

A MACHINE LEARNING APPROACH TO ASSESSING
TÜRKİYE'S RENEWABLE ENERGY POTENTIAL AND
ENVIRONMENTAL PROTOCOL COMPLIANCE

A THESIS
SUBMITTED TO ABDULLAH GÜL UNIVERSITY
SOCIAL SCIENCES INSTITUTE
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF MASTER OF ARTS

By
Nurettin Şahin
May 2025
Kayseri

Nurettin ŞAHİN A MACHINE LEARNING APPROACH TO ASSESSING TÜRKİYE'S
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SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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ABSTRACT

The issue of global warming has been identified as one of the most critical challenges of the 21st century, with the consumption of fossil fuels being identified as a major contributor to greenhouse gas emissions. In response to these challenges, countries worldwide are expediting their transition towards renewable energy sources to meet international climate commitments, such as the Paris Agreement, and to achieve long-term sustainability goals. Türkiye has established a target to achieve net-zero emissions by 2053. This objective is consistent with both the nation's domestic energy strategy and its international commitments. However, the transition from fossil fuels to renewable energy sources is impeded by geographical, economic, and technological constraints. The present study aims to assess the capacity and efficiency of renewable energy in Türkiye with environmental protocols and future electricity demand projections. Electricity generation, transmission data, and national energy plans are used to identify future electricity generation and capacity trends. In the context of this study, a range of machine learning models is executed across diverse scenarios, yielding a series of outcomes. Consequently, the repercussions of regulatory measures and financial investments were examined, and prospective inferences were derived. The findings underscore the pivotal role of scenario-based modeling in formulating sustainable energy policies and directing investment decisions within the context of climate change mitigation.

Keywords: Renewable Energy Capacity, Forecasting, Machine Learning, Energy Protocols

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ÖZET

Küresel ısınma konusu 21. yüzyılın en kritik sorunlarından biri olarak tanımlanmakta ve fosil yakıt tüketimi sera gazı emisyonlarına en büyük katkıyı yapan unsur olarak görülmektedir. Bu sorunlara yanıt olarak dünya genelinde ülkeler, Paris Anlaşması gibi uluslararası iklim taahhütlerini yerine getirmek ve uzun vadeli sürdürülebilirlik hedeflerine ulaşmak için yenilenebilir enerji kaynaklarına geçişlerini hızlandırmaktadır. Türkiye hem ulusal enerji stratejisi hem de uluslararası yükümlülükleriyle uyumlu bir hedef olan 2053 yılına kadar net sıfır emisyona ulaşma hedefini belirlemiştir. Bununla birlikte, coğrafi, ekonomik ve teknolojik kısıtlamalar nedeniyle fosillerden yenilenebilir enerji kaynaklarına geçiş zorlu bir süreçtir. Bu çalışma, çevresel protokoller ve gelecekteki elektrik talebi projeksiyonları ile Türkiye'deki yenilenebilir enerji kapasitesini ve verimliliğini değerlendirmeyi amaçlamaktadır. Gelecekteki elektrik üretim ve kapasite eğilimlerinin belirlenmesi için elektrik üretim-iletim verileri ve ulusal enerji planları kullanılmaktadır. Bu çalışma kapsamında Çoklu makine öğrenimi modeli çeşitli senaryolarda çalıştırılarak sonuçlar elde edilmiştir. Sonuç olarak, düzenleyici tedbirlerin ve finansal yatırımların yansımaları incelenmiş ve ileriye dönük çıkarımlar elde edilmiştir. Bulgular, sürdürülebilir enerji politikalarının oluşturulmasında ve yatırımların yönlendirilmesinde senaryo tabanlı modellemenin önemini vurgulamaktadır.

Anahtar Kelimeler: Yenilenebilir Enerji Kapasitesi, Tahminleme, Makine Öğrenmesi, Enerji Protokolleri

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LIST OF ABBREVIATIONS

AEP	Annual Energy Production
ARDL	Autoregressive Distributed Lag
ARIMA	Autoregressive Integrated Moving Average
BPIE	Buildings Performance Institute Europe
CCMS	Climate Change Mitigation Strategy
CCS	Carbon Capture and Storage
CCU	Carbon Capture and Utilization
CHP	Combined Heat and Power
DFM	Dynamic Factor Model
EMRA	Energy Market Regulatory Authority
ETS	Exponential Smoothing
EU	European Union
FB Prophet	Facebook Prophet
GHG	Greenhouse Gases
GLM	Generalized Linear Model
GLS	Generalized Least Squares
GW	GigaWatt
GWh	Gigawatt-hour
HEMS	Home Energy Management System
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
LCOE	Levelized Cost of Electricity

MAE	Mean Absolute Error
MFA	Ministry of Foreign Affairs
ML	Machine Learning
Mtoe	Million Tonnes of Oil Equivalent
NDC	Nationally Determined Contribution
NG	Natural Gas
NPP	Nuclear Power Plant
NPV	Net Present Value
NRE	Non-Renewable Energy
PV	Photovoltaic
RES	Renewable Energy Sources
RMSE	Root Mean Square Error
SBB	Strateji ve Bütçe Başkanlığı
SDGs	Sustainable Development Goals
SMAPE	Symmetric Mean Absolute Percentage Error
SoC	State of Charge
TEİAŞ	Türkiye Elektrik İletim Anonim Şirketi
toe	Tonne of Oil Equivalent
UNEP	United Nations Energy Programme
UNFCCC	United Nations Framework Convention on Climate Change
VAR	Vector Autoregression
VECM	Vector Error Correction Model
YEKA	Yenilenebilir Enerji Kaynak Alanı

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1. CHAPTER 1

The first chapter is comprised of two primary subjects. As stated in the introduction, energy is identified as a primary contributor to global warming. Subsequently, the contemporary energy outlook of Türkiye is presented, accompanied by an exposition of the nation's primary energy resources. In the Research Background section, the problem examined in the thesis is mentioned, and information about similar studies in the literature is given.

1.1. Introduction

Global warming has visibly affected human life in recent years. Global warming and consequent climate change allow pests and pathogens to spread more effectively. [1]. This situation poses serious risks to children and the elderly. Apart from the health problems, global warming also damages the ecological balance. Compared to before the Industrial Revolution, the temperature of the Earth has increased by 1.1 degrees. [2]. This situation affects natural disasters such as forest fires, floods, and storms. If necessary, precautions are not taken, the Arctic region will be completely ice-free in summer within 15 years. [2]. To take measures against global warming, the main causes of this problem must first be identified. The structure of modern society is based on energy. However, it is seen that the resources used in energy production contribute significantly to global warming. 3 billion people depend on fossil fuels in their daily activities [3]. In addition, 0.3 degrees of the 1-degree increase in temperature is due to fossil fuels. [4]. This makes fossil fuels the main cause of global warming. For this reason, many countries, especially the European Union, are increasing their orientation to renewable energy sources. However, since electricity is not a storable resource, effective energy management is required to meet the demand. [5]. This depends on accurate forecasts of energy demand.

Fossil fuels are widely recognized as the primary contributors to climate change and greenhouse gas emissions. In response to these challenges, both developed and developing countries have expedited their transition to clean and renewable energy sources. This transition is driven by international climate commitments, including the Paris Agreement and the European Green Deal [6]. Türkiye possesses considerable

potential in the realm of renewable energy, particularly regarding wind, solar, and geothermal energy sources. However, the country's energy portfolio remains heavily reliant on carbon-intensive sources, indicating a need for strategic transition towards a more sustainable energy matrix. The current electricity generation mix reveals that coal and natural gas account for more than half of total production, while renewable energy sources remain below the threshold required to meet national emission targets and align with long-term sustainability goals.

This study makes a significant contribution to the field by developing a machine learning-based forecasting framework to analyze renewable energy capacity and utilization rates in Türkiye. This study offers actionable insights into how Türkiye can strategically prioritize renewable technologies to reduce its dependence on fossil fuels and move toward its 2053 Net Zero Emissions Target. Contrary to the extant literature, which has historically focused on techno-economic aspects, policy analysis, or local energy forecasts, this study presents an integrated analysis that incorporates multiple dimensions, including environmental constraints, regulatory frameworks, and economic feasibility.

The impetus for this research is the pressing need for evidence-based energy planning that fosters a sustainable and equitable transition. Electricity, a resource that is challenging to store, necessitates precise demand forecasting and effective management to ensure reliability and affordability. This study addresses these challenges by modeling multiple future scenarios to evaluate different pathways toward a cleaner and more resilient energy system. These methodological innovations enhance the predictive accuracy and policy relevance of the findings, making them applicable not only to Türkiye but also to other developing economies facing similar energy transition challenges.

The motivation for this study arises from the urgent need for climate action and the requirement for scalable solutions that facilitate the decarbonization of the electricity sector. Given the rising global temperatures, the increasing occurrence of extreme weather events, and the growing pressure on governments to meet international climate commitments, transitioning from fossil fuels to renewable energy has become necessary, not optional. However, shifting to a low-carbon future is a

complex, multi-layered process that requires coordinated efforts in technological innovation, economic incentives, and regulatory changes. This study aims to contribute to this transition by providing a structured, data-driven method for forecasting and optimizing energy systems.

Furthermore, the alignment of this research with the United Nations Sustainable Development Goals (SDGs) underscores its broader societal impact. Specifically, the findings support SDG 7 (Affordable and Clean Energy) by promoting the use of cost-effective renewable technologies; support SDG 13 (Climate Action) through scenario-based analysis of strategies to phase out fossil fuels; SDG 11 (Sustainable Cities and Communities) by reducing urban air pollution associated with fossil fuel combustion; and SDG 8 (Decent Work and Economic Growth) by assessing employment opportunities in the renewable energy sector. These contributions underscore the necessity of incorporating environmental, economic, and social considerations into energy planning processes [7].

Moreover, this research emerged from the realization that many countries, including Türkiye, lack a unified framework that combines long-term policy goals with short- and medium-term operational decisions. The proposed methodology addresses this gap by offering a flexible and adaptable modeling approach that can be updated with new data and adjusted to reflect changing policy priorities. This aspect renders the study particularly valuable for stakeholders interested in strategic energy planning, investment decisions, and climate policy implementation. The objective of this study is to furnish decision-makers with reliable, transparent, and actionable insights that support a fair, inclusive, and sustainable energy transition.

In the subsequent section, an examination of Türkiye's energy outlook is conducted, followed by a comprehensive review of the extant literature. The present study will be supported by a review of relevant literature.

1.1.1. Türkiye's Energy Outlook

Türkiye's energy landscape has undergone a significant transformation over the past century, shaped by economic development, population growth, and evolving

technological capabilities. As a country with limited domestic fossil fuel reserves, Türkiye has historically relied on imports to meet a significant portion of its energy needs. However, recent years have seen an increasing emphasis on utilizing domestic resources, particularly renewable energy, to enhance energy security and sustainability [8].

Hydroelectric power plants accounted for 31% of total installed electricity generation capacity [9], highlighting their long-standing significance in the national energy mix [10]. In addition, coal-fired thermal power plants have played a major role in electricity generation since the mid-20th century, with facilities such as the Çatalağzı Thermal Power Plant being among the earliest [11].

Electricity consumption has steadily increased over time, rising from 128.3 TWh in 2000 to 306.7 TWh in 2020, representing an average annual increase of 4.4%. The share of electricity in final energy consumption was recorded at 21.8% in 2020, indicating a growing trend towards electrification across multiple sectors [9].

The following sections provide an overview of Türkiye's main energy sources, distinguishing between renewable and fossil-based resources, and analyzing their historical development and status.

1.1.1.1. Renewable energy sources

Türkiye's geographical location and climatic conditions suggest considerable potential for renewable energy development. The Ministry of Energy and Natural Resources has underscored the pivotal role that renewable energy will play in addressing future energy demands, while concomitantly reducing carbon emissions and enhancing energy security [12].

1.1.1.1.1. Hydropower

Hydropower has been one of the most mature and widely used renewable energy sources in Türkiye. The first major hydroelectric plant, the Sürgücü Hydroelectric Power Plant, was commissioned in the 1930s. By the 1930s, large dams began to be

constructed, and hydropower became the dominant source of electricity generation [10].

As of June 2022, hydroelectric capacity reached 31,558 MW, accounting for 31% of total electricity generation capacity. These plants are described as environmentally friendly and cost-effective in operation [10].

1.1.1.1.2. Wind energy

Türkiye's wind energy potential is particularly high along coastal areas and elevated inland regions. According to the Turkish Wind Atlas, strong wind speeds at 100 meters above ground level indicate high suitability for large-scale wind farms. By 2022, installed wind power capacity had reached significant levels, contributing to the diversification of the energy supply [13].

1.1.1.1.3. Solar energy

With an average annual sunshine duration of 2,741 hours and a solar radiation value of 1,527.46 kWh/m²/year, it is evident that Türkiye possesses considerable solar energy potential [14]. The government has implemented policies designed to promote solar energy, resulting in a consistent increase in installed capacity.

1.1.1.1.4. Geothermal energy

Türkiye ranks among the top countries globally in geothermal energy potential, particularly in Western Anatolia. Applications include electricity generation, district heating, and thermal tourism. As of 2022, about 15% of geothermal heat was used for electricity production [15].

1.1.1.1.5. Biomass

Biomass resources in Türkiye include agricultural residues, forestry waste, animal manure, and municipal solid waste. Recoverable biomass energy potential is approximately 3.9 MTEP/year [16]. These resources offer decentralized energy solutions and contribute to emission reduction efforts [16].

As of 2020, the share of renewable energy sources in electricity generation was approximately 42.4%, with intermittent renewables such as wind and solar contributing 11.7% of total generation. This transition is indicative of Türkiye's advancements towards a more sustainable and robust energy infrastructure [11].

1.1.1.2. Fossil energy sources

Despite the growing emphasis on renewable energy, fossil fuels remain dominant in Türkiye's energy structure. In 2020, fossil fuels accounted for approximately 83.3% of primary energy consumption, with coal, oil, and natural gas being the main contributors [9].

1.1.1.2.1. Coal

Coal, particularly lignite, has historically played a major role in Türkiye's electricity generation. However, new investments in coal-fired power generation face challenges, including environmental concerns and financial viability. Several coal-fired power plants were operational as of 2022, contributing significantly to electricity generation [9].

Projections indicate that by the year 2030, the installed capacity from domestic coal-fired power plants will amount to 1.7 GW. In 2022, an additional 1.3 GW from imported coal-fired power plants was brought online [9].

1.1.1.2.2. Oil

Türkiye is highly dependent on imported oil, with domestic production meeting less than 10% of demand. In 2020, crude oil production was relatively low compared to import volumes, indicating a heavy reliance on foreign supplies. Crude oil reserves were estimated at around 70 million tons as of 2022 [14].

1.1.1.2.3. Natural gas

Natural gas has become increasingly important since the 1990s, especially in electricity generation and industrial use. In 2020, natural gas contributed 23.1% to

electricity generation. Although no large-scale gas-fired power plants were under construction at the time, natural gas remained a key component of the energy mix due to its flexibility and lower carbon footprint compared to coal [9].

As of 2022, the primary energy consumption composition was as follows: coal (21.4%), oil (26.5%), and natural gas (22.5%) [11].

1.2. Research Background

The present chapter is comprised of two sections: the problem statement and the literature review. In the initial section, a comprehensive definition of the problem is articulated. In the subsequent section, an investigation is conducted into extant literature on the subject, with the salient studies being outlined in summary.

1.2.1. *Problem Statement*

The increasing global reliance on fossil fuels has led to significant environmental challenges, with fossil fuel combustion accounting for approximately 30% of global warming per 1°C temperature increase [4]. As a result, fossil fuels are widely recognized as the primary driver of climate change and greenhouse gas emissions. In response, both developed and developing countries have accelerated their transition toward clean and renewable energy sources to meet international climate commitments, such as the Paris Agreement and the European Green Deal [6].

