.00	0.00	2.2	117.0	52.90	6.575
WPP 15.0	0.00	-1.00	1.00	0.00	2.2	64.0	126.0	6.575
WPP 16.0	0.00	1.00	1.00	0.00	2.2	117.0	126.0	6.575
WPP 17.0	-1.00	0.00	-1.00	0.00	0.8	90.5	52.90	6.575
WPP 18.0	1.00	0.00	-1.00	0.00	3.6	90.5	52.90	6.575
WPP 19.0	-1.00	0.00	1.00	0.00	0.8	90.5	126.0	6.575
WPP 20.0	1.00	0.00	1.00	0.00	3.6	90.5	126.0	6.575
WPP 21.0	0.00	-1.00	0.00	-1.00	2.2	64.0	89.45	5.400
WPP 22.0	0.00	1.00	0.00	-1.00	2.2	117.0	89.45	5.400
WPP 23.0	0.00	-1.00	0.00	1.00	2.2	64.0	89.45	7.750
WPP 24.0	0.00	1.00	0.00	1.00	2.2	117.0	89.45	7.750
WPP 25.0	0.00	0.00	0.00	0.00	2.2	90.5	89.45	6.575
WPP 26.0	0.00	0.00	0.00	0.00	2.2	90.5	89.45	6.575
WPP 27.0	0.00	0.00	0.00	0.00	2.2	90.5	89.45	6.575

The descriptive statistical data of the response data employed for Box Behnken design are displayed in **Figure 33**. Unusually observed data have a significant effect on factors (p-value) and R^2 , in general.

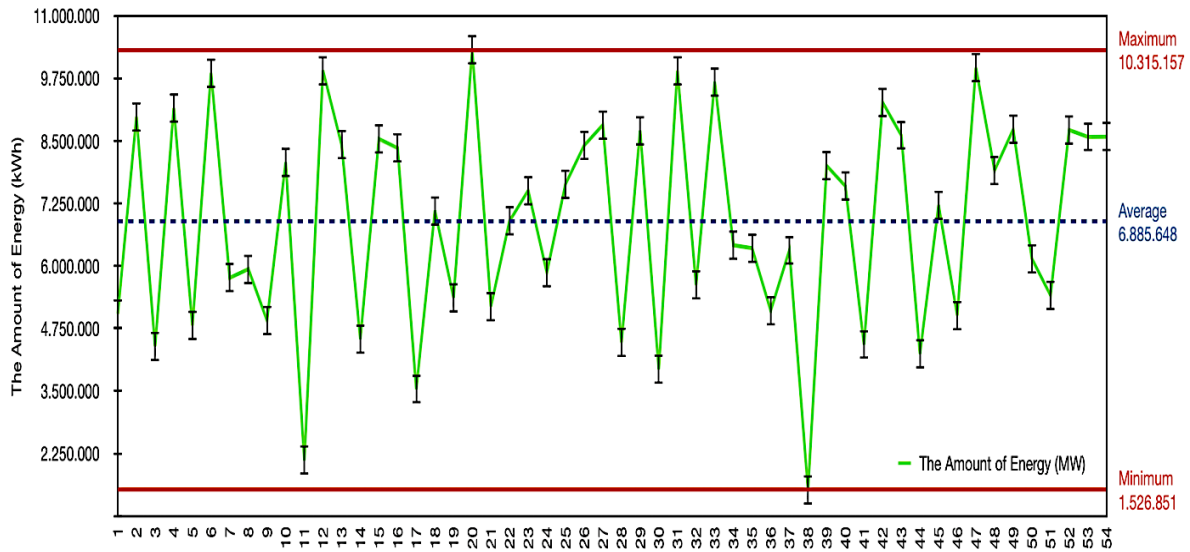


Figure 33: The data of response selected for DOE

In order to minimize the effect of observations with unusual values on the analysis and regression equation, these values were identified and a suitability test was applied. Therefore, normally distributed data of response variables were achieved as shown in **Figure 34** and **Figure 35**.

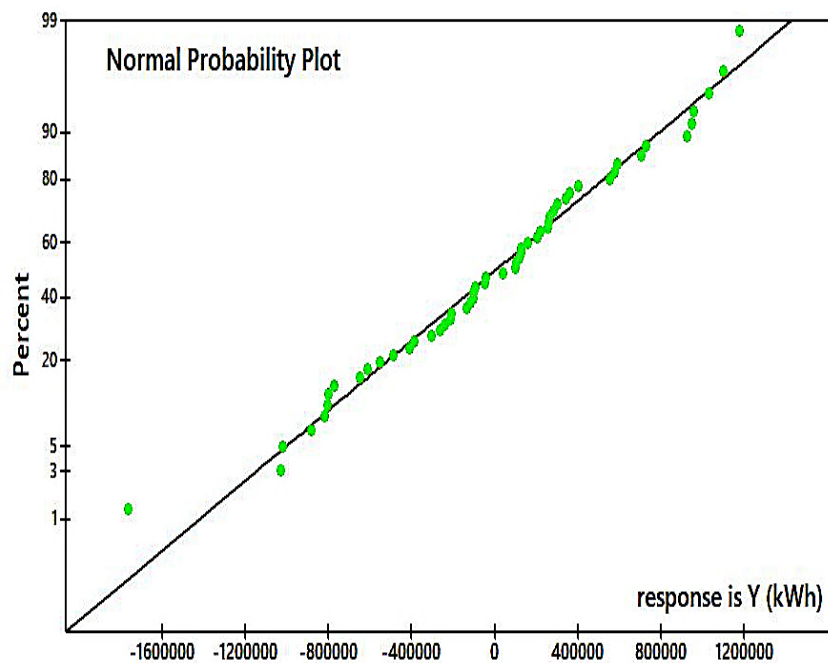


Figure 34: Normal Probability Plot

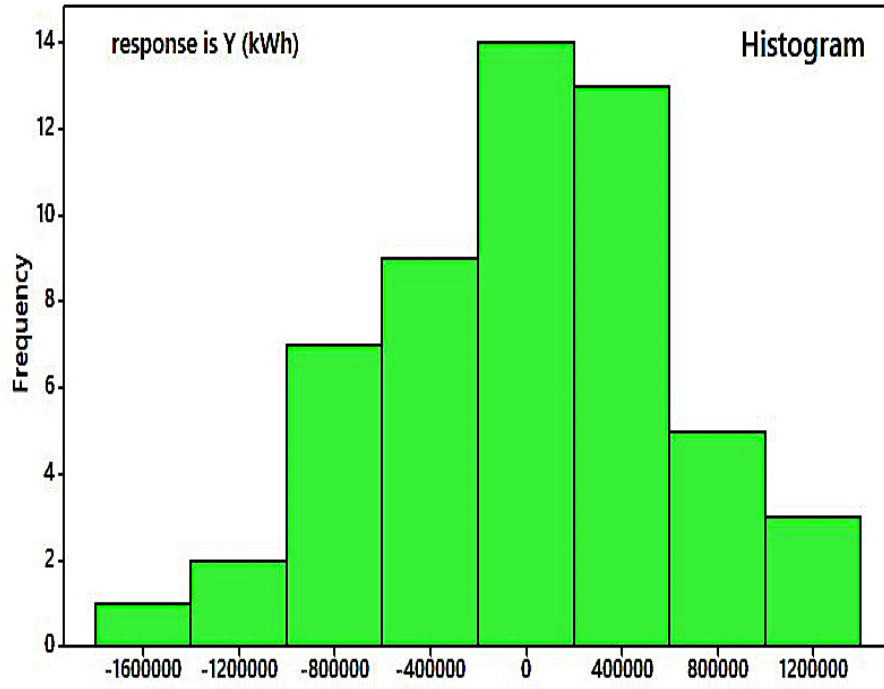


Figure 35: Normal distribution and histogram plot of response

6.3.Implementation of Optimization

The aim of this experiment is to get maximum amount of energy produced in the wind power plants. Therefore, the objective of the proposed nonlinear programming model is to maximize the estimated objective function subject to the boundary constraints over the experimental region. The proposed optimization model is expressed as following:

$$\begin{aligned}
 & \text{Maximize } y = f(x_1, x_2, x_3, \dots, x_n) + \epsilon \\
 & \text{s.t. } -1 \leq x_i \leq +1 \text{ and } i = \{1, 2, \dots, n\} \\
 & \quad x_i \in R^n
 \end{aligned} \tag{23}$$

The nonlinear model that contains all factors neglecting significance levels of the model is given as below:

$$\begin{aligned}
 y_{kWh} = & -51897234 - 848278A + 134692B + 177710C + 14333926D \\
 & - 682673A^2 - 596B^2 - 363C^2 - 935391D^2 + 8582AB \\
 & + 8227AC + 752165AD + 801BC - 19659BD - 26156CD
 \end{aligned} \tag{24}$$

This regression equation is defined as objective function in this study where y_{kWh} refers to the output of the WPPs (as kilowatt-hour). Then the full optimization model is expressed as:

$$\begin{aligned}
 & \text{Maximize } y_{kWh} \\
 & = -51897234 - 848278A + 134692B + 177710C \\
 & + 14333926D - 682673A^2 - 596B^2 - 363C^2 - 935391D^2 \\
 & + 8582AB + 8227AC + 752165AD + 801BC - 19659BD \\
 & - 26156CD
 \end{aligned} \tag{25}$$

subject to

$$\begin{aligned}
 l_i & \leq x_i \leq u_i \\
 x_i & \in R^n
 \end{aligned}$$

where $i = A, B, C, D$.

Furthermore, development of additional optimization models for the mean and standard deviation of response variable are required simultaneously so as to improve the optimization process. The idea behind this concept is to maximize the mean value and minimize the standard deviation of outputs symbolized by y (Ding et al., 2004). The use of RSD method necessitates to minimize the standard deviation to reach target value for industrial problems. Thus, we have extended the developed optimization models with this approach due to the fact that wind power generation is a real industrial issue as worldwide.