In Türkiye, the utilization of fossil fuels remains a significant component of the electricity generation mix. The breakdown of the country's electricity generation is presented below: The following energy sources were identified: 34.6% from coal, 22.2% from natural gas, 20.6% from hydropower, 10.8% from wind, 4.7% from solar, 3.3% from geothermal, and 3.7% from other sources [9]. Despite growing investments in renewable energy and policy incentives such as feed-in tariffs, auctions under the Yenilenebilir Enerji Kaynak Alanı (YEKA) scheme, and grid access improvements, Türkiye remains heavily dependent on carbon-intensive energy sources [17].

While Türkiye possesses considerable potential for renewable energy — particularly wind, solar, and geothermal — there is a need for strategic investment prioritization based on resource efficiency, geographical suitability, and long-term sustainability. The current energy mix suggests that renewable energy technologies are not yet fully optimized to replace fossil fuels at the necessary scale to meet national emission targets and align with international climate goals.

The present study addresses the critical challenge of identifying renewable energy capacity and efficiency for large-scale investments in Türkiye. The objective of the research is to utilize machine learning algorithms for the analysis of renewable energy capacity and utilization rates, with consideration for environmental protocols and national energy targets. The findings will provide data-driven insights into which renewable energy technologies should be prioritized to support Türkiye's energy transition, reduce carbon emissions, and enhance energy security in alignment with its 2053 Net-Zero Emission Target [18].

1.2.2. The Literature Review

The global shift toward renewable energy sources is driven by the urgent need to reduce greenhouse gas emissions and ensure long-term energy security. As fossil fuels remain a major contributor to climate change, many countries have begun implementing national strategies to promote cleaner and more sustainable energy systems [4]. In this context, Türkiye has been actively working to diversify its energy mix, with increasing emphasis on solar, wind, hydroelectric, and biomass energy sources.

This section presents an overview of renewable energy technologies, reviews previous studies on renewable energy forecasting, and explores existing literature related to Türkiye's energy policies and modeling approaches.

1.2.2.1. Forecasting techniques

Electrical energy is an indispensable part of the modern social order. The household appliances we use in our daily lives, the industrial machines in factories,

the X-Rays and ECG used to detect diseases in the health sector, and the lights that illuminate the world at night are all closely linked to the existence of electricity [5] . Although electricity is mainly produced from fossil fuels today, the importance of renewable energy sources is increasing daily. The main reasons for this are the decrease in fossil fuel reserves and the destructive effects of these resources on the environment. According to the United Nations website, electricity generation from renewable energy can take 6 forms: hydroelectric power plants, solar energy, wind energy, geothermal energy, ocean energy, bioenergy. In hydroelectric power plants, electricity is produced by turning the turbines with the power of water flow, while in wind power plants, the power of the wind is used. In addition, photon energy is converted into electrical energy using photovoltaic systems in solar power plants. In addition, it is possible to produce electricity with biomass energy, which has become popular in recent years. Although there are many alternatives for electricity production, the existence of these resources varies according to climate and various other events [19] . Since electricity is not a storable resource, effective energy management is required to meet the demand [5]. For this reason, the need must be met quickly and effectively. However, the volatile and fluctuating nature of renewable energy requires precise forecasting of electricity generation and acting according to the need.

The following subsections are examined to understand the research principles of renewable energy forecasting. Subsection that models evaluation metrics are used in machine learning models, especially in renewable energy forecasting. The following subsections review the studies on wind, hydroelectric, and biomass renewable energy sources, respectively.

1.2.2.1.1. Model evaluation metrics

Evaluation metrics show the performance and accuracy of the model and allow us to improve the model according to the metric values. Coefficient of regression (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Mean Absolute Error (MAE), Normalized Mean Absolute Error (NMAE), and Mean Absolute Percentage Error (MAPE) are used in machine learning models. In general, evaluation metrics can give different values according to

the structure of the model and data. For this reason, it is more appropriate to use more than one metric for a model [20], [21].

The metric results obtained by applying different models to the same data show which model gives better results for the relevant source [20]. When comparing models, the model with a smaller evaluation metric means that it gives more accurate results. However, the coefficient of regression (R2) metric determines how well the model predictions approximate the real data points [20].

1.2.2.1.2. ML models for wind systems

Wind energy enables hourly production and can produce for 24 hours under favorable conditions, since it depends on the weather [22]. In this respect, wind energy is a very popular energy source. However, wind energy can vary depending on weather events [22]. For this reason, it is very difficult to create a forecasting model for wind energy. In the literature, a forecasting model was created by collecting the data from 36 wind turbines located in the northwest of Türkiye [19]. In this study, parameters such as wind speed, wind direction, and turbine capacity were analyzed, and 5 different machine-learning models were tested. These are random forest, gradient boosting machine (GBM), k-nearest neighbor (kNN), decision tree, and extra tree regression. The necessary hyperparameters are selected empirically while creating the models [19]. In this study, firstly, the data are analyzed, and outlier and normalization processes are performed. Afterward, the models are applied to the data, and the results are evaluated [19]. In another study, wind energy forecasting is made from a more general point of view, but from a Türkiye-specific perspective. Using 2017 to 2018 weather data, the study uses a gradient boosting machine (GBM), k-nearest neighbor (kNN), decision tree, and extra tree regression models in the same way as the other study. Unlike the other study, it also uses a support vector machine (SVM) [22].

According to the results, random forest, gradient boosting machine (GBM), k-nearest neighbor (kNN), decision tree, and extra tree regression models appear to be very effective in short-term wind energy forecasting for both research. The evaluation metrics for the first research are as follows: MAE value of 0.0277, MAPE value of 0.3310, RMSE value of 0.0672, MSE value of 0.0045, and R2 value of 0.9651 (Alaraj,

Alsaidan, Rizwan, & Singh, 2021). In the other study, Random Forest has the lowest RMSE value (0.991) [22].

1.2.2.1.3. ML models for hydro power plants

Hydroelectric energy has a more stable structure compared to other renewable sources. Hydroelectric power plants built on dams can reach their maximum production capacity in a short time, depending on the amount of reserved water. Hydroelectric energy is the most used energy source in Türkiye after coal [23]. However, due to the variability of dam reserves depending on temperature and climate, estimation models have an important place in the use of this resource. The study on the Almus Dam in Tokat draws attention to the literature. In this study, a forecasting model is created by using different machine learning models with monthly hydropower production data between 1993 and 2013. These models are Artificial Neural Network (ANN), Support Vector Machine (SVM), and Deep Learning (DL). The article aims to compare the machine learning models used for making short-term predictions [23]. Incoming water, incoming flow, and lake water level are used as the main parameters. First, the author reveals the relationship between these parameters and the amount of energy production, then applies the models and analyzes which model is suitable for the data.

When looking at the results in general, correlation values were taken as the evaluation metric for the three machine-learning models. This shows that the models used in this study were not fully analyzed. Using several different evaluation metrics is a necessary method to fully reveal the model and data relationship [20]. However, the research in question has achieved remarkable results because it works in a very local area. The squared correlation values are 0.587, 0.466, and 0.995 for Artificial Neural Network (ANN), Support Vector Machine (SVM), and Deep Learning (DL), respectively. According to the results, Deep Learning (DL) is the most suitable machine learning [23].

1.2.2.1.4. ML models for biomass systems

Biomass energy is an energy source that has become popular in recent years. In this system, which is based on electricity production from animal manure, Biogas, coal, and CO₂ emissions occur apart from electricity production. It is the source that has the least share in electricity production, where the amount of electricity produced and the difficulty of the process are considered. However, if this system is not used in animal husbandry, CH₄ gas naturally spreads to the atmosphere and negatively affects global warming. Related to this, there is a study conducted in the Western Mediterranean Region of Türkiye. Different machine-learning models have been created with data collected from the provinces such as Antalya, Isparta, and Burdur, where livestock and agriculture are developed in this region. These models are support vector machine (SVM), multi-layer perception (MLP), and linear regression (LR). Mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R²) were used as evaluation metrics [24].

The findings concerning the biogas potential, CO₂ emission, electricity production, and thermal energy estimation SVM models are considered the most optimal models, exhibiting a coefficient of determination value (R²) of 0.999. An analysis of the coal amount estimation reveals that the LR models yield superior outcomes in comparison to the SVM and MLP models, with an R² value of 0.997 [24].

1.2.2.1.5. Energy cost optimization

Economic efficiency is a critical criterion in the planning and operation of energy systems. The intricate interplay among escalating energy demands, evolving production methodologies, and the pursuit of sustainability objectives has culminated in the formidable challenge of maintaining cost-effectiveness in energy management. A multitude of studies in the extant literature address these issues. One such study proposes a multi-objective optimization model for designing an optimal hybrid renewable energy system (HRES) connected to a grid. The primary objectives of the model are threefold: first, to minimize system cost, fuel cost, and emissions; second, to enhance the reliability of renewable energy sources; and third, to achieve these objectives while ensuring the long-term sustainability of the system. The paper's opening section is dedicated to a discussion of the various renewable energy technologies, including solar, wind, and hydro, with a focus on an analysis of their

respective advantages and disadvantages. The subsequent presentation of the multi-objective optimization problem's detailed mathematical formulation incorporates constraints associated with power generation, battery state-of-charge, and limitations imposed by the diesel generator [25].

The authors have implemented a multi-objective evolutionary algorithm to solve the optimization problem and identify the best configuration of the HRES in terms of the number of solar panels, wind turbines, batteries, and diesel generators. The findings indicate the efficacy of the proposed approach in attaining optimal power generation, cost reduction, and emission mitigation in comparison to individual renewable energy systems. The paper provides valuable insights into the design and operation of hybrid renewable energy systems, which may prove useful for researchers and practitioners working in this field [25].

S. Lee and Y. Yoon [26] proposed a novel methodology for minimizing electricity expenditures in energy storage systems (ESS) by integrating a genetic algorithm (GA) with dynamic programming (DP). The study's primary focus was on the scheduling challenges associated with energy storage systems (ESS) under time-of-use (TOU) pricing frameworks, with a particular emphasis on the integration of renewable energy sources. The analysis encompassed scenarios that incorporated and excluded demand charges, offering a comprehensive assessment of the impact on system performance and operational efficiency. The authors developed a combined genetic algorithm (GA) and dynamic programming (DP) method with adjustable base unit sizes in DP to enhance efficiency. To this end, they conducted extensive simulations using various commercial electricity load profiles and renewable energy generation scenarios. Their research demonstrated improved performance in terms of cost savings and computational time, especially when using larger base units (e.g., 10 kWh) in DP. The study demonstrated the efficacy of the proposed method for both cases with and without demand charges, providing practical solutions for ESS scheduling in commercial settings. This research makes a significant contribution to the field of ESS optimization by offering a novel approach that balances economic performance and computational efficiency. This approach has the potential to advance the implementation of smart grid technologies and renewable energy integration.

1.2.2.2. Energy regulation and policy framework in Türkiye

Türkiye has been undergoing a significant transformation in its energy policy framework over the past two decades, driven by increasing energy demand, growing environmental concerns, and the need for greater energy security. The country's regulatory environment reflects both national priorities and international commitments, particularly within the context of climate change mitigation and sustainable development goals.

1.2.2.2.1. National energy strategies and plans

One of the most comprehensive frameworks guiding Türkiye's energy future is the National Energy Plan, which outlines long-term strategies for achieving energy independence and aligning with Türkiye's net-zero emissions target by 2053 [9]. This plan emphasizes diversification of the energy mix, increased use of domestic resources, and integration of renewable energy technologies across sectors.

In parallel, the Second National Energy Efficiency Action Plan focuses on reducing energy intensity through targeted measures in buildings, industry, transportation, and public institutions. These plans are part of Türkiye's broader effort to reduce fossil fuel dependency and improve overall efficiency, in line with EU directives and global best practices [12].

1.2.2.2.2. Renewable energy policies and incentives

Türkiye has implemented various support mechanisms to promote renewable energy sources, including feed-in tariffs, auctions under the Yenilenebilir Enerji Kaynak Alanı (YEKA) scheme, and tax exemptions for renewable energy investments [8].

Several studies have analyzed the effectiveness of these policies. Türkiye has abundant renewable energy potential, particularly in wind, solar, and geothermal—the implementation of supportive policies has been inconsistent due to institutional and financial barriers [27]. Similarly, Basaran et al. (2015) emphasize that alignment with

EU energy policies could enhance Türkiye's renewable energy deployment and integration into regional markets [28].

EU accession negotiations have significantly influenced Türkiye's renewable energy legislation, especially regarding market liberalization and grid access for renewables [29].

Türkiye ratified the Kyoto Protocol and became a party to the United Nations Framework Convention on Climate Change (UNFCCC), demonstrating its commitment to addressing global warming [18]. More recently, Türkiye signed the Paris Agreement in 2016 and submitted its Nationally Determined Contribution (NDC), pledging to reduce greenhouse gas emissions by 41% by 2030 compared to business-as-usual scenarios [6].

In response to these commitments, Türkiye developed its Climate Change Adaptation Strategy and Action Plan (2024–2030) and the Climate Change Mitigation Strategy and Action Plan, aiming to mainstream low-carbon development across all economic sectors. These strategies provide a roadmap for integrating climate resilience into infrastructure planning, energy systems, and land use policies.

The study titled “Türkiye's Decarbonization Roadmap: Net Zero by 2050” highlights the importance of transitioning from coal-based generation to cleaner alternatives such as natural gas, hydrogen, and renewables, while also investing in carbon capture and storage technologies in the medium term [30].

1.2.2.2.3. Research and development in renewable energy

A key component of Türkiye's long-term energy strategy is the role of innovation and R&D investment. An empirical analysis conducted between 1998 and 2021 found a unidirectional causality relationship between renewable energy consumption to R&D expenditures, indicating that increased adoption of renewables has stimulated technological development [31].

This finding underscores the importance of strengthening public-private partnerships and increasing funding for research projects aimed at improving efficiency and reducing costs in renewable energy technologies.

Energy sector reform began in earnest after the enactment of the Electricity Market Law No. 4628 (2001) and the Natural Gas Market Law No. 4646, which introduced market liberalization and encouraged private sector participation. The establishment of the Energy Market Regulatory Authority (EMRA) marked a turning point in the regulation of electricity and natural gas markets [9].

Further legislative developments include amendments to the Renewable Energy Law, which improved licensing procedures and promoted large-scale investments in wind and solar power. However, challenges remain, such as bureaucratic delays and insufficient incentives for small-scale producers [32].

1.2.2.2.4. EU integration and energy policy alignment

Türkiye's progress toward harmonizing its energy policies with the European Union has had a notable impact on its regulatory landscape. EU conditionality has played a critical role in shaping Türkiye's legal and institutional framework, particularly in areas related to cross-border interconnections and transparency in energy pricing [33].

Furthermore, EU directives on energy efficiency and renewable targets have influenced Türkiye's approach to setting national benchmarks and developing monitoring tools [34]. Despite these positive developments, structural weaknesses persist, including limited institutional capacity and a lack of enforcement mechanisms.

1.2.2.2.5. Challenges and future outlook

While Türkiye has made substantial progress in updating its energy regulations and promoting renewable energy, several challenges remain. These include:

- Overreliance on imported fossil fuels
- Inconsistent implementation policy

- Limited financial and technical capacity for decentralized energy systems
- Insufficient awareness and engagement of local communities in energy transition processes

However, recent strategic documents such as the Climate Change Mitigation Strategy and Action Plan and the 12th Development Plan (2024–2028) indicate a clear shift toward more integrated and forward-looking governance models. These plans aim to strengthen policy coherence, enhance stakeholder coordination, and mobilize international financing for green infrastructure projects [35].

1.3. Thesis Structure

The remainder of the thesis adheres to the following structure.

The second chapter of the text provides a detailed exposition of the data structure employed for the purpose of forecasting, as well as the mathematical models that underpin this process. Additionally, the text delves into the intricacies of forecasting models, the application of scenarios, and the assessment of metrics.

The third chapter of the text delineates the implementation of the methodologies and the ensuing outcomes. The results of the study are presented in a scenario-based manner, with the different approaches employed being outlined. The forecasting results are analyzed for varying scenarios, and the scenario-based error rates of the models used are presented.

In the fourth chapter, a comprehensive overview of the thesis is provided, along with a discussion of future research plans and the social implications of the thesis and its contribution to global sustainability.

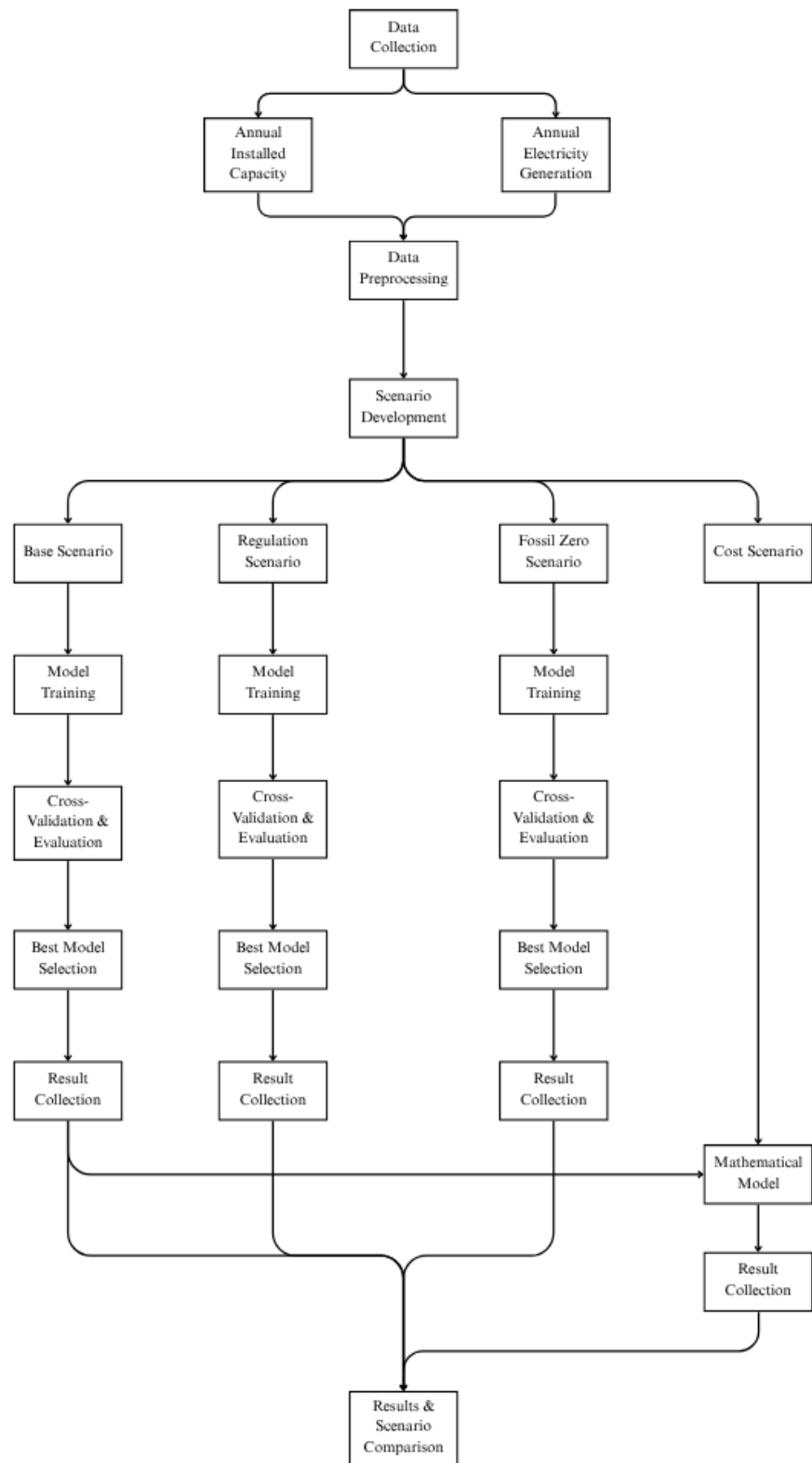
2. CHAPTER 2

2.1. Research Methodology

This chapter is devoted to an examination of the status of the main data, forecast models, and scenarios used. A comprehensive evaluation of the source and status of the data was conducted, culminating in the presentation of a thorough overview of the 19 forecast models. A total of four different scenarios are then described, each using the aforementioned models. The subsequent chart delineates the methodological framework.

As illustrated in Figure 1.2.2.1, the methodology commences with the data collection phase. Subsequently, the collected data undergoes a preliminary editing phase to ensure its viability for subsequent analysis. Subsequent to this, the scenario is configured and the model sets for each scenario are executed. These model sets are then executed on the training data, yielding error rates that are subsequently analyzed. Subsequently, the results are obtained for the prediction time over the models that have been determined to be the most effective. The final stage of the research process involves a comparison of the scenario results.

Figure 1.2.2.1 Methodology Flowchart



2.1.1. Data Structure

The present thesis undertakes a thorough examination of the viability of attaining its stated objectives by means of a meticulous forecast of Türkiye's prospective capacity in alignment with environmental protocols. Therefore, it is imperative that the dataset to be utilized is both historical and accurate, with documentation provided by the state. In recent years, there has been a proliferation of institutions that provide production data, particularly in the domain of renewable energy. However, these institutions were not utilized to collect and disseminate data due to limitations in time and scope. The substantial number of models to be utilized, in conjunction with the considerable period covered by the forecast, necessitates a transition from daily or hourly production forecasts to annual production forecasts. Consequently, it was deemed appropriate to collect data on an annual basis through TEİAŞ, the entity responsible for Türkiye's electricity distribution operations.

This section presents the structure and historical development of Türkiye's electricity generation and installed capacity from renewable and fossil energy sources between 1940 and 2023. The data was obtained from official records published by TEİAŞ covering nearly a century of transformation in Türkiye's energy system [36].

Two primary datasets were used in this study:

Table 2.1.1.1 Annual Electricity Generation by Source

Field Name	Description
Year	Year of electricity generation (1940–2023)
Renewable Energy	Total annual electricity generation from renewable energy
Fossil Energy	Total annual electricity generation from fossil energy

Table 2.1.1.2 Annual Installed Capacity by Source

Field Name	Description
Year	Year of electricity generation (1940–2023)
Renewable Energy Capacity	Total installed capacity of renewable energy

Fossil Energy Capacity	Total installed capacity of fossil energy
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Both datasets are structured with consistent time intervals and standardized units, enabling comparative analysis across decades.

Türkiye's electricity generation has undergone significant changes over the past century. Initially dominated by hydropower and coal, the country gradually transitioned toward natural gas and, more recently, wind and solar energy.

Table 2.1.1.3 summarizes selected years to illustrate key trends in total electricity generation and the share of renewable and fossil sources.

Table 2.1.1.3 Selected Years of Electricity Generation (GWh)

Year	Renewable Energy (GWh)	Fossil Energy (GWh)	Total Generation (GWh)	Renewable Energy Share (%)
1940	13.80	383.00	396.80	3.48%
1970	3,032.80	5,590.20	8,623.00	35.17%
2000	30,987.40	93,934.20	124,921.60	24.81%
2010	55,380.10	155,827.60	211,207.70	26.22%
2020	123,900.50	182,802.60	306,703.10	40.40%
2023	131,304.10	199,844.80	331,148.90	39.65%

From Table 2.1.1.3, it is evident that although fossil fuels have historically dominated electricity generation, the contribution of renewable energy has grown significantly since the 2000s. By 2023, renewables accounted for nearly 40% of total electricity production, primarily driven by hydroelectric power and an increasing share from wind and solar.

Table 2.1.1.4 provides insight into the infrastructure development of the electricity sector. Over time, Türkiye has expanded both its fossil and renewable energy capacities, with a noticeable acceleration in renewable investments after 2010.

Table 2.1.1.4 Selected Years of Installed Capacity (GW)

Year	Renewable Capacity (GW)	Fossil Capacity (GW)	Total Capacity (GW)	Renewable Energy Share (%)
1940	0.0100	0.2100	0.2200	3.59%
1970	0.7300	1.5100	2.2300	32.45%
2000	11.2100	11.1800	22.3900	50.08%
2010	17.2500	15.8300	33.0800	52.14%
2020	48.1000	30.9800	79.0800	60.82%
2023	61.0700	31.9600	93.0400	65.65%

The data reveals a major shift in Türkiye’s energy mix, particularly from 2010 onwards. While fossil fuel capacity grew steadily during earlier decades, renewable capacity has surged in recent years, largely due to policy incentives such as feed-in tariffs and auctions under the Yenilenebilir Enerji Kaynak Alanı (YEKA) scheme.

Türkiye’s energy system has experienced a remarkable transformation over the last eight decades. In the early years (1940–1970), hydropower was the dominant renewable source, while fossil fuels—mainly lignite and oil—supported industrialization and urbanization. During this period, fossil energy constituted most of the total generation, with limited investment in alternative technologies.

From 1970 to 2000, fossil fuel consumption rose sharply due to economic expansion and infrastructure development. Coal and natural gas became dominant in new power plant constructions. However, the beginning of the 21st century marked a turning point, as Türkiye started to invest heavily in renewable energy sources, especially wind and solar. Policy reforms, including market liberalization and support mechanisms like YEKA tenders, played a crucial role in accelerating this transition.

Between 2010 and 2023, renewable energy capacity increased from 17.2 GW to 61.1 GW, representing a growth of over 255%. This increase was primarily driven by the expansion of solar and wind power installations, supported by favorable geographic conditions and growing international pressure to reduce carbon emissions. Meanwhile, fossil energy capacity only increased from 15.8 GW to 31.96 GW, showing a much slower rate of growth compared to renewables.

In terms of actual electricity generation, the share of renewables reached 131,304 GWh (39.7%) in 2023, compared to 199,845 GWh (60.3%) from fossil fuels. This represents a substantial shift from earlier decades, where fossil fuels often contributed more than 80% of total generation. The rapid growth in renewable energy output aligns with Türkiye's broader goals of improving energy security, reducing dependence on imported fuels, and meeting climate targets such as the Paris Agreement and the national net-zero emission goal set for 2053.

When comparing the two datasets, it becomes clear that while fossil fuels still contribute a larger portion of electricity generation, their growth has slowed significantly in recent years. On the other hand, renewable energy sources have shown exponential growth in both installed capacity and actual generation, indicating a long-term structural shift in the country's energy strategy.

A combined view of the datasets shows that while fossil fuels have historically been the mainstay of Türkiye's electricity supply, renewable energy has gained momentum starting in the early 2000s. Between 1940 and 2023:

- Renewable energy generation increased by more than 4000%.
- Fossil fuel generation increased by around 400%, but with greater volatility due to price fluctuations and geopolitical factors.
- Renewable installed capacity grew by more than 7800%, reflecting a strong commitment to clean energy deployment.

These figures highlight the importance of policy-driven investments and technological advancements in shaping Türkiye's energy future. The government's focus on diversification, grid modernization, and regional energy cooperation will be essential to sustain this trend.

2.1.2. Evaluation Metrics

In machine learning and forecasting models, the evaluation of model performance is a critical step to ensure accuracy, reliability, and generalization capability. Various metrics are used to assess how well a model predicts outcomes,

especially in energy forecasting applications such as renewable and fossil-based electricity generation prediction.

This study employs three widely accepted error measurement metrics:

- Symmetric Mean Absolute Percentage Error (SMAPE)
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)

These metrics allow for both relative and absolute comparisons between predicted and actual values, providing insights into the model's predictive capabilities across different scenarios.

2.1.2.1. Symmetric mean absolute percentage error (SMAPE)

SMAPE is a symmetric variation of the traditional Mean Absolute Percentage Error (MAPE) that addresses some of its limitations, particularly asymmetry and instability when actual values approach zero. It provides a normalized measure of forecast accuracy, making it especially useful in contexts where percentage errors are more interpretable than absolute errors.

Mathematical Definition:

(Equation 1. SMAPE)

$$SMAPE = \frac{100\%}{n} \sum_{t=1}^n \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2}$$

Where:

F_t: The forecast value at time *t*

A_t: The actual value at time *t*

n: Total number of observations

t: Observation with the specific time stamp

SMAPE ranges from 0% to 200%, with lower values indicating better accuracy. Unlike MAPE, SMAPE avoids infinite or undefined results and penalizes overestimation and underestimation equally. This makes it a more balanced metric for

evaluating forecasts in renewable energy modeling, where actual values can be highly variable or near-zero.

A low SMAPE value (e.g., below 10%) indicates high accuracy in percentage terms, while a high SMAPE (e.g., above 50%) suggests significant discrepancies between predicted and actual values, especially in volatile datasets like energy production [37].

2.1.2.2. Mean absolute error (MAE)

MAE calculates the mean absolute error (MAE) across a set of predictions, disregarding the direction of errors. The proposed model offers a straightforward interpretation of the average error, expressed in the same unit as the data. This feature facilitates intuitive comprehension for decision-makers.

Mathematical Definition:

(Equation 2. MAE)

$$MAE = \frac{1}{n} \sum_{t=1}^n |F_t - A_t|$$

Where:

F_t : The forecast value at time t

A_t : The actual value at time t

n : Total number of observations

t : Observation with the specific time stamp

MAE is a simple and robust metric that treats all individual differences equally and does not exaggerate large errors. In this study, MAE is preferred for reporting average error magnitudes in gigawatt-hours (GWh), as it directly reflects the deviation in the same unit as the target variable.

A low MAE value indicates small average deviations between predicted and observed values, suggesting consistent model behavior. Conversely, a high MAE

implies larger average errors, which may indicate poor model fit or issues with input data quality.

MAE is a more natural and unambiguous measure of average error compared to RMSE. It is also less sensitive to outliers and provides a clearer picture of the central tendency in prediction errors [38].

2.1.2.3. Root mean square error (RMSE)

RMSE is defined as the square root of the mean of the squared differences between the predicted and observed values. This metric assigns greater weight to larger errors due to the squaring operation, rendering it more sensitive to outliers than MAE.

Mathematical Definition:

(Equation 3. RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (F_t - A_t)^2}{n}}$$

Where:

F_t : The forecast value at time *t*

A_t : The actual value at time *t*

n: Total number of observations

t: Observation with the specific time stamp

RMSE is particularly useful when large errors are undesirable and should be penalized more heavily. However, RMSE is often misinterpreted as a direct measure of average error. RMSE depends not only on the average error but also on the variance of the error distribution and the number of observations *n*. Therefore, it should not be used as a standalone measure of average error [38].

A low RMSE typically corresponds to low variability in errors and small deviations from actual values. A high RMSE, on the other hand, may be caused by either a few very large errors or a generally dispersed error pattern. Thus, RMSE is most informative when used in conjunction with MAE.

2.1.3. Forecasting Models

This section provides a concise yet comprehensive overview of the machine learning and time series forecasting models used in this study to analyze Türkiye's renewable and fossil-based electricity generation and installed capacity data. Each model has been selected based on its suitability for capturing specific characteristics of the dataset, such as trend, seasonality, multivariate dependencies, or nonlinear patterns. The following subsections provide brief descriptions and application areas for each model.

2.1.3.1. Window regression

Window regression is a modeling approach where a fixed window of past observations is used as input features to predict future values. It assumes linear relationships between lagged inputs and outputs. This method is commonly applied in short-term energy production and consumption modeling, especially when stationarity can be assumed or achieved through differencing [37].