The optimization model for minimum standard deviation of the response was given as:

$$\begin{aligned}
 & \text{Minimize } \hat{y}_\sigma = 17411963 - 143235A - 66017B + 10071C - 4195339D \\
 & - 3560A^2 + 281B^2 - 172C^2 + 304941D^2 + 2765AB + 2036AC \\
 & - 26994AD + 44BC - 94BD + 1642CD
 \end{aligned}$$

(26)

Subject to

$$\begin{aligned}
 \hat{y}_\mu & = -51897234 - 848278A + 134692B + 177710C + 14333926D - \\
 & 682673A^2 - 596B^2 - 363C^2 - 935391D^2 + 8582AB + 8227AC + \\
 & 752165AD + 801BC - 19659BD - 26156CD = 6885648
 \end{aligned}$$

and the optimization model with maximum mean of the response variable was given as:

$$\begin{aligned}
\text{Maximize } \hat{y}_\mu = & -51897234 - 1848278A + 134692B + 177710C \\
& + 14333926D - 682673A^2 - 596B^2 - 363C^2 - 935391D^2 \\
& + 8582AB + 8227AC + 752165AD + 801BC - 19659BD \\
& - 26156CD
\end{aligned}$$

Subject to (27)

$$\begin{aligned}
\hat{y}_\sigma = & 17411963 - 143235A - 66017B + 10071C - 4195339D - 3560A^2 + \\
& 281B^2 - 172C^2 + 304941D^2 + 2765AB + 2036AC - 26994AD + 44BC - \\
& 94BD + 1642CD = 461089
\end{aligned}$$

This regression equation is defined as objective function in this study where y_{kWh} refers to the output of the WPPs (as kilowatt-hour). Then the full optimization model is expressed as:

to maximize y_{kWh}

$$= \{[TP(A), h(B), l(C), v(D)]_1, [TP(A), h(B), l(C), v(D)]_2, \dots, [TP(A), h(B), l(C), v(D)]_j\}$$

subject to

$$\begin{aligned}
0.8\text{MW} \leq x_{Aj} \leq 3.6\text{MW} & \quad \text{the value of factor A for the } j^{th} \text{ WPP} \\
64\text{m} \leq x_{Bj} \leq 117\text{m} & \quad \text{the value of factor B for the } j^{th} \text{ WPP} \\
52.9\text{m} \leq x_{Cj} \leq 126\text{m} & \quad \text{the value of factor C for the } j^{th} \text{ WPP} \\
5.4\text{m/sec} \leq x_{Dj} \leq 7.75\text{m/sec} & \quad \text{the value of factor D for the } j^{th} \text{ WPP}
\end{aligned} \tag{28}$$

$$\begin{aligned}
& x_{ij}, \text{nonnegative} \\
& x_{ij} \in R^n
\end{aligned}$$

where $i = \{A, B, C, D\}$, and $j = \{\text{the assigned of WPP}\}$. According to the BBD of experiment, a total of 27×2 different WPPs have been designed with different factor values for optimum WPP design, generating maximum annual energy. The limits of the constraints have been determined by BBD.

Determining the optimum values which minimizes performance deviation from the target value is preferable. The additional optimization models were introduced as below:

$$\text{Minimize } \hat{y}_\sigma = f(x_1, x_2, x_3, \dots, x_n)_\sigma \tag{29}$$

$$\text{Subject to } f(x_1, x_2, x_3, \dots, x_n)_\mu = \tau_\mu$$

$$\tau_\sigma, x_i, \text{nonnegative}$$

$$x_i \in R^n$$

and;

$$\text{Maximize } \hat{y}_\mu = f(x_1, x_2, x_3, \dots, x_n)_\mu$$

$$\text{Subject to } f(x_1, x_2, x_3, \dots, x_n)_\sigma = \tau_\sigma$$

(30)

$$\tau_\sigma, x_i, \text{nonnegative}$$

$$x_i \in R^n$$

where τ_μ and τ_σ are the target values of the mean and standard deviation of output. $\hat{y}_\mu$ and $\hat{y}_\sigma$ represent the functions of regressions.

7. RESULTS AND DISCUSSION

This study involves the application of Box-Behnken design that is part of the design of experiment with a total of 54 runs (27 base runs with two replications), while considering four variables, each with three levels, for the wind power plants to provide maximum energy produced. The factors, which are turbine power, hub height, rotor diameter and wind speed denoted as A, B, C and D, respectively, were analyzed statistically. Furthermore, R^2 , the value of the coefficient of multiple terms for the regression showing the statistical measure of how close the data are to the fitted regression line, was calculated as 0.9179 (R^2 adj is 0.8885). With regard to the statistical analysis, the individual and interactive effects of factors were determined by calculating F-value, t-Ratio and P-value. According to **Table 14**, it is seen that the overall model, the factors (linear) and the interactions with themselves (square) are important for the production of wind energy (p – value ≤ 0.05). However, when the 2-way interactions are considered, it is understood that the interactions of factor A (turbine power) with factors B (hub height) and C (rotor diameter) are insignificant in terms of the amount of energy generated (p – value ≥ 0.05).

Table 14: Analysis of variance

Source	Model Types	F-Value (1.5017)	t-Ratio (2.02)	Prob> t Prob> F	Status
Model		31.160	29.00	<0.001	Significant
A	Linear	237.87	15.42	<0.001	Significant
B		4.6400	-2.15	0.037	Significant
C		62.040	7.88	<0.001	Significant
D		12.040	-3.47	0.001	Significant
AA	Square	37.440	-6.12	< 0.002	Significant
BB		3.6600	-1.191	0.063 *	Significant*
CC		4.9100	-2.22	<0.033	Significant
DD		34.880	-5.91	<0.001	Significant
AB	2-way Interaction	1.5900	1.26	0.215	Insignificant
AC		2.7800	1.67	0.103	Insignificant
AD		24.010	3.07	<0.001	Significant
BC		9.4400	4.90	<0.004	Significant
BD		5.8800	-2.42	<0.020	Significant
CD		19.790	-4.45	<0.001	Significant

Note: p -value < 0.05, if the individual and interactive effects of the factors that could influence the response and are statistically significant; *at the margin of statistical provisionally significance (p -value < 0.1); Prob>|t| the p -value associated with a two-tailed test.

Figure 36 is a demonstration of the absolute effect values belonging to standardized effects from the largest to the smallest as below. In addition, a reference red-dotted line points out which factors are statistically significant, comparatively. The bars on the right side of the

red line indicate the importance of them on the result. This figure confirms that all factors and interactions with themselves and each other are significant except the interaction of factor A with factors B and C (BB interaction is provisionally important; $p\text{-value} < 0.1$).

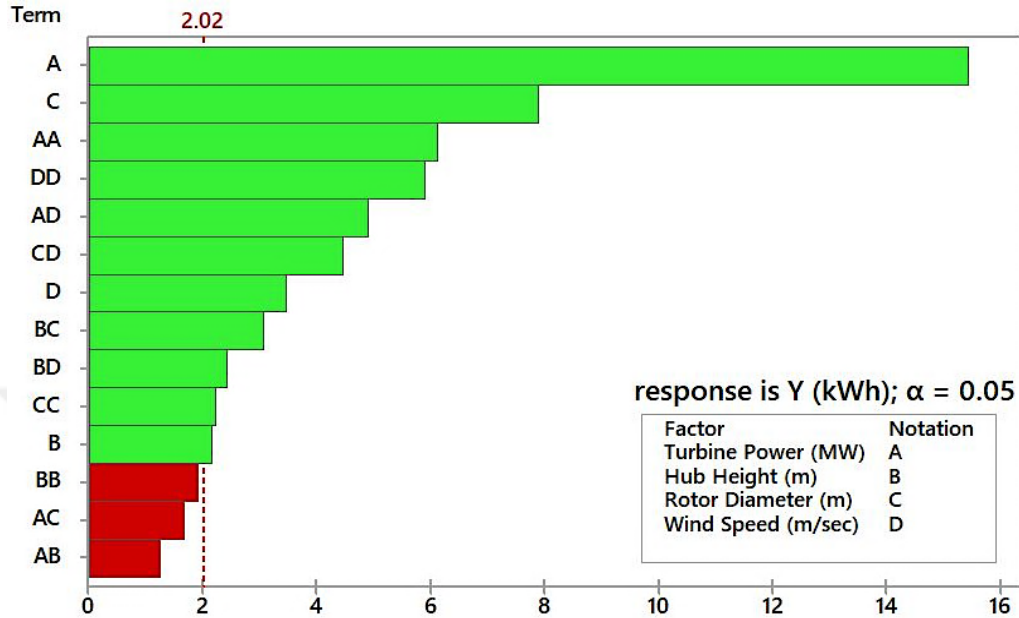


Figure 36: Pareto chart of the standardized effects

Plots of main effects were made to show how the mean of response changed concerning the levels of each factor. The impact of factors (A, B, C and D) on the response variable (y) is separately demonstrated in **Figure 37**. It has been observed that the response variable increases up to a certain point with the increase of factors A and C. Increasing the level of factor B had a very low positive effect on the outcome. As seen from the figure, the increase in the level of wind speed (factor D) escalated the result variable up to a certain point and then started decreasing. The similarity between these separate curves that show the effect of each factor on energy production in WPPs was that they all followed a nonlinear trend.