2.1.3.2. Rolling regression

Rolling regression is a methodological framework for analyzing time series data, where the linear regression model is applied to overlapping windows. The text emphasizes the practical applications of the subject and the efficacy of its implementation. Rolling regression models are a type of statistical model that utilizes dependent variables, such as stock price, and independent variables, such as time or economic indicators, to provide dynamic information about associations over time [39].

2.1.3.3. PyTorch forecasting

PyTorch Forecasting is a Python library that is built on top of the PyTorch deep learning framework. The system under consideration supports various recurrent neural network (RNN)-based architectures, including long short-term memory (LSTM), gated recurrent unit (GRU), and transformer models, which have been tailored for time series forecasting tasks. This tool is particularly suitable for high-dimensional and complex time series data, such as multi-source renewable energy generation prediction involving wind speed, solar irradiance, and temperature [40].

2.1.3.4. Basic linear model

A fundamental tenet of a basic linear regression model is the assumption of a linear relationship between the predictor variables and the target variable. The model has been demonstrated to be effective in the modeling of fundamental energy forecasting problems in scenarios where relationships are approximately linear, such as the prediction of power output based on solar irradiation levels [41].

2.1.3.5. Univariate regression

Univariate regression is a predictive modeling technique that involves the use of a single input variable, also known as a "feature", to predict a single output variable. This contrasts with multivariate regression, in which multiple input variables are utilized to predict a single output variable. Univariate regression methods are designed to identify the relationship between the input and output variables, thereby facilitating the estimation of predictions. Common univariate regression methods include linear regression, polynomial regression, and logistic regression [42].

2.1.3.6. Datepart regression

Datepart regression incorporates temporal components (e.g., hour, day of week, month, year) into the model to capture seasonal patterns in the data. It is useful for load forecasting and short-term renewable energy modeling, where periodicity plays a significant role [43].

2.1.3.7. Vector error correction model (VECM)

VECM is designed for non-stationary but cointegrated time series data. It captures both long-run equilibrium relationships and short-run dynamics. It is applicable to analyze long-term interactions among multiple energy-related time series, such as electricity prices, fossil fuel costs, and renewable generation [44].

2.1.3.8. Preprocessing regression

Refers to applying regression techniques after preprocessing steps such as normalization, outlier removal, or feature engineering. It is used in any forecasting task where raw data needs transformation before modeling, particularly useful for handling missing data and irregular sampling in historical energy datasets [45].

2.1.3.9. Multivariate regression

Multivariate regression extends linear regression by incorporating multiple explanatory variables. It is widely used in renewable energy forecasting, where meteorological factors (e.g., wind speed, solar radiation, ambient temperature) affect output [43].

2.1.3.10. Dynamic factor model

Dynamic factor models extract common latent factors from large datasets and use them to forecast key variables. These models reduce dimensionality while retaining most of the information contained in the original variables. They are ideal for modeling aggregated energy production across different regions or sources in Türkiye, especially under heterogeneous input conditions [46].

2.1.3.11. Preprocessing experts (domain-specific preprocessing)

Involves domain-specific preprocessing methods such as decomposition, standardization, and scaling tailored to the energy sector. It is used to prepare time series data for forecasting by removing noise and extracting interpretable components [47].

2.1.3.12. Facebook prophet (FB prophet)

Developed by Meta (formerly Facebook), this model automatically detects trends, seasonality, and holiday effects in time series data. It is well-suited for daily and hourly energy forecasts with strong periodicity and external event effects (e.g., weekends, holidays) [48].

2.1.3.13. Neural prophet

Neural Prophet enhances FB Prophet by integrating neural networks to model nonlinearities and interactions. It improves upon Prophet for complex systems where linear assumptions are insufficient, such as energy generation affected by variable weather conditions [49].

2.1.3.14. Exponential smoothing (ETS)

Exponential smoothing applies weighted averages to past observations, assigning exponentially decreasing weights over time. It is effective for short-term energy demand and production forecasting [43].

2.1.3.15. Autoregressive integrated moving average (ARIMA)

ARIMA combines autoregression (AR), differencing (I), and moving average (MA) components to model non-stationary time series. It is widely used in electricity demand and generation forecasting due to its robustness in modeling trends and cycles [50].

2.1.3.16. Autoregressive distributed lag (ARDL)

ARDL extends traditional autoregressive models by incorporating lags of both dependent and independent variables, allowing for both short- and long-run relationships. It is used to examine the relationship between energy generation and climate variables in Türkiye [51].

2.1.3.17. Generalized linear models (GLM)

GLM extends ordinary least squares regression by allowing response variables to follow distributions from the exponential family, such as Poisson, Gamma, or Normal. It is applicable when energy consumption or generation follows count-like behavior, e.g., hourly meter readings or discrete energy events [52].

2.1.3.18. Generalized least squares (GLS)

GLS accounts for heteroskedasticity or autocorrelation in the error terms, providing more efficient estimates than ordinary least squares (OLS). It is used when error variance is not constant, e.g., in energy forecasting with structural breaks or volatility [53].

2.1.3.19. Vector autoregression (VAR)

VAR models the interdependencies among multiple time series, making it suitable for multivariate energy systems. It is used to analyze interactions between energy generation, consumption, and external variables like temperature or wind speed [54].

Table 2.1.3.1 Forecasting Models

Model Name	Type	Input Type	Use Case / Remarks
Window Regression	Linear Regression	Univariate	Predict future values using a fixed window of historical data
Rolling Regression	Linear Regression	Univariate	Applies regression over moving windows for dynamic time series modeling
PyTorch Forecasting	Deep Learning	Multivariate	Recurrent neural networks for complex temporal dependencies
Basic Linear Model	Linear Regression	Univariate	Simple linear relationship between input and output variables
Univariate Regression	Linear Regression	Univariate	Uses one independent variable to predict the target
Datepart Regression	Linear Regression	Multivariate	Incorporates date/time components to capture seasonality and periodicity

Vector Error Correction Model (VECM)	Time Series	Multivariate	Captures long-run equilibrium and short-run dynamics in cointegrated series
Preprocessing Regression	Preprocessing + Regression	Multivariate	Applies regression after normalization, outlier removal, or feature engineering
Multivariate Regression	Linear Regression	Multivariate	Considers multiple input variables (e.g., weather, policy indicators)
Dynamic Factor Model	Time Series	Multivariate	Extracts latent factors from large datasets for aggregated forecasting
Preprocessing Experts (Domain-Specific Preprocessing)	Preprocessing Tool	Multivariate	Domain-specific preprocessing (e.g., decomposition, scaling) for better forecasting
Facebook Prophet (FB Prophet)	Time Series / Heuristic	Univariate	Detects trends, seasonality, and event effects (e.g., holidays, weekends)
Neural Prophet	Deep Learning / Hybrid	Multivariate	Enhances Prophet with neural networks for nonlinear patterns
Exponential Smoothing (ETS)	Time Series	Univariate	Assigns exponentially decreasing weights to past observations
Autoregressive Integrated Moving Average (ARIMA)	Time Series	Univariate	Models' trends and cycles in time series without exogenous variables
Autoregressive Distributed Lag (ARDL)	Linear Regression	Multivariate	Examines short- and long-run relationships between energy generation and external factors
Generalized Linear Models (GLM)	Linear Regression	Multivariate	Suitable for non-normal distributions (e.g., count-based generation data)
Generalized Least Squares (GLM)	Linear Regression	Multivariate	Accounts for heteroskedasticity or autocorrelation in error terms
Vector Autoregression (VAR)	Time Series	Multivariate	Models' interdependencies among multiple time series (e.g., demand, generation)

Table 2.1.3.1 above provides a structured overview of the 19 forecasting models used in this study, categorized according to their methodological features, linearity, input types, and applicability to power generation forecasting. The models encompass a wide spectrum, ranging from classical linear regression techniques to advanced deep learning and hybrid approaches. This comprehensive methodological framework

offers a multifaceted approach to analyzing Türkiye's future electricity generation capacity. The multivariate dependence of the data set used and the wide range of forecasts necessitated the use of a comprehensive set of models. Simpler models, such as ARIMA and exponential smoothing, are well-suited for short-term forecasts with clearly defined temporal structures. Conversely, more complex models, including LSTM/GRU-based deep learning and Neural Prophet, are adept at managing high-dimensional and variable datasets. In scenario-based approaches, this comprehensiveness and diversity have been demonstrated to increase accuracy. This diversified modeling approach facilitates a comparative assessment of forecast accuracy across different energy sources and time horizons, thereby providing evidence-based insights into Türkiye's long-term energy transition pathways.

The subsequent section will discuss four distinct scenarios that were developed for the scenario-based approach.

2.1.4. Scenarios

The following section will discuss four distinct scenarios. In order to facilitate a comprehensive analysis of the results and to ascertain the impact of different approaches on the outcomes, scenario-based forecasting is employed.

Table 2.1.4.1 Scenarios

Scenario	Objective	Methodology / Modeling Approach
Base Scenario	Set a foundation for future projections without relying on outside assumptions	Machine learning models trained in historical generation data
Regulation Scenario	Analyze energy capacity under national policies and environmental goals	Time series modeling with policy-driven capacity inputs
Fossil Zero Scenario	Explore full decarbonization of electricity generation by 2050	Extends the Regulation Scenario with a fossil phase-out assumption
Cost Scenario	Find the most economically efficient mix of renewable and fossil energy sources	Extends the Base Scenario with a Linear Programming (LP) optimization

Table 2.1.4.1 offers a comprehensive overview of the various scenarios. The base scenario is estimated using production data, while the regulation scenario uses production data as well as forward-looking installed capacity data. The fossil zero scenario is predicated on the objective of eliminating fossil fuel use by the year 2050. It employs a cost-focused approach, leveraging a forward-looking energy demand and cost model to optimize the base scenario result. This section will provide information on the four scenarios in the following order: base, regulation, fossil zero, and cost scenarios.

2.1.4.1. Base scenario

The base scenario represents the fundamental modeling approach used in this study, where only historical data on annual electricity generation from renewable and fossil energy sources are used to project future trends without incorporating external assumptions or policy interventions. This scenario serves as a reference point for all other forecasting cases, allowing for a direct comparison of how additional variables and model enhancements affect prediction accuracy and long-term projections.

The dataset used in the base scenario spans from 1940 to 2023 and includes annual electricity generation values in gigawatt-hours (GWh) for both renewable energy and fossil energy sources. These data were obtained from the official records of the Turkish Electricity Transmission Corporation (TEİAŞ), which aggregates information from over 1,200 power plants across the country, including hydroelectric, wind, solar, geothermal, coal-fired, natural gas, and oil-based generation units [8], [36].

This long-term dataset enables the identification of structural changes in Türkiye's electricity generation mix and provides a robust foundation for time series modeling. The primary objective of the base scenario is to understand the natural progression of energy production patterns and to establish a benchmark for evaluating more complex forecasting approaches that incorporate policy preferences, technological developments, and climate change mitigation strategies.

In this scenario, machine learning models are trained solely on past observations, assuming that future generations will follow similar trends observed historically. Therefore, no additional features such as carbon prices, installed capacity expansions, or energy efficiency improvements are included in the modeling process. Instead, the focus is on capturing the inherent dynamics of the energy system based on its historical behavior.

By analyzing the 84-year trajectory of electricity generation, the base scenario also highlights key inflection points in the evolution of Türkiye's energy infrastructure. This makes it possible to assess whether the current trend alone is sufficient to meet national renewable energy targets or if targeted interventions are necessary.

2.1.4.2. Regulation scenario

This study utilizes a combination of historical and forward-looking datasets to model Türkiye's renewable energy capacity and utilization rates in alignment with environmental protocols and national policy preferences. The primary dataset includes annual electricity generation values from both renewable and fossil-based sources for the period 1940–2023. This data was obtained from the official records of the Turkish Electricity Transmission Corporation (TEİAŞ), which aggregates reports from over 1,200 power plants across the country [8], [36]. As described in the base scenario, this dataset serves as the foundation for time series analysis and provides insights into the structural changes in Türkiye's electricity generation mix over nearly a century.

In addition to the generation data, the installed capacity figures for renewable and fossil-based sources were also integrated into the modeling process. These values, covering the same historical period (1940–2023), reflect the potential output of each energy source and allow for more accurate forecasting by incorporating technological constraints and expansion trends. The historical installed capacity data indicates that renewable energy sources have grown significantly since the early 2000s, particularly wind and solar technologies, while fossil fuel-based capacity has stabilized or declined slightly after years of rapid growth [9].

To account for regulatory influences and long-term policy goals, a forward-looking installed capacity dataset was introduced, extending projections up to 2050. This dataset was constructed based on strategic documents such as the Twelfth Development Plan (2024–2028), the Climate Change Mitigation Strategy and Action Plan (2024–2030), and the Türkiye National Energy Plan 2022, which outlines the country’s roadmap toward achieving net-zero emissions by 2053 [12].

These plans emphasize the increasing role of renewable energy sources in meeting future demand, aiming to raise the share of renewables in total installed capacity to 69.1% by 2053, with particular focus on wind and solar technologies. They also project a decline in coal-fired generation and limited new investments in natural gas infrastructure, aligning with international commitments under the Paris Agreement and the Kyoto Protocol [8][55],[6].

The forward-looking dataset shows a significant increase in renewable energy capacity, growing from 61.07 GW in 2023 to an estimated 196.40 GW by 2050, indicating more than a threefold increase in less than three decades. In contrast, fossil-based installed capacity is projected to rise from 31.96 GW in 2023 to 57.02 GW by 2050, suggesting a continued reliance on fossil fuels despite the expansion of renewables. This trend reflects ongoing investments in natural gas infrastructure and the gradual phase-out of coal-fired plants over time, rather than an immediate decline in fossil-based generation capacity [9].

These projections are not only informed by technical feasibility but also shaped by regulatory frameworks and climate action strategies. For instance, the Climate Change Mitigation Strategy and Action Plan (2024–2030) sets clear targets for reducing greenhouse gas emissions, promoting domestic energy production, and improving grid flexibility through battery storage and hydrogen integration [12]. Similarly, the Türkiye National Energy Plan 2022 forecasts a continuous rise in intermittent renewables such as wind and solar, supported by increased investment and favorable geographic conditions [12].

By integrating these regulatory assumptions and policy-driven capacity expansions, the regulation scenario offers a structured view of how Türkiye’s energy

system may evolve under consistent implementation of climate policies. It enables a comparison between current trends and targeted outcomes, helping to assess whether the nation can meet its sustainability objectives without compromising energy security or economic development.

2.1.4.3. Fossil zero scenario

The fossil zero scenario builds upon the assumptions and modeling framework of the regulation scenario but introduces a complete phase-out of fossil fuel-based electricity generation by 2050. This scenario reflects an ambitious transition pathway aligned with Türkiye's net-zero emissions target for 2053, aiming to eliminate coal, natural gas, and oil-based power generation in favor of renewable energy sources, nuclear energy, and emerging technologies such as hydrogen and synthetic methane.

Like the regulation scenario, this approach integrates historical data on annual electricity generation (1940–2023) and installed capacity (1940–2023), sourced from the official reports of the Turkish Electricity Transmission Corporation (TEİAŞ). These datasets provide a long-term view of Türkiye's energy infrastructure development and serve as a foundation for forecasting future trends using machine learning models [36].

In addition to historical data, forward-looking projections up to 2050 are used to guide model training and scenario analysis. The dataset includes projected increases in renewable energy and a gradual reduction in fossil-based installed capacity starting from 2035 onwards. Unlike the regulation scenario, which assumes a stabilization of fossil fuel usage at around 60 GW by 2050, the Fossil Zero scenario envisions a systematic decline in fossil-based generation capacity, reaching zero by 2050 [9].

This transition is based on policy documents such as the Türkiye National Energy Plan 2022, the Climate Change Mitigation Strategy and Action Plan (2024–2030), and the long-term vision outlined in the Twelfth Development Plan (2024–2028). These strategic frameworks emphasize the increasing role of renewables and the need to reduce dependence on imported fuels, particularly after 2035 [9], [12].