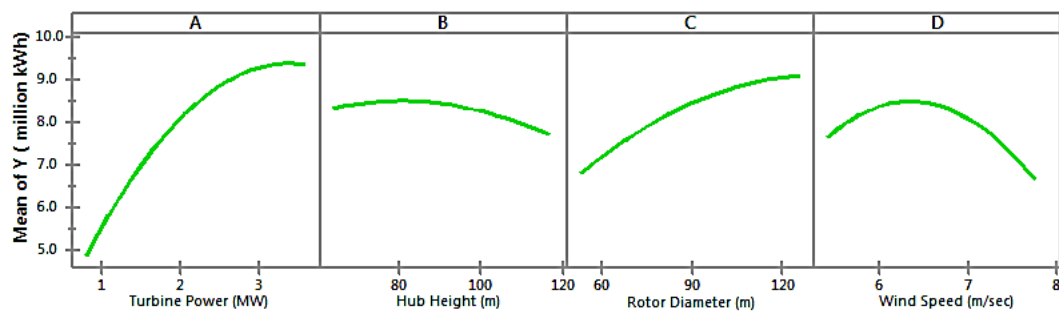
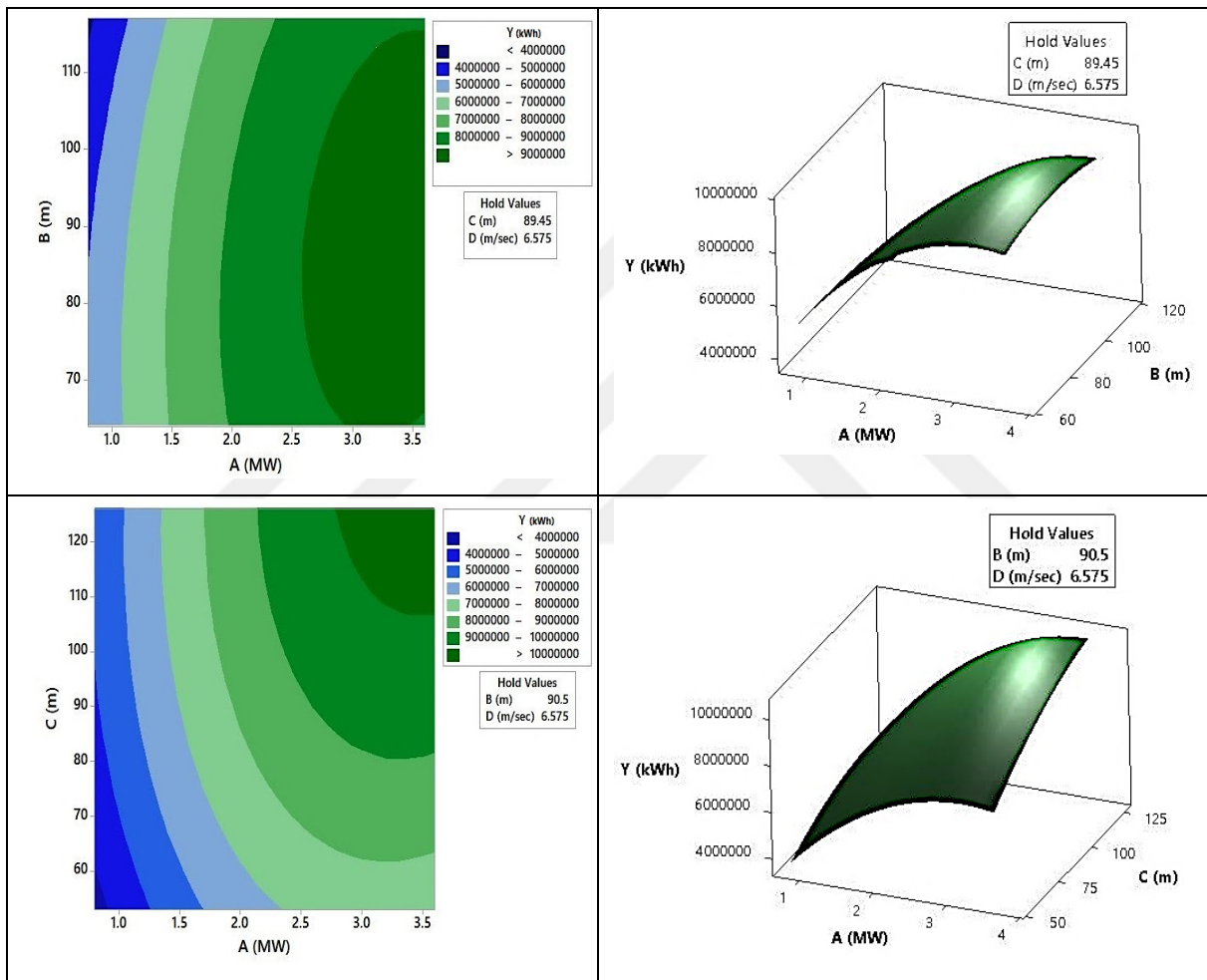
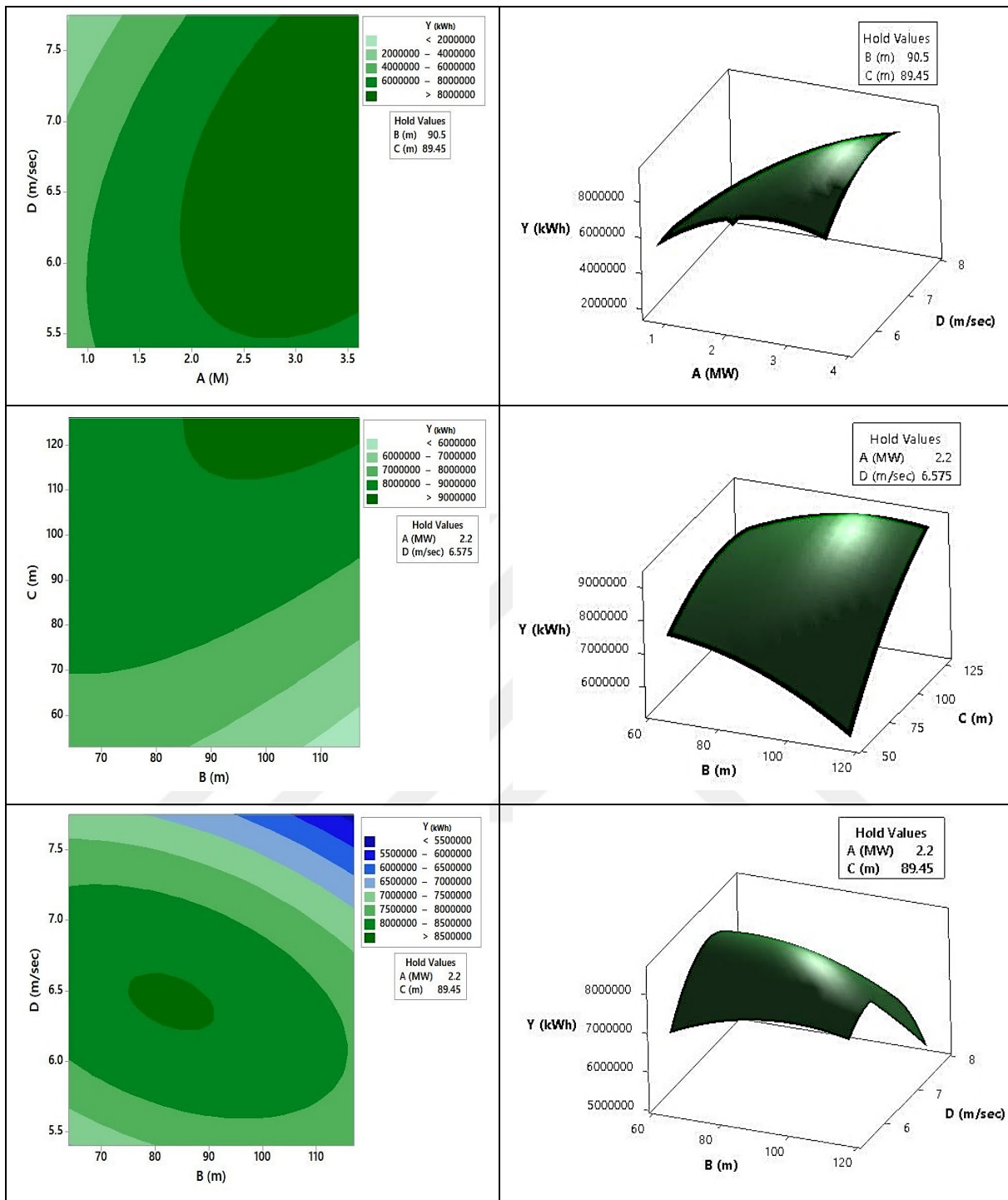


Figure 37: Main effects of factors on response variable

Contour and surface plots were generated to indicate the correlation between three variables, two of which were any two factors and the other was the result. Contour plots help to visualize the impact of the factors on the response in 2D, in which x and y axes express the factors while contours stand for the output. Surface plots contribute to get a clearer idea of the result in 3D, as compared to contour charts. The interactive effects of the factors, two at a time, on the produced wind energy as response variable are illustrated in **Figure 38**. For both plots, the darker the green, the greater the amount of energy generated.





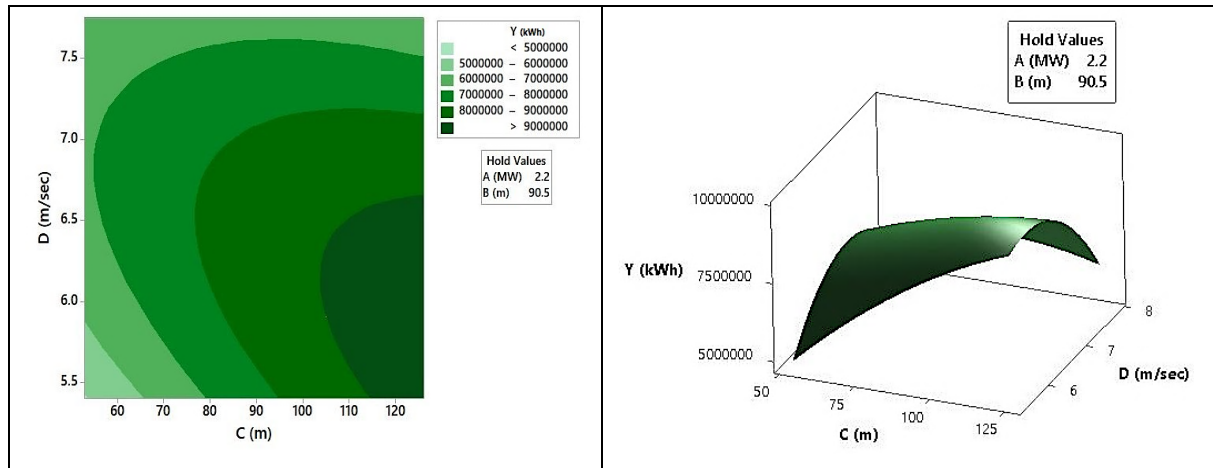


Figure 38: Contour and surface plots showing interactive effects of factors

After investigating individual and interactive impacts of each factor on response with their significance degrees by statistical analysis, a nonlinear optimization model (i.e.; defined in the previous section) was established in order to find out the optimum values of input and output variables. The results of the optimization model based on desirability function are depicted in **Figure 39**.

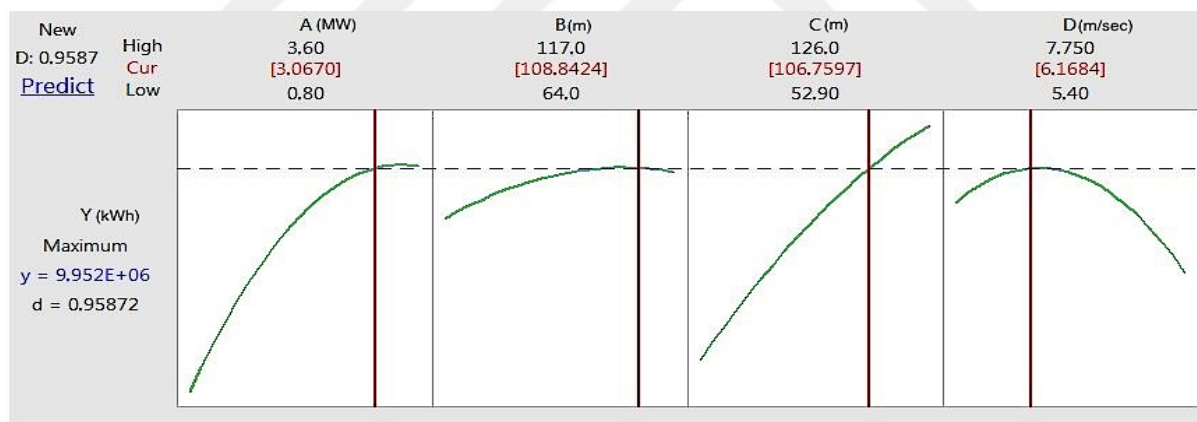


Figure 39: Optimization Results according to Desirability Function

The desirability values check the validity of the results obtained in the optimization models. Desirability value, ranging from 0.0 to 1.0, evaluates how well the combination of variables meets the objectives defined for the answers. The closer this value to 1.0, the better the desired objective function value is. The optimum results with high desirability value (0.9587) for factors A, B, C, D were calculated as 3.0670 MW, 108.8424 m, 106.7597 m, 6.1684 m/sec, respectively, to produce the maximum amount of annual energy which is estimated to be 9.952 million kWh per unit turbine. The best ten feasible solutions, according to their desirability values, are represented in descending order in **Table 15**. This table includes the top

ten feasible results for turbine power (A), hub height (B), rotor diameter (C) and wind speed (D) and gives the annual average amount of energy per unit turbine with these configurations.

Table 15: Best 10 solutions based on desirability value

Feasible Solutions	A (MW)	B (m)	C (m)	D (m/sec)	Target ₀ (million kWh)	Desirability Values
1.0	3.06700	108.842	106.759	6.16840	9.9552	0.95870
2.0	3.60000	103.627	125.319	7.28635	9.8343	0.94530
3.0	3.25161	77.4070	116.904	5.92158	9.5293	0.91058
4.0	1.68100	116.695	126.000	5.40000	9.2783	0.88203
5.0	3.60000	68.0000	118.867	7.33282	9.1664	0.86929
6.0	3.60000	64.0000	56.0950	7.73137	8.8958	0.83849
7.0	2.13088	74.5810	126.000	5.49682	8.6917	0.81527
8.0	2.20000	90.5000	89.4500	6.57500	8.4555	0.78839
9.0	3.16695	112.383	81.2810	6.18659	8.3459	0.77593
10.0	2.27123	64.3830	79.5340	6.47867	8.2612	0.76629

The optimization process was improved with additional optimization models developed for the mean and standard deviation of the response variable. The optimization results when the mean of output is maximized while keeping the standard deviation constant is stated as Target₁ ($\max y_{kWh}$ of output subject to constant $\hat{y}_\sigma$). The optimization results of the mean of output for the factors A, B, C, D and the response were calculated as 2.9395 MW, 101.1193 m, 94.7760 m, 6.4038 m/sec, and 9.390 million kWh per unit turbine, respectively, with the desirability value of 0.9246 (see **Figure 40**).

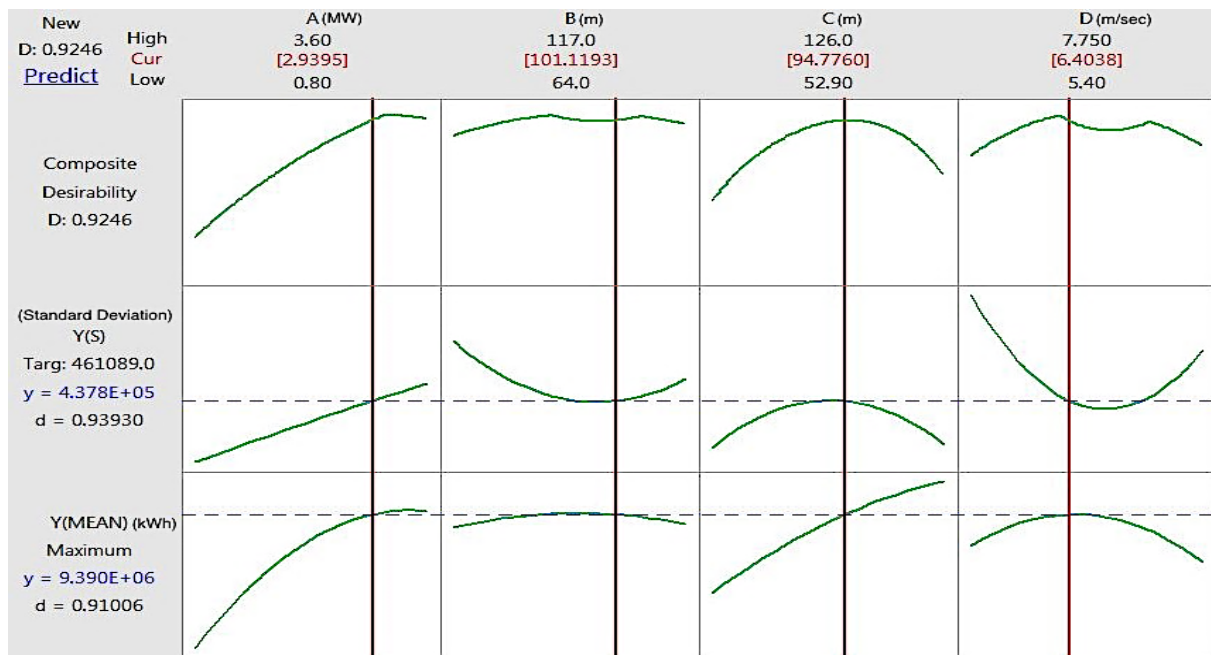


Figure 40: Optimization results for Target₁ (maximize $\hat{y}$ subject to constant σ)

The second optimization model presents the situation in which standard deviation is minimized while holding mean of response at a constant level that is expressed as Target₂ (min $\hat{y}_\sigma$ subject to constant y_{kWh}). The optimum results, with high desirability value of 0.9144, for the factors A, B, C, D and the response were computed as 1.7665 MW, 106.2929 m, 95.4418 m, 6.8004 m/sec, and 7.143 million kWh per unit turbine, respectively. The minimized standard deviation value of response was computed as 0.24680 million kWh (see **Figure 41**).

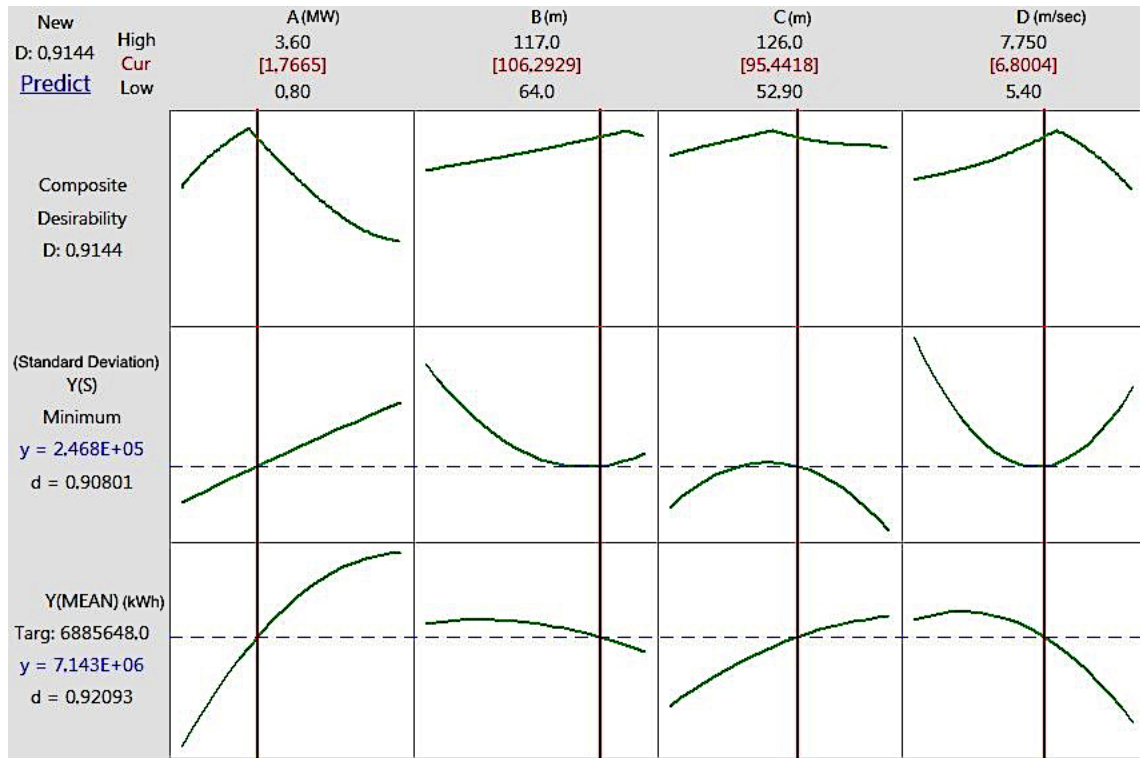


Figure 41: Optimization results for Target₂ (minimize σ subject to constant $\hat{y}$)

The multi-objective optimization (max y_{kWh} and min $\hat{y}_\sigma$) of output results, in which mean of response is maximized (Target₁) while standard deviation is minimized (Target₂), simultaneously, are shown in **Figure 42**. It can be evaluated as the combinational representation of the results of the optimization models concerning both mean and standard deviation of output. The optimum results, having desirability value of 0.9156, for the factors A, B, C, D and the output were calculated as 2.7100MW, 94.5152m, 112.0857m, 6.6581 m/sec, and 9.684 million kWh per unit turbine, respectively. The minimized standard deviation value of output was 0.28630 million kWh.