According to the forward-looking installed capacity data:

- In 2024, fossil-based installed capacity stands at 46.89 GW, while renewable energy capacity is at 65.47 GW.
- By 2035, fossil-based capacity remains relatively high at 60.61 GW, but it begins to decline afterward.
- From 2036 onward, fossil fuel-based capacity decreases annually and reaches 57.02 GW by 2050, indicating a gradual retirement of coal and gas-fired plants in line with their technical lifespans.
- Meanwhile, renewable energy capacity continues to grow, reaching 196.4 GW by 2050, more than triple its 2023 value of 61.07 GW.

This trajectory suggests a strategic shift away from fossil fuels, where new investments in coal or gas-fired power plants are not considered viable beyond 2035. Instead, the gap left by decommissioned fossil plants is filled through increased deployment of wind, solar, and storage technologies, supported by nuclear power expansion and hydrogen integration.

The Fossil Zero scenario assumes that by 2050, all electricity generation will come from domestic and clean energy sources, including:

- Wind and solar farms
- Hydroelectric and geothermal plants
- Nuclear power plants (e.g., Akkuyu)
- Battery storage systems
- Demand-side response mechanisms
- Green hydrogen and synthetic methane production units

This scenario also aligns with Türkiye's international commitments under the Paris Agreement and the Kyoto Protocol, reinforcing the country's contribution to global climate goals. It represents a policy-driven decarbonization strategy that prioritizes sustainability, energy independence, and environmental protection.

By comparing the base scenario (which assumes no regulatory interventions) with the regulation scenario (which follows national policy preferences), the Fossil Zero scenario serves as an aspirational benchmark for evaluating how far-reaching

changes in energy infrastructure can be achieved without relying on carbon-intensive sources.

2.1.4.4. Cost scenario

This study incorporates electricity generation costs into the modeling process to evaluate the economic viability of renewable and fossil-based energy sources under different scenarios. The cost scenario is built upon the base dataset containing annual electricity generation values from 1940 to 2023, sourced from the official reports of TEİAŞ.

The predominant methodology employed for the evaluation of generation costs is the Levelized Cost of Electricity (LCOE). The LCOE is an extensively utilized metric for the appraisal of the economic viability of disparate electricity generation technologies over the course of their lifecycle. It is defined as the average total cost per unit of electricity generated, accounting for all capital, operational, and maintenance expenses spread across the project's lifespan [56]. The LCOE is a particularly useful metric for comparing energy sources such as coal, natural gas, wind, solar, nuclear, and hydroelectric power on a consistent financial basis.

The levelized cost of electricity (LCOE) is determined by dividing the net present value (NPV) of the total cost of constructing and operating an onshore total discounted electricity output by the duration of its lifetime.

(Equation 4. LCOE)

$$LCOE = \frac{\sum_{t=1}^n \frac{(I_t + M_t + F_t)}{(1+r)^t}}{\sum_{t=1}^n \frac{(E_t)}{(1+r)^t}}$$

Where:

- I_t : Investment costs in year t
- M_t : Operations and maintenance (O&M) costs in year t
- F_t : Fuel costs in year t (zero for renewables)
- E_t : Electricity generation in year t
- r : Discount rate (reflecting the time value of money and project risk)

- n : Lifetime of the system in years

Equation 4 ensures that both future costs and revenues are discounted to their present values, making it possible to compare projects with different lifespans, capital intensities, and operational profiles.

Recent reports published by the International Renewable Energy Agency (IRENA), Renewable Power Generation Costs in 2023, indicate that the LCOE of wind and solar energy has continued to decline globally. According to IRENA's findings, utility-scale solar photovoltaic systems now have a global weighted average LCOE below \$0.05/kWh, while onshore wind averages around \$0.04/kWh. These values suggest that renewables have become more economically competitive than many fossil-based alternatives, especially when externalities such as carbon emissions are internalized through policy mechanisms [57].

In contrast, fossil-fuel-based generation continues to face cost variability due to global market dynamics, fuel price fluctuations, and environmental regulations. Coal-fired power plants, which historically provided relatively low-cost electricity, now exhibit higher lifecycle costs due to stricter emission controls and reduced investment attractiveness. Natural gas-fired plants remain flexible and efficient but are subject to volatility in gas prices and geopolitical uncertainties affecting supply chains.

Table 2.1.4.2 2023 Weighted Average LCOE

Energy Source	Weighted Average Cost (USD/kWh)
Renewable Energy	0.0677
Fossil Energy	0.1000

Table 2.1.4.2 presents a comparative overview of the levelized cost of electricity generation for renewable and fossil fuel-based energy sources in Türkiye. According to data from 2023, the weighted average cost of renewable energy generation is approximately 0.07 USD per kilowatt-hour (USD/kWh). This finding suggests that renewable energy technologies have become increasingly cost-competitive in

comparison to traditional fossil fuel-based power generation. This finding is consistent with global trends documented by the International Renewable Energy Agency (IRENA) in its 2023 report, Renewable Power Generation Costs. The report indicates a decline in the costs of wind and solar technologies, attributable to advancements in manufacturing processes, enhanced efficiency, and the implementation of policy frameworks that are conducive to development [57].

The cost scenario assumes that future investments will prioritize technologies with lower LCOE values. Historical data shows that the share of renewables in electricity generation increased significantly after 2010, coinciding with falling technology costs and improved grid integration.

To ensure consistency with real-world applications, the cost scenario uses current LCOE benchmarks rather than speculative future cost reductions. While long-term forecasts anticipate continued declines in renewable energy costs, particularly for solar and offshore wind, these assumptions are reserved for later phases of the study. For this phase, actual LCOE values from 2020 to 2023 were used to train the models, allowing for a realistic assessment of recent economic trends without assuming aggressive technological breakthroughs.

This approach aligns with Türkiye's broader energy strategy, which emphasizes the importance of cost-effective and sustainable energy solutions. As outlined in the Türkiye National Energy Plan, the country aims to achieve net-zero emissions by 2053 while ensuring the affordability and reliability of electricity supply [9]. The cost scenario contributes to this objective by identifying the most economically viable pathways for expanding renewable capacity and phasing out high-cost fossil fuel options.

The decreasing LCOE of renewables is primarily driven by technological advancements, economies of scale, and supportive policies such as auctions, feed-in tariffs, and tax incentives. In particular, the LCOE of solar photovoltaic systems has fallen dramatically since 2010, making them one of the most cost-efficient energy sources worldwide. Similarly, wind energy has seen steady improvements in turbine efficiency and financing structures, further reducing its levelized cost [57].

For fossil fuels, LCOE remains highly sensitive to fuel prices. Natural gas, for instance, saw significant cost fluctuations during the period 2020–2023 due to global supply chain disruptions and geopolitical tensions. Coal-fired generation also became less competitive due to rising carbon prices and stricter environmental regulations. These factors contribute to greater uncertainty in forecasting fossil fuel-based generation costs, reinforcing the rationale for transitioning toward cleaner and more stable energy sources [57].

The cost scenario serves as a crucial component in evaluating the transition pathways proposed in other modeling approaches, including the regulation and Fossil Zero scenarios. It allows for a direct comparison between the economic performance of different energy sources and supports decision-making processes related to investment prioritization, infrastructure planning, and policy design.

3. CHAPTER 3

3.1. Method Application and Results

This section delineates the methodological approach and presents the ensuing results. The application of forecasting models to the scenarios is emphasized, and the forecasting results are analyzed.

3.1.1. Forecasting

The objective of this thesis is to analyze and forecast Türkiye’s energy capacity within the framework of environmental protocols. While this task generally involves a detailed assessment of energy production at monthly, daily, or even hourly intervals, the primary focus of this study is on evaluating Türkiye’s long-term energy capacity and its policy implications. Consequently, the analysis centers on annual production estimates. The model is employed to simulate various scenarios in order to derive policy-relevant insights and strategic outcomes.

3.1.1.1. Data gathering and preprocessing

The dataset used in this study was obtained from the official website of the Turkish Electricity Transmission Corporation (TEİAŞ). TEİAŞ operates under the supervision of the T.C. Ministry of Energy and Natural Resources and is responsible for managing Türkiye's national electricity transmission system [8],[36]. The data published by TEİAŞ is considered highly reliable as it is based on annual reports submitted by more than 1,200 power plants across the country, including both public and private facilities. These plants cover a wide range of generation technologies such as hydroelectric, wind, solar, geothermal, biomass, coal-fired, natural gas, and oil-based generators [36].

The dataset is comprised of two primary components:

Annual Electricity Generation by Source, containing yearly renewable and fossil fuel-based electricity generation values in gigawatt-hours (GWh).

Annual Installed Capacity by Source, indicating the total installed capacity for renewable and fossil fuel-based sources in gigawatts (GW).

These datasets span from 1940 to 2023, offering a long-term historical perspective on Türkiye's electricity generation and infrastructure development. Each dataset contains 84 rows, representing each year within the specified time frame, allowing for nearly a century-long analysis of the energy sector. The data is structured into three fields: Year, Renewable Energy Output (in GWh or GW), and Fossil Energy Output (in GWh or GW), providing a consistent and comparable structure over time.

Before being used for modeling, several preprocessing steps were applied to ensure accuracy and consistency. First, missing or inconsistent values were addressed by cross-referencing with older versions of TEİAŞ reports and publications from the Energy Market Regulatory Authority (EMRA). Second, all values were standardized into consistent units, GWh for generation and GW for installed capacity, to allow direct comparison between renewable and fossil energy outputs. Third, the data was aggregated by source to facilitate trend analysis and model input structuring. Fourth,

outliers and sudden fluctuations were reviewed to confirm whether they reflected actual policy changes or major technological additions rather than reporting errors. Finally, normalization was applied where necessary to improve performance in machine learning models and reduce skewness in the distribution of values.

This dataset has been frequently referenced in national and international studies due to its alignment with standards set by organizations such as the International Energy Agency (IEA) and Eurostat, making it suitable not only for descriptive analysis but also for forecasting and policy evaluation applications [9]. It serves as a foundational element for analyzing Türkiye's transition toward renewable energy and assessing the role of various energy sources in meeting future demand.

3.1.1.2. Forecasting approach

This study employs a multi-scenario forecasting framework based on historical data and forward-looking assumptions to analyze Türkiye's electricity generation capacity and utilization trends up to 2053. The dataset used in the modeling process includes annual electricity generation and installed capacity values from renewable and fossil-based sources between 1940 and 2023, as well as projected capacity figures extending up to 2050. Given the long-time span and the relatively limited number of data points compared to high-frequency datasets, forecasting over extended periods presents significant challenges in terms of accuracy and reliability.

To address these limitations, the forecasting methodology incorporates several techniques aimed at improving robustness and reducing uncertainty. These include cross-validation strategies, ensemble modeling using multiple algorithms, and iterative training procedures with increasing generation numbers. By applying cross-validation across different time windows, the models are tested under various conditions to identify those that produce the most stable and accurate results.

The model employs 19 estimation techniques and is applied to all scenarios except the cost scenario. These models are executed on the dataset to identify the most effective set of models. At this stage, cross-validation is performed for each scenario, and the results are analyzed to detect potential errors and assess model performance.

In the cross-validation process, a backward validation approach is utilized, where the dataset is split into training and testing subsets, and a five-year-ahead forecast is generated. The number of cross-validation folds is set to five, and evaluation metrics are computed based on the output of the first model. This procedure is then iteratively repeated across all models until the full set is evaluated.

In the case of the cost scenario, an optimization model is developed using linear programming (LP). This model takes the results of the base scenario as input and optimally allocates renewable and fossil fuel-based generation to meet energy demand at the lowest possible cost.

The forecasting approach is applied across four distinct scenarios. The base, regulation, fossil zero, and cost scenarios are of particular interest. In the Base Scenario, external policy and economic assumptions are not taken into account, and predictions are based exclusively on historical trends in energy production and consumption. The Regulation Scenario is predicated on the integration of national energy strategies and international climate commitments. The Fossil Zero Scenario posits a complete phase-out of coal-fired power plants by 2050 and a gradual reduction in natural gas usage, reflecting Türkiye's net-zero emissions target.

In the initial three scenarios, a total of 19 machine learning and statistical forecasting models are utilized to generate projections. These models are trained on historical data and evaluated using error metrics such as Symmetric Mean Absolute Percentage Error (SMAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). To enhance the precision of forecasts, each model is executed across multiple generations and time intervals. This approach facilitates comparative analysis and the selection of the most reliable model set. The error rates obtained are displayed in the following table. Table 3.1.1.1 contains the top 15 models that yielded the best results.

Table 3.1.1.1 Error Rates of Applied Models

Applied Model	SMAPE	MAE	RMSE
GLM	4.7698	4528.0650	5820.9372
Multivariate Regression	5.4975	8408.8248	9581.6240
Datepart Regression	5.7050	6269.5144	7016.6352
ETS	7.1253	9592.9334	10853.9730
ARDL	7.9133	7196.8112	7783.2550
GLS	8.4484	5984.2220	6735.7173
VECM	8.9231	4082.1932	5156.5198
VAR	9.4125	4363.7246	5045.0700
Rolling Regression	9.8365	10004.3304	11012.5338
ARIMA	9.9302	6426.9136	8054.6345
Preprocessing Experts	10.4343	5077.5527	5907.2829
Window Regression	11.7247	6214.2256	8658.6332
Basic Linear Model	13.9590	11894.5558	14264.0011
Univariate Regression	14.8037	11124.8800	12248.4106
Dynamic Factor	73.2611	32295.5056	32551.1581

The forecasting horizon spans 27 years, from 2024 to 2050, which introduces additional complexity due to uncertainties in future policies, technological developments, and market dynamics. To manage this challenge, forecasts are initially generated over shorter horizons (5–10 years) where models can be more effectively validated against recent trends. Once the best-performing models are identified, they are then extended to cover the full forecasting period. This stepwise approach ensures greater stability and reduces the risk of overestimating or underestimating future energy outputs.

In contrast, the Cost Scenario adopts a different methodological structure. It builds upon the output of the Base Scenario but integrates levelized cost of electricity (LCOE) values derived from IRENA reports and forward-looking investment cost estimates. This scenario applies a cost minimization logic to determine the most economically viable energy mix, considering constraints such as technical feasibility, policy preferences, and future demand projections.

In this scenario, a linear programming (LP) based optimization model is developed to minimize the total energy production cost over a defined time horizon.

The model incorporates two primary energy sources: renewable and fossil-based generation. Additionally, an unmet demand penalty term is introduced to account for potential shortfalls in energy supply.

Let T denote the number of time periods considered in the planning horizon (e.g., hours or days). For each time period $t \in \{1, \dots, T\}$, the following parameters and decision variables are defined:

Parameters:

- R_t^{pred} : Predicted renewable energy capacity at time t (GWh)
- F_t^{pred} : Predicted fossil fuel-based energy capacity at time t (GWh)
- D_t : Demanded energy at time t (GWh)
- c^R : Unit production cost of renewable energy (USD/GWh)
- c^F : Unit production cost of fossil fuel-based energy (USD/GWh)
- c^P : Penalty cost for unmet demand (USD/GWh)

Decision Variables:

- x_t^R : Amount of renewable energy produced at time t (GWh)
- x_t^F : Amount of fossil fuel-based energy produced at time t (GWh)
- u_t : Unmet energy demand at time t (GWh)

Objective Function:

The objective function is based on minimization. The objective is to minimize the total cost of production. In the function, forecasts of renewable and fossil production are multiplied by LOCE values. In the event that demand is not met, the cost of penalty is added to the total by multiplying the outsourced energy by the cost of penalty. The constraints ensure that production equals demand, thereby preventing the objective function from choosing a value of zero. In the final case, the model attempts to minimize costs while attempting to meet demand.