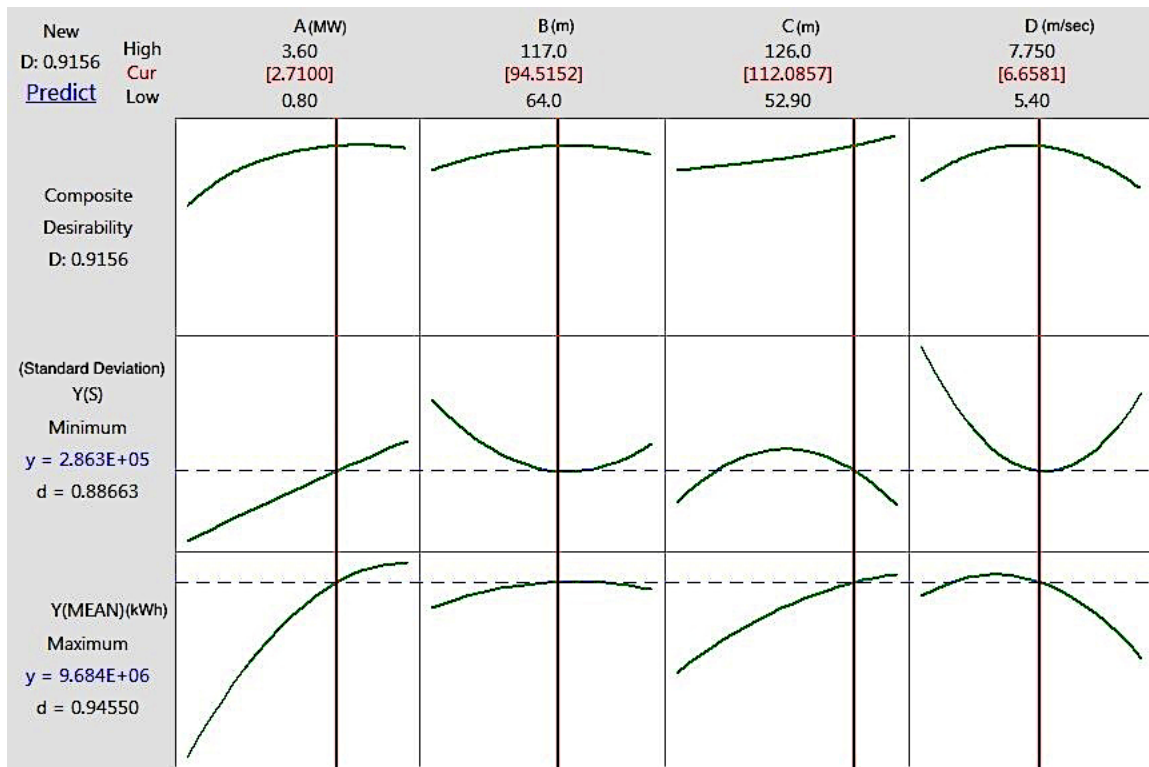


Figure 42: Optimization results for Target₁ and Target₁ (maximize $\hat{y}$ and minimize σ)

The results of all optimization models with their desirability values were displayed together in **Table 16**. The averages of all optimum results were computed for the factors A, B, C, D as 2.62075 MW, 102.6925 m, 102.2658 m, and 6.50767 m/sec, respectively, with a high average desirability value of 0.92833, to get maximum energy production which was 9.952 million kWh in Target₀, 9.537 million kWh in Target₁ per unit turbine. The average of the standard deviation of the response variable was calculated as 0.26655 million kWh in Target₂.

Table 16: The results of all optimization models

Optimization Models	Input Factors				Target ₀ $\hat{y}_{kWh}$	Target ₁ $\hat{y}_{\mu}$	Target ₂ $\hat{y}_{\sigma}$	Composite Desirability (0.0 < CD > 1.0)
	A (MW)	B (m)	C (m)	D (m/se)	Maximize (million kWh)	Maximize (million kWh)	Minimize (million kWh)	
Target ₀	3.0670	108.8424	106.7597	6.1684	9.952	Constant	Constant	0.95872
Target ₁	2.9395	101.1193	94.7760	6.4038	-	9.390	Constant	0.92460
Target ₂	1.7665	106.2929	95.4418	6.8004	-	Constant	0.24680	0.91440
Multi-Objective	2.7100	94.5152	112.0857	6.6581	-	9.684	0.28630	0.91560
Average	2.62075	102.6925	102.2658	6.50767	9.952	9.537	0.26655	0.92833

In terms of the validation of the method used, I have optimized each decision variable separately by fixing the other three decision variables according to the mean value of parameters

which was determined as the reference case. **Table 17** shows the comparative results of decision variables of multi-objective functions' optimization models and the findings after validation process. The percent difference between the optimum values of each variable is way below 1%, demonstrating that the applied method and the results are more than 99% confident.

Table 17: The comparison of the decision variables' results.

	A (MW)	B (m)	C (m)	D (m/sec)	Optimum ¹	Optimum ²	Differences (%)
A (MW)	0.8–3.6	Fixed (86.294)	Fixed (101.97)	Fixed (6.80)	2.710	2.723	0.4790%
B (m)	Fixed (2.627)	64–117	Fixed (101.97)	Fixed (6.80)	94.5152	95.05	0.5658%
C (m)	Fixed (2.627)	Fixed (86.294)	52.9–126	Fixed (6.80)	112.0857	112.709	0.5560%
D (m/sec)	Fixed (2.627)	Fixed (86.294)	Fixed (101.97)	5.4–7.75	6.6581	6.6106	0.7100%

Optimum¹: The optimum results of the decision variables based on multi-objective functions' optimization models.

Optimum²: The optimum results of the decision variables based on a reference case in which one constraint is optimized at a time and three other constraints are fixed.

The European Wind Energy Union classifies wind speeds as nearly good for 6.5 m/sec, good for 7.5 m/sec and very good for 8.5 m/sec which is suitable for energy generation from wind (Fazelpour, Soltani, & Rosen, 2015). All of the optimization models developed propose that even in areas in nearly good wind speed group, the higher amount of wind energy can be produced with optimizing other variables. Yang et al. studied wind turbine blade optimization for the improvement of the aerodynamic and also structural performance in areas with low wind speed. The new blade was compared with a commercial 2.1 MW horizontal-axis wind turbine having a 122.3 m rotor diameter in order to demonstrate that the proposed design was efficient. The yearly energy generation they obtained was 8.0076 million kWh with an annual average wind speed of 7.5 m/s (H. Yang, Chen, Pang, & Chen, 2019). Even though they considered higher wind speed and higher rotor diameter, the produced energy they achieved was lower as compared to this study.

Lee et al. investigated the optimization of hub height to get maximum annual net profit. They limited the hub height value between 30 m and 300 m in the optimization model developed for WPPs. The optimum hub height value they find is 125.8 m with $V = 7$ m/sec and $\alpha = 0.25$ for case 1 and 219.2 m with $V = 5$ m/sec and $\alpha = 0.3$ for case 2 (Lee, Kim, & Lee, 2015). One of the most important factors affecting the initial capital cost in WPPs is the hub height.

Therefore, I can assume that the hub height value we calculated in this study, which is 105 m, is more reasonable in terms of cost. Lee et al. calculated the optimum hub height value as 75 m, which is calculated by considering the cost of establishment. However, the amount of energy produced according to the calculated hub height is low in their study (Lee et al., 2015). Cheng et al. studied the optimization of rotors for higher power capture from the wind. They tried to optimize Darrieus-type vertical axis wind turbine rotor having a constant turbine power of 5 MW. The optimum value was computed as 120.96 m for rotor diameter and 143 m for hub height. Moreover, the reference height for wind speed was considered as 79.78 m (Cheng, Wang, & Ong, 2018).

There is no doubt that the WPPs in Turkey have been installed in different regions with unequal quantities that makes the data having an inhomogeneous nature which constitutes uncertainties. In addition, some of the WPPs were ignored in this study due to lack or contradictory data (i.e., especially for the hub height and the amount of annual produced energy) and the fact that some wind farms have not started production yet. Additionally, some WPPs have different types of turbines (i.e., distinct turbine power, hub height and rotor diameter). Nevertheless, the data of the energy generation amount is available for the entire facility in total. Thus, these were not taken into account in order to avoid confusion in the calculations. In short, it was observed that the desirability values, which indicated how much the combination of the variables have achieved the target defined for the response variable(s), for all of the developed optimization models were close to 1 and very similar to each other. This closeness supports the feasibility of my study, which might assist not only operators but also researchers, entrepreneurs and governments for the future.

8. CONCLUSIONS

This study focuses on gaining maximum benefit from wind energy that has the potential to meet increasing energy demands in a cost effective and environmentally friendly way without depending on fossil fuel sources. In this respect, the data of operating wind power plants in Turkey were collected to apply the design of experiment and optimization techniques together in wind energy field for the first time in such a comprehensive manner. Turbine power, hub height, rotor diameter and wind speed (at 50 m) were selected as decision variables whose limits required for the design were determined using Box plots. Both the individual and also interactive effects of controllable and uncontrollable factors on wind power generation were investigated with the help of Box-Behnken design. The results showed that all the input factors were significant for wind energy production based on P-value which is the sign of importance of the results. The 2-way interactions of the design parameters that is the interaction of factors with each other were found to be significant too, except the interactions of turbine power with hub height and rotor diameter.

After analyzing individual and interactive impacts of each factor on response with significance degrees, a nonlinear optimization model was established in order to find out the optimum values of input and output variables. The optimum results with high desirability value (0.9587) for the factors A, B, C, D were calculated as 3.0670 MW, 108.8424 m, 106.7597 m, 6.1684 m/sec, respectively, to produce maximum amount of energy which was 9952000 kWh per unit turbine, annually. The optimization process was improved with additional optimization models developed for the mean and standard deviation of the response variable in the way of maximizing mean of output, minimizing standard deviation of response and combining them both. It was observed that the desirability values for all of the developed optimization models were close to 1 and very similar to each other. The analogy between these results advocates the feasibility of our study to gain the maximum amount of energy from renewable energy sources, with regard to serving as a guideline that contributes to supply escalating energy needs by more sustainable and clean ways for the future.

REFERENCES

- Abdelaziz, E. A., Saidur, R., & Mekhilef, S. (2011). A review on energy saving strategies in industrial sector. *Renewable and Sustainable Energy Reviews*, 15(1), 150–168.
<https://doi.org/10.1016/j.rser.2010.09.003>
- Antony, J. (2014). Design of Experiments for Engineers and Scientists. In *Design of Experiments for Engineers and Scientists*. <https://doi.org/10.1016/B978-0-08-099417-8.00006-7>
- Apergis, N., Payne, J. E., Menyah, K., & Wolde-Rufael, Y. (2010). On the causal dynamics between emissions, nuclear energy, renewable energy, and economic growth. *Ecological Economics*, 69(11), 2255–2260. <https://doi.org/10.1016/j.ecolecon.2010.06.014>
- Arslan, H., Baltaci, H., Akkoyunlu, B. O., Karanfil, S., & Tayanc, M. (2020). Wind speed variability and wind power potential over Turkey: Case studies for Çanakkale and İstanbul. *Renewable Energy*, 145, 1020–1032.
<https://doi.org/10.1016/j.renene.2019.06.128>
- Ashok, S. (2007). Optimised model for community-based hybrid energy system. *Renewable Energy*, 32(7), 1155–1164. <https://doi.org/https://doi.org/10.1016/j.renene.2006.04.008>
- Asif, M., & Muneer, T. (2007). Energy supply, its demand and security issues for developed and emerging economies. *Renewable and Sustainable Energy Reviews*, 11(7), 1388–1413. <https://doi.org/10.1016/j.rser.2005.12.004>
- Autrique, L., & Lormel, C. (2008). *Numerical Design of Experiment for Sensitivity Analysis — Application to Skin Burn Injury Prediction*. 55(4), 1279–1290.
- Bilgen, S. (2014). Structure and environmental impact of global energy consumption. *Renewable and Sustainable Energy Reviews*, 38, 890–902.
<https://doi.org/10.1016/j.rser.2014.07.004>
- Bodansky, D. (2005). Nuclear Energy. In *Nuclear Energy: Principles, Practices, and Prospects: Second Edition*. <https://doi.org/10.1007/b138326>
- Canadell, P., Le Quéré, C., Peters, G., Andrew, R., Jackson, R., & Haverd, V. (2017). Fossil fuel emissions hit record high after unexpected growth: Global Carbon Budget 2017. Retrieved from <https://theconversation.com/fossil-fuel-emissions-hit-record-high-after-unexpected-growth-global-carbon-budget-2017-87248>
- Çapik, M., Yilmaz, A. O., & Çavuşoğlu, I. (2012). Present situation and potential role of renewable energy in Turkey. *Renewable Energy*, 46, 1–13.
<https://doi.org/10.1016/j.renene.2012.02.031>

- Carton, J. G., & Olabi, A. G. (2010). Design of experiment study of the parameters that affect performance of three flow plate configurations of a proton exchange membrane fuel cell. *Energy*, 35(7), 2796–2806. <https://doi.org/10.1016/j.energy.2010.02.044>
- Chan, C. M., Bai, H. L., & He, D. Q. (2018). Blade shape optimization of the Savonius wind turbine using a genetic algorithm. *Applied Energy*. <https://doi.org/10.1016/j.apenergy.2018.01.029>
- Cheng, Z., Wang, K., & Ong, M. C. (2018). Assessment of performance enhancement of a semi-submersible vertical axis wind turbine with an optimized Darrieus rotor. *Engineering Structures*. <https://doi.org/10.1016/j.engstruct.2018.04.038>
- Chu, S., & Majumdar, A. (2012). Opportunities and challenges for a sustainable energy future. *Nature*, 488(7411), 294–303. <https://doi.org/10.1038/nature11475>
- Covert, T., Greenstone, M., & Knittel, C. R. (2016). Will We Ever Stop Using Fossil Fuels? *Journal of Economic Perspectives*, 30(1), 117–138. <https://doi.org/10.1257/jep.30.1.117>
- Craig, C. C., & Fisher, R. A. (1936). The Design of Experiments. *The American Mathematical Monthly*, 43(3), 180. <https://doi.org/10.2307/2300364>
- Cullen, J. (2013). Measuring the environmental benefits of wind-generated electricity. *American Economic Journal: Economic Policy*. <https://doi.org/10.1257/pol.5.4.107>
- Dincer, I. (2000). Renewable energy and sustainable development: a crucial review. *Renewable and Sustainable Energy Reviews*, 4(2), 157–175. [https://doi.org/10.1016/S1364-0321\(99\)00011-8](https://doi.org/10.1016/S1364-0321(99)00011-8)
- Ding, R., Lin, D. K. J., & Wei, D. (2004). Dual-response surface optimization: A weighted MSE approach. *Quality Engineering*. <https://doi.org/10.1081/QEN-120027940>
- Dittmar, M. (2012). Nuclear energy: Status and future limitations. *Energy*, 37(1), 35–40. <https://doi.org/10.1016/j.energy.2011.05.040>
- Dziak, J. J., Nahum-Shani, I., & Collins, L. M. (2012). Multilevel Factorial Experiments for Developing Behavioral Interventions: Power, Sample Size, and Resource Considerations. *Psychological Methods*, 17(2), 153–175. <https://doi.org/10.1037/a0026972>
- EIA. (2017). International Energy Outlook 2017 Overview. *U.S. Energy Information Administration*, IEO2017(2017), 143. [https://doi.org/www.eia.gov/forecasts/ieo/pdf/0484\(2016\).pdf](https://doi.org/www.eia.gov/forecasts/ieo/pdf/0484(2016).pdf)
- Ellabban, O., Abu-Rub, H., & Blaabjerg, F. (2014). Renewable energy resources: Current status, future prospects and their enabling technology. *Renewable and Sustainable Energy Reviews*, 39, 748–764. <https://doi.org/10.1016/j.rser.2014.07.113>

- Erdem, Z. B. (2010). The contribution of renewable resources in meeting Turkey's energy-related challenges. *Renewable and Sustainable Energy Reviews*, 14(9), 2710–2722. <https://doi.org/10.1016/j.rser.2010.07.003>
- Fadaee, M., & Radzi, M. A. M. (2012). Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review. *Renewable and Sustainable Energy Reviews*, 16(5), 3364–3369. <https://doi.org/https://doi.org/10.1016/j.rser.2012.02.071>
- Farghal, S. A., & Aziz, M. R. A. (1988). Generation expansion planning including the renewable energy sources. *IEEE Transactions on Power Systems*, 3(3), 816–822. <https://doi.org/10.1109/59.14527>
- Fazelpour, F., Soltani, N., & Rosen, M. A. (2015). Wind resource assessment and wind power potential for the city of Ardabil, Iran. *International Journal of Energy and Environmental Engineering*, 6(4), 431–438. <https://doi.org/10.1007/s40095-014-0139-8>
- Ferreira, S. L. C., Bruns, R. E., Ferreira, H. S., Matos, G. D., David, J. M., Brandão, G. C., ... dos Santos, W. N. L. (2007). Box-Behnken design: An alternative for the optimization of analytical methods. *Analytica Chimica Acta*, 597(2), 179–186. <https://doi.org/10.1016/j.aca.2007.07.011>
- G. Fishbone, L., & Abilock, H. (1981). MARKAL, a linear-programming model for energy system analysis: technical description of the BNL version. In *International Journal of Energy Research* (Vol. 5). <https://doi.org/10.1002/er.4440050406>
- Gao, X., Yang, H., Lin, L., & Koo, P. (2015). Wind turbine layout optimization using multi-population genetic algorithm and a case study in Hong Kong offshore. *Journal of Wind Engineering and Industrial Aerodynamics*. <https://doi.org/10.1016/j.jweia.2015.01.018>
- Garcia-Gonzalez, J., Muela, R. M. R. de la, Santos, L. M., & Gonzalez, A. M. (2008). Stochastic Joint Optimization of Wind Generation and Pumped-Storage Units in an Electricity Market. *IEEE Transactions on Power Systems*, 23(2), 460–468. <https://doi.org/10.1109/TPWRS.2008.919430>
- Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. *Energy Strategy Reviews*, 24, 38–50. <https://doi.org/10.1016/j.esr.2019.01.006>
- Gu, Z. (2018). History review of nuclear reactor safety. *Annals of Nuclear Energy*, 120, 682–690. <https://doi.org/10.1016/j.anucene.2018.06.023>
- Gul, M., Tai, N., Huang, W., Nadeem, M. H., & Yu, M. (2020). Evaluation of Wind Energy Potential Using an Optimum Approach based on Maximum Distance Metric.

- Sustainability*, 12(5), 1999. <https://doi.org/10.3390/su12051999>
- Hatami, M., Cuijpers, M. C. M., & Boot, M. D. (2015a). Experimental optimization of the vanes geometry for a variable geometry turbocharger (VGT) using a Design of Experiment (DoE) approach. *Energy Conversion and Management*, 106, 1057–1070. <https://doi.org/10.1016/j.enconman.2015.10.040>
- Hatami, M., Cuijpers, M. C. M., & Boot, M. D. (2015b). Experimental optimization of the vanes geometry for a variable geometry turbocharger (VGT) using a Design of Experiment (DoE) approach. *Energy Conversion and Management*. <https://doi.org/10.1016/j.enconman.2015.10.040>
- Hossain, F. M., Hasanuzzaman, M., Rahim, N. A., & Ping, H. W. (2015). Impact of renewable energy on rural electrification in Malaysia: a review. *Clean Technologies and Environmental Policy*. <https://doi.org/10.1007/s10098-014-0861-1>
- Inzlicht, M., Schmeichel, B. J., & Macrae, C. N. (2014). Why self-control seems (but may not be) limited. *Trends in Cognitive Sciences*, 18(3), 127–133. <https://doi.org/10.1016/j.tics.2013.12.009>
- Islam, M. A., Sakkas, V., & Albanis, T. A. (2009). *Application of statistical design of experiment with desirability function for the removal of organophosphorus pesticide from aqueous solution by low-cost material*. 170, 230–238. <https://doi.org/10.1016/j.jhazmat.2009.04.106>
- Kaygusuz, K. (2007). Energy for Sustainable Development: Key Issues and Challenges. *Energy Sources, Part B: Economics, Planning, and Policy*, 2(1), 73–83. <https://doi.org/10.1080/15567240500402560>
- Kaygusuz, K. (2010). Wind energy status in renewable electrical energy production in Turkey. *Renewable and Sustainable Energy Reviews*, 14(7), 2104–2112. <https://doi.org/10.1016/j.rser.2010.03.022>
- Kaygusuz, K. (2012). Energy for sustainable development: A case of developing countries. *Renewable and Sustainable Energy Reviews*. <https://doi.org/10.1016/j.rser.2011.11.013>
- Khare, V., Nema, S., & Baredar, P. (2016). Solar–wind hybrid renewable energy system: A review. *Renewable and Sustainable Energy Reviews*, 58, 23–33. <https://doi.org/10.1016/j.rser.2015.12.223>
- Kumar, A., Prasad, B., & Mishra, I. M. (2008). Optimization of process parameters for acrylonitrile removal by a low-cost adsorbent using Box–Behnken design. *Journal of Hazardous Materials*, 150(1), 174–182. <https://doi.org/10.1016/j.jhazmat.2007.09.043>
- Kusiak, A., & Song, Z. (2010). Design of wind farm layout for maximum wind energy