(Equation 5. Objective Function)

$$\min \sum_{t=1}^T (c^R \times x_t^R + c^F \times x_t^F + c^P \times u_t)$$

Constraints:

The constraints imposed on the model serve to refine it, thereby yielding the optimal result. The model's exit paths are constrained, ensuring that its operation is constrained to a specific set of results.

(Equation 6. Constraints 1)

$$x_t^R + x_t^F + U_t \geq D_t$$

Equation 6 is intended to guarantee that the total production of energy is commensurate with demand. The summation of renewable and fossil energy production is conducted, and in the event of a failure to meet demand, the amount of outsourced energy is incorporated into the total.

(Equation 7. Constraints 2)

$$x_t^R \leq 1.30 \times R_t^{pred}, \quad x_t^F \leq 1.30 \times F_t^{pred}, \quad x_t^R \geq 0, \quad x_t^F \geq 0, \quad U_t \geq 0$$

In order to prevent potential model errors, Equation 7 ensures that the production variables are restricted to non-negative values. This guarantees that the model does not produce unrealistic negative outputs. Additionally, a flexibility margin of 30% has been incorporated for both renewable and fossil fuel-based energy production. This margin can be regarded as an additional reserve capacity that production facilities may utilize in case of shortfalls in meeting demand. This approach aligns with commonly accepted short-term dispatch flexibility standards in power systems operations [58].

By integrating historical trends, regulatory frameworks, and cost efficiency considerations, this forecasting approach provides a structured and adaptable methodology for analyzing Türkiye's transition toward cleaner and more sustainable energy sources. The results serve as a foundation for assessing whether current trajectories are sufficient to meet long-term sustainability goals or if targeted interventions are necessary.

3.1.2. Results

The forecasting results for Türkiye’s electricity generation under the four scenarios—Base, Regulation, Fossil Zero, and Cost—reveal distinct trends in the evolution of renewable and fossil-based energy sources from 1940 to 2053. The graph illustrates these projections based on historical data up to 2023 and forward-looking assumptions derived from national policy frameworks, climate change mitigation strategies, and economic efficiency considerations. Renewable energy generation has shown a steady increase since the early 2000s, with wind and solar technologies contributing significantly to this growth. Fossil fuel-based generation, particularly coal and natural gas, has remained dominant until recently but is projected to decline under most scenarios after 2030.

Figure 3.1.2.1 Model Results

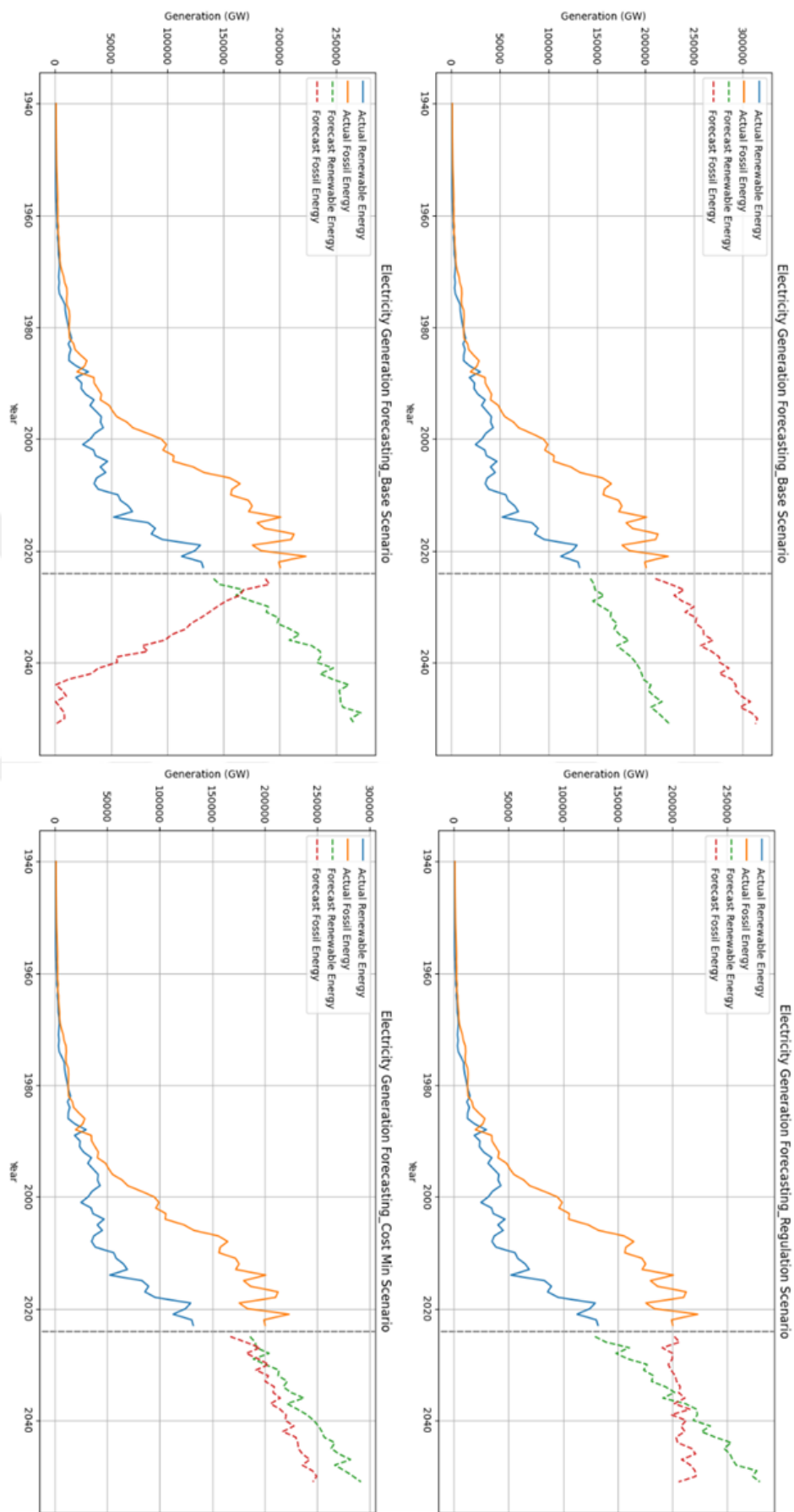


Figure 3.1.2.1 illustrates the aggregate results of four distinct scenarios. A comparison is made between the current state of the data and the forecast results on a scenario basis. Table 3.1.2.1 presents the result data for the four scenarios.

Table 3.1.2.1 Model Result

Year	Base Scenario		Regulation Scenario		Fossil Zero Scenario		Cost Scenario	
	Renewable Energy (GWh)	Fossil Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)
2024	142,590.59	209,397.75	128,617.20	201,297.61	140,690.37	186,741.04	185,367.77	166,620.57
2025	146,338.87	225,109.11	138,732.32	205,918.16	145,521.21	190,156.73	190,240.53	181,207.45
2026	147,236.43	239,086.13	160,076.62	190,097.40	167,383.93	167,434.26	191,407.36	194,915.20
2027	156,611.52	228,760.44	147,756.25	199,607.99	160,455.82	163,716.45	203,594.98	181,776.98
2028	145,113.67	236,799.23	158,735.95	199,310.69	173,992.98	151,641.55	188,647.78	193,265.13
2029	153,689.91	249,326.96	176,341.44	195,724.05	189,255.54	143,824.03	199,796.88	203,219.98
2030	163,874.59	240,078.27	173,098.02	198,211.62	187,529.53	136,665.17	213,036.97	190,915.89
2031	163,219.80	251,841.79	182,094.53	201,924.29	198,577.01	129,204.69	212,185.74	202,875.85
2032	169,956.53	250,728.94	180,313.02	203,255.01	197,231.67	120,441.55	220,943.49	199,741.98
2033	167,001.78	258,698.97	193,279.13	206,658.63	208,312.60	115,727.65	217,102.32	208,598.43
2034	172,609.48	259,169.83	201,543.23	205,069.28	217,225.46	103,401.41	224,392.33	207,386.99
2035	182,174.13	268,904.30	190,733.93	210,861.42	207,854.12	97,234.22	236,826.37	214,252.06
2036	169,780.09	255,932.62	211,148.86	201,302.58	227,889.51	76,880.09	220,714.12	204,998.59
2037	177,330.60	267,161.95	221,506.31	215,322.69	235,461.53	82,030.70	230,529.78	213,962.76
2038	184,439.87	275,172.74	222,284.44	198,669.44	235,717.92	54,096.40	239,771.84	219,840.78
2039	189,266.01	275,684.65	218,477.75	212,048.72	232,486.33	54,675.80	246,045.81	218,904.84
2040	192,833.61	285,149.44	234,244.04	207,433.74	247,191.92	38,053.43	250,683.70	227,299.36
2041	195,361.75	275,308.67	226,033.51	210,734.74	235,353.95	31,606.88	253,970.28	216,700.15
2042	196,983.73	288,104.36	238,544.38	202,729.29	246,500.29	11,536.17	256,078.84	229,009.24
2043	204,803.63	292,321.17	253,386.89	204,291.36	261,041.98	0.00	266,244.72	230,880.08
2044	202,142.35	292,074.16	246,628.58	216,861.77	252,343.81	6,066.83	262,785.05	231,431.46
2045	207,882.48	297,747.03	252,092.45	220,670.62	253,298.94	9,446.10	270,247.23	235,382.28
2046	216,303.95	307,325.70	254,504.10	207,939.93	253,509.61	0.00	281,195.14	242,434.51
2047	204,799.66	296,731.95	257,860.33	215,996.24	255,732.19	3,879.67	266,239.55	235,292.05
2048	212,006.87	308,524.00	276,677.63	220,137.06	271,750.12	7,592.79	275,608.93	244,921.94
2049	218,254.49	314,440.49	272,885.97	220,931.86	262,593.13	7,960.28	283,730.84	248,964.15
2050	224,022.16	312,523.43	279,550.27	205,083.24	266,195.72	0.00	291,228.81	245,316.78

In the Base Scenario, which assumes no major policy changes beyond current trends, renewable energy generation continues to grow at a moderate pace, reaching approximately 131,304 GWh by 2023. By 2053, it is expected to rise further, driven by market dynamics and technological advancements rather than regulatory incentives. However, fossil fuel-based generation remains relatively high throughout the projection period, indicating that without additional interventions, the transition toward renewables may not be sufficient to meet long-term sustainability targets.

The Regulation Scenario encompasses both domestic and international climate commitments, including Türkiye's net-zero emission target for 2053 and the Climate Change Mitigation Strategy and Action Plan (2024–2030). In this scenario, there is a more pronounced shift toward renewable energy sources, with installed capacity growing from 61.07 GW in 2023 to an estimated 121.89 GW by 2035. This trajectory is consistent with the objectives delineated in the Türkiye National Energy Plan 2022, which prioritizes the augmentation of the share of renewables in total electricity generation and the mitigation of reliance on imported fuels [35], [30], [9].

The Fossil Zero Scenario delineates a more aggressive pathway, projecting a complete phase-out of coal-fired power plants by 2050 and a gradual reduction in natural gas usage. This scenario is predicated on the assumption that all new investments will be directed toward clean energy technologies, such as wind, solar, and hydrogen-based systems, while existing fossil fuel infrastructure will be retired according to its technical lifespan. By the year 2050, it is projected that fossil-based generation will reach zero, enabling Türkiye to achieve full decarbonization in the electricity sector.

The Cost Scenario introduces economic considerations into the modeling process, using levelized cost of electricity (LCOE) values to determine the most economically viable generation mix. This approach builds upon the outputs of the Base Scenario but integrates cost minimization logic, prioritizing technologies with lower LCOE values. Based on IRENA reports and recent studies, wind and solar are projected to remain the most cost-effective options, leading to a significant increase in their share of total generation. In contrast, coal and oil-based generation are expected to decline due to rising costs and stricter environmental regulations [57].

When analyzing the overall composition of the graph and table, it becomes evident that all scenarios point toward a future where renewable energy dominates the electricity generation mix. However, the extent and timing of this dominance vary depending on the assumptions made in each scenario. While the Base Scenario shows a slower transition, the Regulation and Fossil Zero Scenarios indicate faster adoption

of clean energy technologies. The Cost Scenario highlights the importance of economic viability in shaping long-term energy planning decisions.

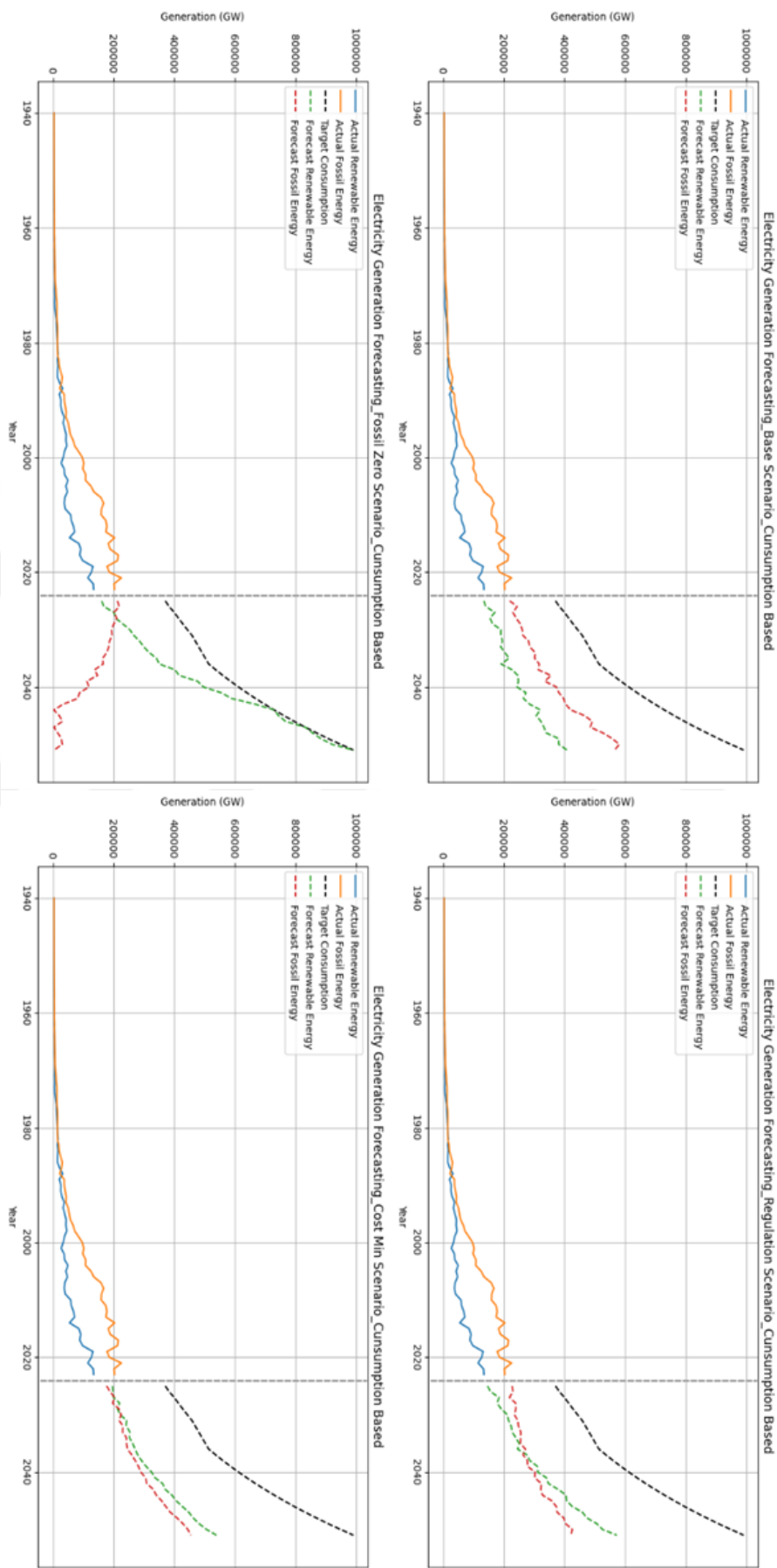
Despite the projected increases in renewable energy output across all scenarios, the total generation capacity may still fall short of meeting future demand, especially during peak periods or under conditions of high industrial activity. This suggests that additional measures, such as energy efficiency improvements, demand-side management, and increased interconnection capacity with neighboring countries, will be necessary to ensure system reliability.

The results also reflect the structural transformation of Türkiye's energy system over time. From 1940 to the early 2000s, fossil fuels were the primary source of electricity generation. However, starting in the mid-2000s, renewable energy began to play a more prominent role, particularly hydropower. Since 2010, wind and solar have gained momentum, supported by policy incentives such as feed-in tariffs and auctions under the YEKA scheme.

These findings are consistent with broader global trends, where renewable energy sources are increasingly favored due to their declining costs and environmental benefits. According to the International Renewable Energy Agency (IRENA), the LCOE of wind and solar power has fallen below that of many fossil fuel alternatives, making them the preferred choice for future investments. This supports the assumption that Türkiye can continue expanding its renewable energy capacity without compromising economic feasibility [57].

Overall, the results suggest that while Türkiye is on a clear path toward decarbonization, the speed and scale of the transition depend heavily on policy implementation, investment priorities, and technological development. Without targeted interventions, the country may not fully realize its net-zero emission goal by 2053. Therefore, strategic planning, regulatory support, and continuous model-based evaluation will be crucial for achieving sustainable and reliable electricity generation in the coming decades.

Figure 3.1.2.2 Model Results Demand-Based



The forecasting results presented in Figure 3.1.2.2 reflect a scenario where electricity generation is adjusted to align with projected consumption levels, ensuring that supply meets demand over the long-term horizon from 2024 to 2050. These demands are derived from Türkiye's strategic reports [9]. In these reports, consumption targets are not modified to assess the impact of the targeted consumption amounts on the model. This approach represents a significant shift from the base modeling framework, as it introduces forward-looking assumptions regarding energy demand, policy interventions, and technological developments. Unlike the first graph, which focused on historical trends and unadjusted projections, this version incorporates consumption-based constraints, meaning that total electricity generation is scaled up or down dynamically to match anticipated demand under each scenario. The following table illustrates the outcomes of revising the scenario results and equating them to the demand. A comparison of the results in the initial table with those in Table 3.1.2.2 reveals a substantial increase in the values.

Table 3.1.2.2 Model Results Demand-Based

Year	Base Scenario		Regulation Scenario		Fossil Zero Scenario		Cost Scenario	
	Renewable Energy (GWh)	Fossil Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)
2024	131,125.69	216,564.03	125,338.16	222,512.31	157,839.53	209,503.46	184,642.77	172,906.73
2025	137,368.68	240,727.74	140,471.21	237,784.37	164,822.16	215,377.84	188,535.84	190,630.25
2026	167,303.41	226,970.77	197,395.48	196,897.69	198,354.00	198,413.64	204,597.06	190,935.36
2027	151,690.78	237,342.24	159,332.82	229,822.92	203,262.01	207,392.51	209,381.18	190,495.40
2028	159,254.21	250,967.49	186,117.98	224,176.22	227,100.57	197,926.85	208,827.63	208,836.16
2029	187,146.44	257,446.34	227,840.40	216,756.64	249,952.75	189,950.64	227,744.12	214,506.91
2030	187,105.68	259,665.22	214,550.72	232,268.97	263,367.03	191,932.97	241,312.57	209,730.27
2031	192,162.85	278,515.16	229,845.28	240,869.74	282,518.52	183,821.48	242,773.60	225,735.40
2032	186,552.61	282,149.67	218,021.06	250,749.59	296,387.76	180,992.24	247,576.33	225,479.18
2033	200,215.84	300,239.10	244,607.58	255,883.96	313,985.81	174,434.19	253,377.85	241,052.16
2034	214,280.85	298,423.61	262,136.11	250,574.40	338,385.33	161,074.67	266,847.14	239,215.47
2035	187,983.00	313,693.25	224,203.66	277,568.50	347,799.35	162,700.65	258,961.57	247,148.45
2036	224,048.12	310,833.38	284,397.17	250,456.77	398,900.64	134,571.86	282,209.01	251,965.48
2037	243,357.99	352,395.16	303,614.03	292,146.39	413,442.57	144,036.19	299,567.13	276,997.65
2038	245,113.79	331,951.44	318,993.96	258,005.24	473,824.35	108,740.96	309,560.90	270,257.58
2039	240,412.34	370,093.60	301,518.54	309,020.38	492,868.62	115,912.12	318,470.85	291,171.82
2040	269,773.47	378,575.98	350,554.33	297,742.61	551,306.22	84,869.66	340,186.43	302,055.41
2041	261,571.54	393,666.14	329,666.44	325,589.50	586,094.22	78,709.57	351,563.95	308,462.66
2042	281,643.21	400,724.48	375,166.87	307,124.99	663,660.75	31,059.22	366,510.97	322,045.31
2043	317,252.55	417,422.77	420,175.50	314,374.46	725,982.36	0.00	397,864.14	332,432.78
2044	303,788.95	463,270.76	397,230.10	369,814.47	740,840.34	17,811.23	400,146.36	362,696.58
2045	319,288.77	488,624.52	416,136.42	391,767.61	764,288.79	28,502.10	420,412.06	379,915.97
2046	329,319.33	481,781.08	443,150.27	367,866.00	828,466.48	0.00	438,464.68	381,332.65
2047	336,231.49	523,177.30	453,946.78	405,415.19	852,809.65	12,937.82	450,967.67	411,621.65
2048	377,799.70	554,744.66	513,310.79	419,124.52	880,115.39	24,590.71	483,665.34	434,916.76
2049	377,989.31	577,449.96	513,230.72	442,131.87	917,601.58	27,816.30	498,894.68	451,518.05
2050	405,449.86	562,371.03	563,054.95	404,564.73	987,961.69	0.00	532,737.79	445,155.66

In this context, the model assumes that by 2053, Türkiye will have achieved a balanced energy system, where electricity production is fully aligned with domestic consumption needs. This adjustment ensures greater energy independence, reducing reliance on imported fuels and enhancing national energy security. Such alignment is essential for meeting future electricity demand driven by industrial growth, urbanization, and increased electrification of transport and heating systems. The plan emphasizes that without this balance, energy imports would continue to rise, leading to higher costs and exposure to international market volatility [9].

Under the Regulation and Fossil Zero Scenarios, the increase in renewable energy generation is further amplified to meet rising demand. For instance, wind and solar capacities are projected to grow from 121.89 GW in 2035 to nearly 196.4 GW

by 2050, indicating a strong commitment to expanding clean energy infrastructure. This trajectory supports the country's net-zero emission target and contributes to the decarbonization of the power sector. Meanwhile, fossil fuel-based generation is gradually reduced, not only due to environmental concerns but also because of economic inefficiencies associated with high carbon prices and declining investment attractiveness.

The Cost Scenario builds upon this logic by integrating economic efficiency into the optimization process. It assumes that the most cost-effective technologies, mainly wind and solar, will dominate new investments, while older and less efficient fossil plants will be retired earlier than their technical lifespan. This approach allows for a more realistic assessment of how energy policy and market dynamics can shape the future electricity mix, especially when aligned with consumption forecasts.

A key implication of this analysis is that adjusting generation output based on projected consumption levels leads to a more resilient and sustainable energy system. By ensuring that supply is responsive to demand changes, the model avoids both energy shortages and unnecessary overcapacity, which could lead to inefficient use of resources. Furthermore, this dynamic adjustment mechanism enables better integration of variable renewable sources, supported by hydrogen, battery storage, and demand-side response technologies.

These findings suggest that consumption-adjusted forecasting models provide a more accurate basis for strategic planning, particularly in the context of long-term energy transitions. Aligning generation with demand projections helps identify necessary capacity expansions, grid upgrades, and flexibility requirements, making it possible to assess whether current policy frameworks are sufficient to support a reliable and self-sufficient electricity system by 2053.

Figure 3.1.2.3 Model Results Nuclear Added

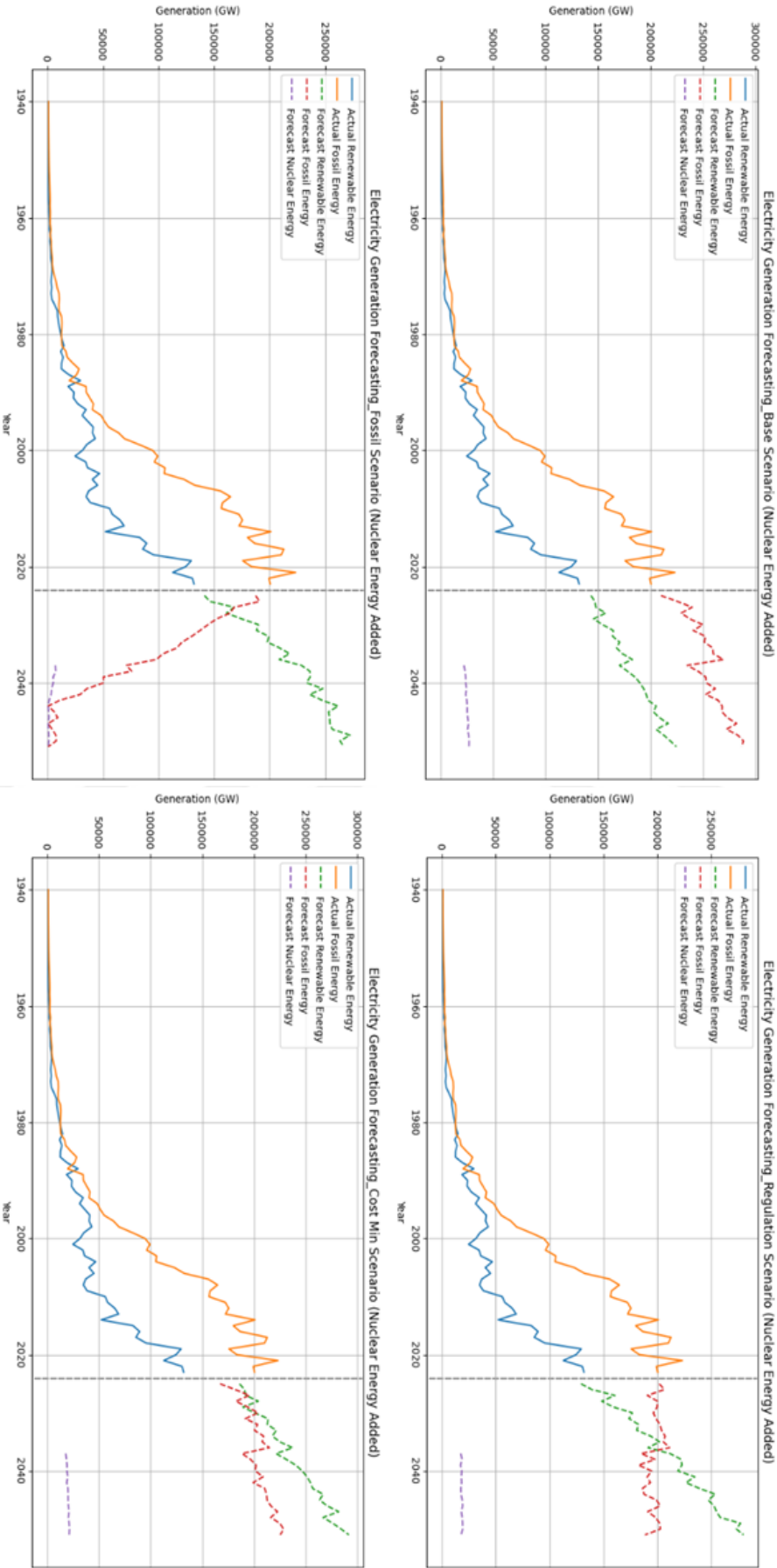


Figure 3.1.2.3 illustrates the electricity generation trends under four scenarios with the addition of nuclear energy as a key component of Türkiye's future energy mix. Unlike the previous graph, which focused solely on renewable and fossil-based generation, this version integrates nuclear power to reflect strategic planning assumptions outlined in the Türkiye National Energy Plan 2022 [9]. The inclusion of nuclear energy significantly enhances the model's capacity to meet rising electricity demand while reducing carbon emissions and reliance on imported fuels.

According to the projections, nuclear energy begins contributing to electricity generation after 2035, with its installed capacity expected to reach 7.2 GW, aligning with national policy preferences and long-term decarbonization targets. This development supports the gradual phase-out of coal-fired plants and stabilizes the transition toward a cleaner energy system by providing continuous baseload power that complements intermittent renewables like wind and solar [9]. The impact of nuclear energy is evident in Table 3.1.2.3.

Table 3.1.2.3 Model Results Nuclear Added

Year	Base Scenario			Regulation Scenario			Fossil Zero Scenario			Cost Scenario		
	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)
2024	142,590.59	209,397.75		128,617.20	201,297.61		140,690.37	186,741.04		185,367.77	166,620.57	
2025	146,338.87	225,109.11		138,732.32	205,918.16		145,521.21	190,156.73		190,240.53	181,207.45	
2026	147,236.43	239,086.13		160,076.62	190,097.40		167,383.93	167,434.26		191,407.36	194,915.20	
2027	156,611.52	228,760.44		147,756.25	199,607.99		160,455.82	163,716.45		203,594.98	181,776.98	
2028	145,113.67	236,799.23		158,735.95	199,310.69		173,992.98	151,641.55		188,647.78	193,265.13	
2029	153,689.91	249,326.96		176,341.44	195,724.05		189,255.54	143,824.03		199,796.88	203,219.98	
2030	163,874.59	240,078.27		173,098.02	198,211.62		187,529.53	136,665.17		213,036.97	190,915.89	
2031	163,219.80	251,841.79		182,094.53	201,924.29		198,577.01	129,204.69		212,185.74	202,875.85	
2032	169,956.53	250,728.94		180,313.02	203,255.01		197,231.67	120,441.55		220,943.49	199,741.98	
2033	167,001.78	258,698.97		193,279.13	206,658.63		208,312.60	115,727.65		217,102.32	208,598.43	
2034	172,609.48	259,169.83		201,543.23	205,069.28		217,225.46	103,401.41		224,392.33	207,386.99	
2035	182,174.13	268,904.30		190,733.93	210,861.42		207,854.12	97,234.22		236,826.37	214,252.06	
2036	169,780.09	234,434.28	21,498.34	211,148.86	184,393.16	16,909.42	227,889.51	70,422.16	6,457.93	220,714.12	187,778.71	17,219.88
2037	177,330.60	244,720.34	22,441.60	221,506.31	197,235.59	18,087.11	235,461.53	75,140.12	6,890.58	230,529.78	195,989.89	17,972.87
2038	184,439.87	252,058.23	23,114.51	222,284.44	181,981.21	16,688.23	235,717.92	49,552.30	4,544.10	239,771.84	201,374.15	18,466.63
2039	189,266.01	252,527.14	23,157.51	218,477.75	194,236.63	17,812.09	232,486.33	50,083.03	4,592.77	246,045.81	200,516.83	18,388.01
2040	192,833.61	261,196.89	23,952.55	234,244.04	190,009.30	17,424.43	247,191.92	34,856.94	3,196.49	250,683.70	208,206.21	19,093.15
2041	195,361.75	252,182.74	23,125.93	226,033.51	193,033.02	17,701.72	235,353.95	28,951.90	2,654.98	253,970.28	198,497.34	18,202.81
2042	196,983.73	263,903.59	24,200.77	238,544.38	185,700.03	17,029.26	246,500.29	10,567.14	969.04	256,078.84	209,772.46	19,236.78
2043	204,803.63	267,766.19	24,554.98	253,386.89	187,130.88	17,160.47	261,041.98	0.00	0.00	266,244.72	211,486.15	19,393.93
2044	202,142.35	267,539.93	24,534.23	246,628.58	198,645.38	18,216.39	252,343.81	5,557.22	509.61	262,785.05	211,991.22	19,440.24
2045	207,882.48	272,736.28	25,010.75	252,092.45	202,134.28	18,536.33	253,298.94	8,652.63	793.47	270,247.23	215,610.17	19,772.11
2046	216,303.95	281,510.34	25,815.36	254,504.10	190,472.98	17,466.95	253,509.61	0.00	0.00	281,195.14	222,070.01	20,364.50
2047	204,799.66	271,806.46	24,925.48	257,860.33	197,852.56	18,143.68	255,732.19	3,553.78	325.89	266,239.55	215,527.52	19,764.53
2048	212,006.87	282,607.98	25,916.02	276,677.63	201,645.54	18,491.51	271,750.12	6,954.99	637.79	275,608.93	224,348.50	20,573.44
2049	218,254.49	288,027.49	26,413.00	272,885.97	202,373.58	18,558.28	262,593.13	7,291.62	668.66	283,730.84	228,051.16	20,912.99
2050	224,022.16	286,271.46	26,251.97	279,550.27	187,856.25	17,226.99	266,195.72	0.00	0.00	291,228.81	224,710.17	20,606.61

In the Base Scenario, nuclear energy plays a supplementary role, helping to balance supply without altering the overall trajectory of fossil fuel use. However, under the Regulation and Fossil Zero Scenarios, nuclear becomes a core element in achieving the net-zero emission target by 2053. It ensures grid stability and enables higher penetration of variable renewable sources by acting as a dispatchable and low-carbon alternative during periods of low wind or solar availability.