- capture. *Renewable Energy*, 35(3), 685–694.
<https://doi.org/https://doi.org/10.1016/j.renene.2009.08.019>
- Kusiak, A., & Zheng, H. (2010). Optimization of wind turbine energy and power factor with an evolutionary computation algorithm. *Energy*.
<https://doi.org/10.1016/j.energy.2009.11.015>
- Lee, J., Kim, D. R., & Lee, K.-S. (2015). Optimum hub height of a wind turbine for maximizing annual net profit. *Energy Conversion and Management*, 100, 90–96.
<https://doi.org/10.1016/j.enconman.2015.04.059>
- Liu, B., & Zhang, Y. (2011). CO₂ Modeling in a Deep Saline Aquifer: A Predictive Uncertainty Analysis Using Design of Experiment. *Environmental Science & Technology*, 45(8), 3504–3510. <https://doi.org/10.1021/es103187b>
- Markarian, S., Fazelpour, F., & Markarian, E. (2019). Optimization of wind farm layout considering wake effect and multiple parameters. *Environmental Progress & Sustainable Energy*, 38(5), 13193. <https://doi.org/10.1002/ep.13193>
- Menyah, K., & Wolde-Rufael, Y. (2010). CO₂ emissions, nuclear energy, renewable energy and economic growth in the US. *Energy Policy*, 38(6), 2911–2915.
<https://doi.org/10.1016/j.enpol.2010.01.024>
- Mgbemene, C. A. (2011). The effects of industrialization on climate change. *Fulbright Alumni Association of Nigeria 10th Anniversary Conference Development, Environment and Climate Change: Challenges for Nigeria, University of Ibadan*.
- Miao, H., Dong, D., Huang, G., Hu, K., Tian, Q., & Gong, Y. (2020). Evaluation of Northern Hemisphere surface wind speed and wind power density in multiple reanalysis datasets. *Energy*, 200, 117382. <https://doi.org/10.1016/J.ENERGY.2020.117382>
- Ming, M., Wang, R., Zha, Y., & Zhang, T. (2017). Multi-Objective Optimization of Hybrid Renewable Energy System Using an Enhanced Multi-Objective Evolutionary Algorithm. *Energies*, Vol. 10. <https://doi.org/10.3390/en10050674>
- Ministry of Energy and Natural Resources. (2020). Wind. Retrieved from <https://www.enerji.gov.tr/en-US/Pages/Wind>
- Minitab. (2020a). Factorial and fractional factorial designs. Retrieved July 25, 2020, from <https://support.minitab.com/en-us/minitab/18/help-and-how-to/modeling-statistics/doe/supporting-topics/factorial-and-screening-designs/factorial-and-fractional-factorial-designs/#:~:text=A full factorial design is,contain only 2-level factors.>
- Minitab. (2020b). What are response surface designs, central composite designs, and Box-Behnken designs?

- Montgomery, D. (2009). Introduction to statistical quality control. In *John Wiley & Sons Inc.*
[https://doi.org/10.1002/1521-3773\(20010316\)40:6<9823::AID-ANIE9823>3.3.CO;2-C](https://doi.org/10.1002/1521-3773(20010316)40:6<9823::AID-ANIE9823>3.3.CO;2-C)
- Montgomery, D. C. (2012). Design and Analysis of Experiments. In *Design.*
<https://doi.org/10.1198/tech.2006.s372>
- Negm, H. M., & Maalawi, K. Y. (2000). Structural design optimization of wind turbine towers. *Computers and Structures*. [https://doi.org/10.1016/S0045-7949\(99\)00079-6](https://doi.org/10.1016/S0045-7949(99)00079-6)
- Ohlenfrorst, K. (2019). GWEC Global Wind Report 2018. In *Wind Global Energy Council.*
- Palkar, R. R., & Shilapuram, V. (2017). Particuology Detailed parametric design methodology for hydrodynamics of liquid – solid circulating fluidized bed using design of experiments. *Particuology*, 31, 59–68. <https://doi.org/10.1016/j.partic.2016.04.005>
- Panda, D., Satapathy, A. K., & Sarangi, S. K. (2019). Thermo-hydrodynamic analysis and optimal design of a GM cycle cryorefrigerator using response surface methodology and particle swarm optimization. *Science and Technology for the Built Environment*, 25(10), 1467–1481. <https://doi.org/10.1080/23744731.2019.1649461>
- Panwar, N. L., Kaushik, S. C., & Kothari, S. (2011). Role of renewable energy sources in environmental protection: A review. *Renewable and Sustainable Energy Reviews*, 15(3), 1513–1524. <https://doi.org/10.1016/j.rser.2010.11.037>
- Pearce, J. M. (2012). Limitations of Nuclear Power as a Sustainable Energy Source. *Sustainability*, 4(6), 1173–1187. <https://doi.org/10.3390/su4061173>
- Ramesh Palkar, R., & Shilapuram, V. (2017). Detailed parametric design methodology for hydrodynamics of liquid–solid circulating fluidized bed using design of experiments. *Particuology*. <https://doi.org/10.1016/j.partic.2016.04.005>
- Rekab, K., & Shaikh, M. (2005). *Statistical design of experiments with engineering applications* (1st ed.). CRC Press.
- REN21. (2018). Renewables 2018 global status report. In *Paris: Renewable energy policy network for the 21st Century*. <https://doi.org/10.978-3-9818911-3-3>
- Rout, B. K., & Mittal, R. K. (2009). Screening of factors influencing the performance of manipulator using combined array design of experiment approach. *Robotics and Computer-Integrated Manufacturing*, 25(3), 651–666.
<https://doi.org/10.1016/j.rcim.2008.05.004>
- Santhakumar, S., Palanivel, I., & Venkatasubramanian, K. (2019). Building a low cost wind turbine in highways for rural house electricity demand. *Environmental Progress & Sustainable Energy*, 38(1), 278–285. <https://doi.org/10.1002/ep.12917>
- Schubel, P. J., & Crossley, R. J. (2012). Wind Turbine Blade Design. *Energies*, 5(9), 3425–

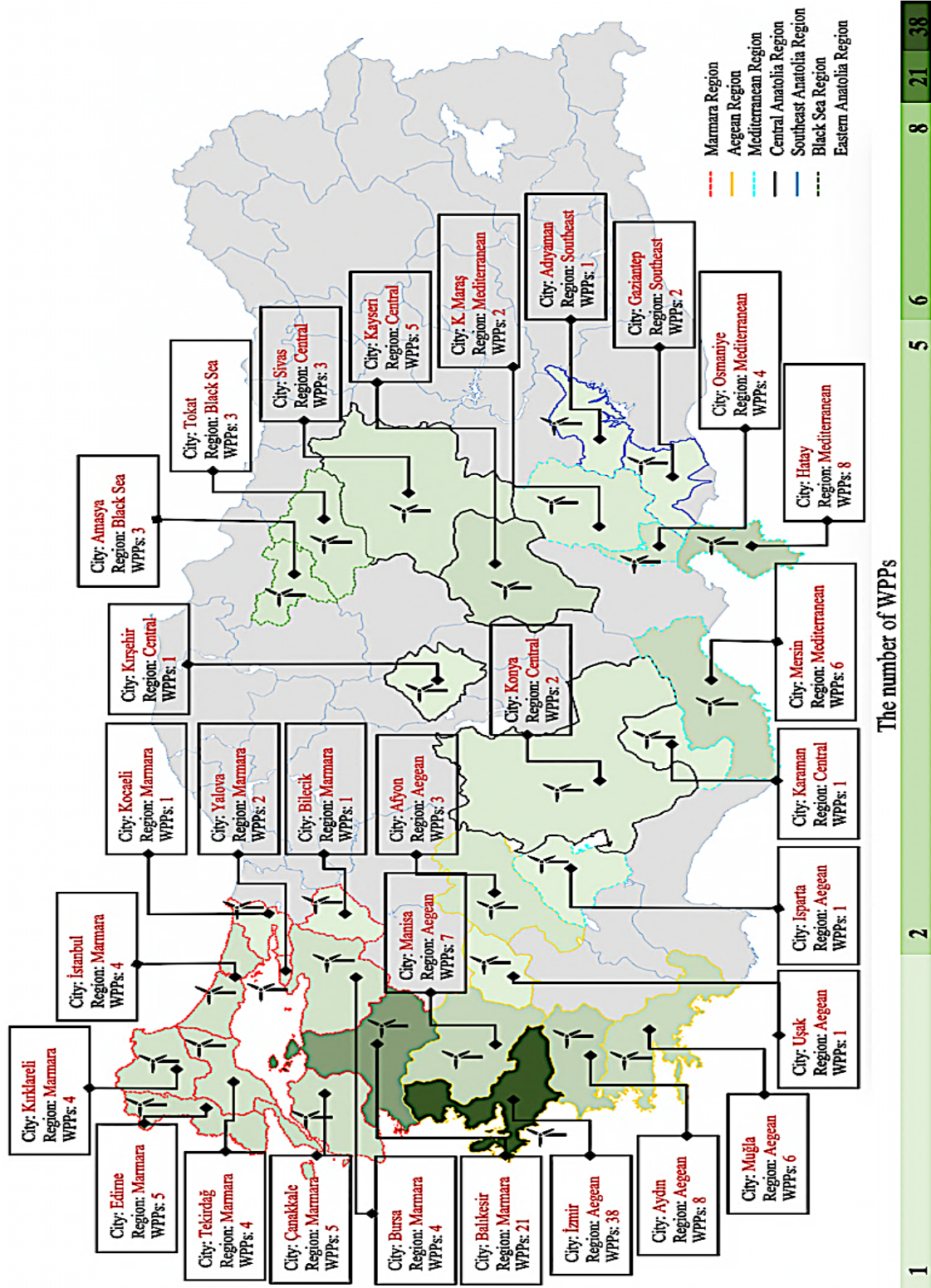
3449. <https://doi.org/10.3390/en5093425>
- Sofuoğlu, H. (2006). *A technical note on the role of process parameters in predicting flow behavior of plasticine using design of experiment*. 178, 148–153.
<https://doi.org/10.1016/j.jmatprotec.2006.03.161>
- Song, D., Liu, J., Yang, J., Su, M., Wang, Y., Yang, X., ... Joo, Y. H. (2020). Optimal design of wind turbines on high-altitude sites based on improved Yin-Yang pair optimization. *Energy*, 193, 116794. <https://doi.org/10.1016/J.ENERGY.2019.116794>
- Suganthi, L., & Samuel, A. A. (2012). Energy models for demand forecasting—A review. *Renewable and Sustainable Energy Reviews*, 16(2), 1223–1240.
<https://doi.org/10.1016/j.rser.2011.08.014>
- Sundararajan, K. (2018). Design of Experiments – A Primer. Retrieved from
<https://www.isixsigma.com/tools-templates/design-of-experiments-doe/design-experiments-%s-primer/#comments>
- Toklu, E. (2013). Overview of potential and utilization of renewable energy sources in Turkey. *Renewable Energy*, 50, 456–463. <https://doi.org/10.1016/j.renene.2012.06.035>
- U.S. Energy Information Administration. (2019). *International Energy Outlook 2019 with projections to 2050*. Retrieved from <https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf>
- Ulutaş, B. H. (2005). Determination of the appropriate energy policy for Turkey. *Energy*, 30(7), 1146–1161. <https://doi.org/10.1016/j.energy.2004.08.009>
- Uy, M., & Telford, J. K. (2009). *Optimization by Design of Experiment Techniques*.
- Vining, G. G., & Myers, R. H. (1990). Combining Taguchi and Response Surface Philosophies: A Dual Response Approach. *Journal of Quality Technology*.
<https://doi.org/10.1080/00224065.1990.11979204>
- Wahdame, B., Candusso, D., Franc, X., & Harel, F. (2009). *Design of experiment techniques for fuel cell characterisation and development*. 34, 967–980.
<https://doi.org/10.1016/j.ijhydene.2008.10.066>
- Wang, L., Zuo, M. J., Xu, J., Zhou, Y., & Tan, A. C. (2019). Optimizing wind farm layout by addressing energy-variance trade-off: A single-objective optimization approach. *Energy*, 189, 116149. <https://doi.org/10.1016/J.ENERGY.2019.116149>
- Winston, W. (2004). Operations research-Applications and Algorithms 4e. In *THOMSON*.
[https://doi.org/10.1016/S0076-5392\(08\)62705-8](https://doi.org/10.1016/S0076-5392(08)62705-8)
- Wołoszyn, J., & Gołaś, A. (2014). Sensitivity analysis of efficiency thermal energy storage on selected rock mass and grout parameters using design of experiment method. *Energy Conversion and Management*. <https://doi.org/10.1016/j.enconman.2014.03.059>

- World Health Organization. (2016). Ambient Air Pollution: A global assessment of exposure and burden of disease. *World Health Organization*.
- World Nuclear Association. (2018). *World Nuclear Performance Report 2018*. Retrieved from https://www.world-nuclear.org/getattachment/Our-Association/Publications/Annual-Reports-and-Brochures/At-Work-Annual-Report-2018/At_Work_2018_web.pdf.aspx
- Wormbs, G., Larsson, A., Alm, J., Tunklint-aspelin, C., Strinning, O., Danielsson, E., & Larsson, H. (2004). *The use of Design of Experiment and sensory analysis as tools for the evaluation of production methods for milk*. 73, 67–71.
<https://doi.org/10.1016/j.chemolab.2003.12.013>
- Yang, H., Chen, J., Pang, X., & Chen, G. (2019). A new aero-structural optimization method for wind turbine blades used in low wind speed areas. *Composite Structures*, 207, 446–459. <https://doi.org/10.1016/j.compstruct.2018.09.050>
- Yang, Y., Li, H., Yao, J., & Gao, W. (2019). Research on the characteristic parameters and rotor layout principle of dual-rotor horizontal axis wind turbine. *Energy*, 189, 116270. <https://doi.org/10.1016/J.ENERGY.2019.116270>
- Yu, W., Varavei, A., & Sepehrnoori, K. (2015). Optimization of Shale Gas Production Using Design of Experiment and Response Surface Methodology. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*.
<https://doi.org/10.1080/15567036.2013.812698>
- Yurkiewicz, J. (2007). Operations research: Applications and algorithms, by Wayne L. Winston, duxbury Press, Boston, 1987, 1025 pages. *Networks*.
<https://doi.org/10.1002/net.3230190512>
- Zhao, L., & Zeng, B. (2012). Robust unit commitment problem with demand response and wind energy. *2012 IEEE Power and Energy Society General Meeting*, 1–8.
<https://doi.org/10.1109/PESGM.2012.6344860>

A.1. Some of the data collected for this study (representation)

The screenshot displays a complex Excel spreadsheet with multiple tabs at the bottom: Sayfa1, Sheet11, Zorlu A.S. Demirciler RES, Zorlu A.S. Santepe RES, Ziyaret A.S., Ziyaret RES, ZT En. Cericakya RES, YGT E.I. Adares RES, Yeni Belem En. Senbük RES, and Yaylaköy A.S. V. The spreadsheet is filled with data organized in columns and rows. Key columns include 'Time Series...' with values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Coordinates (E)' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'General' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Conditional Formatting' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Format as Table' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Cell Styles' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Insert' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Delete' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Format' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'AutoSum' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100. The 'Sort & Filter' column shows values like 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 3

A.2. Locations information of WPPs used for developed method



RESUME

Yasemin AYAZ ATALAN

Education Information

- 2020 **Ph.D., (with High Honors), Industrial Engineering,**
Marmara University, Istanbul, TR
- 2015 **Ph.D. Research, Industrial Engineering,**
Clemson University, Clemson, USA
- 2013 **M.S., (with Honors), Civil and Environmental Engineering,**
Lehigh University, Bethlehem, USA
- 2009 **B.S., (with High Honors), Environmental Engineering,**
Sivas Cumhuriyet University, Sivas, TR

Academic Experiences

- 2018- **Research Assistant,** Yozgat Bozok Üniversitesi, Yozgat, TR
2016-2018 **Teaching Assistant,** Marmara Üniversitesi, İstanbul, TR
2015-2016 **Research Assistant,** Yozgat Bozok Üniversitesi, Yozgat, TR
2013-2015 **Research Assistant,** Clemson Üniversitesi, Clemson, ABD
2011-2013 **Research Assistant,** Lehigh Üniversitesi, Bethlehem, ABD

Areas of Research

- Renewable Energy** (Wind Power, Biofuels Energy),
Optimization (Stochastic and Nonlinear Programming),
Statistics (Design of Experiments-Quality Characteristics),
Simulation (Discrete Event Simulation Models for Renewable Energy)

Articles Published in SCI, SSCI, AHCI and ESCI Indexed Journals

Ayaz Atalan, Y., Tayanç, M. Erkan, K, Atalan, A., (2020). Development of Nonlinear Optimization Models for Wind Power Plants using Box-Behnken Design of Experiment: A Case Study for Turkey. Sustainability, 12 (15), 1-17, 6017; <https://doi.org/10.3390/su12156017>

Articles Published in TRDIZIN and Other Indexed Journals

Atalan, A., Donmez, C., **Ayaz Atalan, Y.,** (2018). Yüksek-Eğitimli Uzman Hemşire İstihdamı ile Acil Servis Kalitesinin Yükseltilmesi için Simülasyon Uygulaması: Türkiye Sağlık Sistemi. Marmara Journal of Pure and Applied Sciences, 30(4), 318-338. <https://doi.org/10.7240/marufbd.395255>.

Referred Conference / Congress / Symposium Publications in Proceedings

Atalan, A., **Ayaz Atalan, Y.** (2019). "Future of Renewable Energy Production: OECD Study. 3rd International Conference on Advanced Engineering Technologies (ICADET'19) (25), 218-222, Bayburt, TR.

Atalan, A., **Ayaz Atalan, Y.** (2019). "Logistic Performance Index of OECD Members by Estimation Series. 3rd International Conference on Advanced Engineering Technologies (ICADET'19), (25), 214-217, Bayburt, TR.

Atalan, A., **Ayaz Atalan, Y.** (2019). "Optimizing the Number of Healthcare Resources: Emergency Service Practice", Gevher Nesibe 3. Uluslararası Sağlık Bilimleri Kongresi, Malatya, TR.

Atalan, A., **Ayaz Atalan, Y.** (2019). "The Importance of Discrete-Event Simulation in Hospital Management", Gevher Nesibe 3. Uluslararası Sağlık Bilimleri Kongresi, Malatya, TR.

Ayaz Atalan, Y., Atalan, A. (2019). "Application of Design of Experiment for Hospital Management", Gevher Nesibe 3. Uluslararası Sağlık Bilimleri Kongresi, Malatya, TR.

Ayaz Atalan, Y., Atalan, A. (2019). "Developing Replication Method for Design of Experiment ", Gevher Nesibe 3. Uluslararası Sağlık Bilimleri Kongresi, Malatya, TR.

Atalan, A., **Ayaz Atalan, Y.** (2018). " Implementation of Statistical Optimization Model to Improve Quality of Healthcare System in Turkey", International Congress on Engineering and Life Science (ICELIS'18), Kastamonu University, Kastamonu, TR.

Atalan, A., **Ayaz Atalan, Y.** (2018). "Reduction of Intensity with Employment of Highly-Educated Advanced Nurses in Emergency Services: Application of Discrete-Event Simulation", International Congress on Engineering and Life Science (ICELIS'18), Kastamonu University, Kastamonu, TR.

Ayaz Atalan, Y., Atalan, A. (2018). "Optimization Applications for Renewable Energy", International Congress on Engineering and Life Science (ICELIS'18), Kastamonu University, Kastamonu, TR.

Ayaz Atalan, Y., Atalan, A. (2018). " Application of Statistical Optimization Model for Wind Energy Performance", International Congress on Engineering and Life Science (ICELIS'18), Kastamonu University, Kastamonu, TR.

Atalan, A., **Ayaz Atalan, Y.** (2018). "Enhancing the Quality of Healthcare Service: Application of Simulated Experimental Design and Optimization" 5th International Congress on Healthcare and Hospital Management, Rome, IT. DOI: 10.4172/2375-4273-C11-068.

Ayaz Atalan, Y. (2018). 7th Turkish Wind Energy Congress, Ankara, TR.

Awarded Research and Project Grants

2010 **Ministry of National Education** YLSY Scholarship

2011 **Master Project**, producing biofuel by using algae that is fed by CO₂, Lehigh University, USA

2008 **Capstone Project I**, Biogas, Sivas Cumhuriyet University, Sivas, TR

2008 **Capstone Project II**, Renewable Energy Resources, Sivas Cumhuriyet University, Sivas, TR

2008 **Capstone Project III**, Sewerage Design, Sivas Cumhuriyet University, Sivas, TR

Softwares for Analysis and Calculations in Engineering and Social Sciences

Minitab, Maple, Numbers, Simulation

Courses Taught

Journals and Book Chapters Reviewer

Environmental process and sustainable energy