The Cost Scenario further emphasizes the economic viability of integrating nuclear energy into the electricity generation mix. Despite high initial investment costs, nuclear power offers long-term operational efficiency and predictable pricing, making it an attractive option for ensuring both affordability and sustainability in the energy sector.

The integration of nuclear energy signifies a pivotal shift in Türkiye's energy strategy, with implications for enhancing energy security, aligning with climate objectives, and establishing a more dependable and balanced electricity supply infrastructure. This transition is consistent with global trends observed in other countries undergoing a similar transition toward low-carbon and diversified energy portfolios.

Figure 3.1.2.4 Model Results Demand-Based Nuclear Added

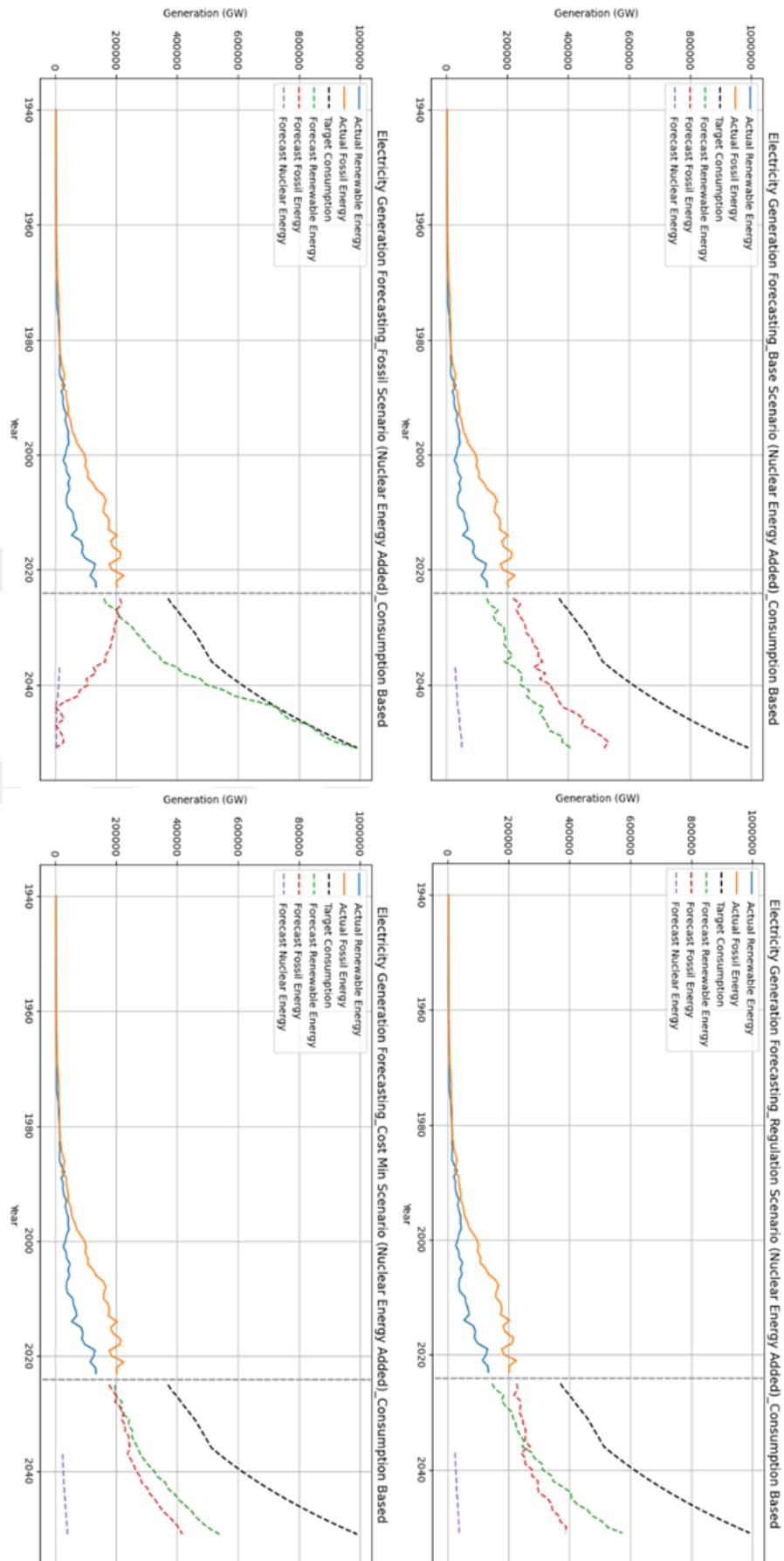


Figure 3.1.2.4 illustrates the projected electricity generation trends under four distinct scenarios after aligning production with anticipated consumption levels. This version builds upon earlier forecasting models by incorporating forward-looking assumptions related to Türkiye’s long-term energy strategy, particularly those outlined in the Türkiye National Energy Plan 2022. Unlike previous graphs that focused solely on historical generation data and policy-driven capacity expansions, this scenario-based approach ensures that supply is adjusted dynamically to match demand forecasts, aiming to achieve a fully balanced and self-sufficient energy system by 2053 [9]. Table 3.1.2.4 presents the results of the consumption-based and nuclear added scenarios.

Table 3.1.2.4 Model Results Demand-Based Nuclear Added

Year	Base Scenario			Regulation Scenario			Fossil Zero Scenario			Cost Scenario		
	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)	Renewable Energy (GWh)	Fossil Energy (GWh)	Nuclear Energy (GWh)
2024	131,125.69	216,564.03		143,208.57	224,134.43		157,839.53	209,503.46		193,454.00	173,889.00	
2025	137,368.68	240,727.74		153,042.08	227,157.92		164,822.16	215,377.84		194,722.96	185,477.04	
2026	167,303.41	226,970.77		181,376.17	215,391.47		198,354.00	198,413.64		196,582.48	200,185.16	
2027	151,690.78	237,342.24		174,677.65	235,976.86		203,262.01	207,392.51		216,951.95	193,702.57	
2028	159,254.21	250,967.49		188,431.13	236,596.30		227,100.57	197,926.85		209,944.41	215,083.01	
2029	187,146.44	257,446.34		208,493.39	231,409.99		249,952.75	189,950.64		218,083.49	221,819.89	
2030	187,105.68	259,665.22		212,252.85	243,047.15		263,367.03	191,932.97		240,116.46	215,183.54	
2031	192,162.85	278,515.16		221,129.69	245,210.31		282,518.52	183,821.48		238,400.04	227,939.96	
2032	186,552.61	282,149.67		224,413.46	252,966.54		296,387.76	180,992.24		250,719.39	226,660.61	
2033	200,215.84	300,239.10		236,040.21	252,379.79		313,985.81	174,434.19		249,088.39	239,331.61	
2034	214,280.85	298,423.61		247,564.40	251,895.60		338,385.33	161,074.67		259,565.45	239,894.55	
2035	187,983.00	313,693.25		242,457.17	268,042.83		347,799.35	162,700.65		268,024.04	242,475.96	
2036	224,048.12	284,723.38	26,110.00	273,103.94	238,497.61	21,870.96	398,900.64	123,267.83	11,304.04	276,583.04	235,310.75	21,578.72
2037	243,357.99	322,793.97	29,601.19	282,685.13	251,710.96	23,082.66	413,442.57	131,937.15	12,099.04	289,128.49	245,808.85	22,541.42
2038	245,113.79	304,067.52	27,883.92	307,623.25	251,846.92	23,095.13	473,824.35	99,606.72	9,134.24	303,914.10	255,244.51	23,406.70
2039	240,412.34	339,005.74	31,087.86	308,935.82	274,657.96	25,186.97	492,868.62	106,175.51	9,736.62	322,158.82	262,545.69	24,076.24
2040	269,773.47	346,775.59	31,800.38	337,396.21	273,682.18	25,097.49	551,306.22	77,740.61	7,129.05	333,649.74	277,113.94	25,412.20
2041	261,571.54	360,598.18	33,067.96	344,045.00	293,815.05	26,943.74	586,094.22	72,097.97	6,611.60	358,723.21	280,369.82	25,710.77
2042	281,643.21	367,063.62	33,660.86	375,552.75	292,357.17	26,810.05	663,660.75	28,450.24	2,608.97	366,743.88	300,426.10	27,549.99
2043	317,252.55	382,359.26	35,063.51	401,929.55	296,832.38	27,220.44	725,982.36	0.00	0.00	388,813.78	308,846.43	28,322.16
2044	303,788.95	424,356.02	38,914.74	403,687.28	325,147.29	29,817.00	740,840.34	16,315.09	1,496.14	403,390.59	325,419.06	29,841.92
2045	319,288.77	447,580.06	41,044.46	422,741.57	338,965.18	31,084.14	764,288.79	26,107.92	2,394.18	423,728.32	338,061.32	31,001.26
2046	329,319.33	441,311.47	40,469.61	455,942.99	341,231.51	31,291.97	828,466.48	0.00	0.00	444,896.02	351,350.54	32,219.92
2047	336,231.49	479,230.40	43,946.89	471,117.09	361,481.43	33,148.95	852,809.65	11,851.05	1,086.78	459,584.63	372,045.16	34,117.68
2048	377,799.70	508,146.11	46,598.55	503,833.62	367,199.20	33,673.29	880,115.39	22,525.09	2,065.62	479,020.74	389,927.80	35,757.57
2049	377,989.31	528,944.16	48,505.80	522,442.21	387,445.72	35,529.96	917,601.58	25,479.73	2,336.57	503,560.60	404,741.27	37,116.01
2050	405,449.86	515,131.87	47,239.17	569,884.15	382,959.03	35,118.51	987,961.69	0.00	0.00	536,250.62	413,767.34	37,943.73

The model assumes that future electricity generation will be driven not only by technological developments and resource availability but also by evolving economic and regulatory frameworks. In line with national goals for decarbonization and energy independence, the projections reflect increasing shares of renewable energy sources, supported by nuclear power and hydrogen technologies. The integration of these

elements aims to ensure grid stability and reliability, especially as fossil fuel-based generation is reduced or phased out entirely in certain scenarios.

In all scenarios, renewable energy continues to grow steadily, with wind and solar leading the expansion. The Base Scenario follows historical trends and projects moderate increases in renewables, while the Regulation Scenario incorporates policy incentives such as carbon pricing and renewable support mechanisms. The Fossil Zero Scenario assumes a complete phase-out of coal-fired plants by 2050 and limited natural gas usage beyond that point. Finally, the Cost Scenario prioritizes cost-efficient technologies, favoring wind, solar, and nuclear energy due to their declining levelized costs and high scalability.

A key feature of this analysis is the alignment of generation with projected electricity demand, ensuring that each scenario meets forecasted consumption needs without excessive reliance on imports or unsustainable infrastructure investments. This dynamic adjustment reflects real-world conditions where supply must respond to demand fluctuations and supports the assessment of whether current investment trajectories are sufficient to meet future energy requirements sustainably.

Overall, the findings indicate that a well-coordinated mix of renewable energy, nuclear power, and flexibility-enhancing technologies such as hydrogen and battery storage can enable Türkiye to achieve its net-zero emission target by 2053. These results emphasize the importance of strategic planning, consistent policy implementation, and scenario-based modeling in guiding the country's energy transition.

4. CHAPTER 4

4.1. Conclusion and Future Prospects

This section offers a comprehensive overview of the thesis. Furthermore, the social impact of the thesis result and its application to the Sustainable Development Goals are discussed. Consequently, the subsequent section delineates the projected future processes.

4.1.1. Conclusions

This study presents a multi-scenario forecasting approach to analyze the transition of Türkiye's electricity generation mix toward renewable energy sources under varying policy and economic assumptions. Based on historical data from 1940 to 2023 and forward-looking projections up to 2053, four distinct scenarios—Base, Regulation, Fossil Zero, and Cost—were developed using machine learning and optimization techniques to evaluate future energy pathways in alignment with national and international climate commitments.

The findings indicate that renewable energy sources are expected to dominate electricity generation by 2053, regardless of the scenario considered. Historical trends show that renewable energy production has increased significantly since the early 2000s, particularly wind and solar technologies. By 2023, annual renewable energy generation reached approximately 131,304 GWh, while fossil-based generation stood at 199,845 GWh. However, forward-looking projections suggest that this gap will narrow substantially over time, with renewables surpassing fossil fuels by 2035 and continuing to grow afterward.

Under the Base Scenario, which assumes no additional policy interventions beyond current trends, renewable energy continues to expand due to declining technology costs and increasing market adoption. Nevertheless, fossil fuels remain a significant contributor to total generation until 2053, indicating that without further action, Türkiye may not fully meet its net-zero emission target solely through natural progression.

In contrast, the Regulation Scenario integrates national strategies such as the Türkiye National Energy Plan 2022 and the Climate Change Mitigation Strategy and Action Plan (2024–2030). This scenario projects a more rapid shift toward renewables, supported by carbon pricing mechanisms and targeted investments in clean energy infrastructure. By 2053, fossil fuel-based generation is expected to decline to less than half of its 2023 level, reinforcing the country's commitment to decarbonization.

The Fossil Zero Scenario envisions a complete phase-out of coal-fired power plants and a gradual reduction in natural gas usage by 2050. Under this pathway, wind and solar energy become the primary contributors to electricity generation, complemented by battery storage, hydrogen, and demand-side response systems. This scenario aligns most closely with Türkiye's long-term sustainability goals and highlights the potential for achieving a fully decarbonized electricity sector within the projected timeframe.

The Cost Scenario introduces economic efficiency into the modeling process, prioritizing technologies with a lower levelized cost of electricity (LCOE). Wind and solar energy emerge as the most economically viable options, supported by IRENA reports showing their LCOE values below many fossil alternatives. This scenario suggests that transitioning to renewables is not only environmentally beneficial but also financially sustainable, especially when integrated with nuclear energy and grid flexibility measures.

An important finding of this analysis is the strategic role of nuclear energy in ensuring baseload stability and supporting the integration of intermittent renewables. According to the projections derived from the Türkiye National Energy Plan 2022, nuclear capacity is expected to reach 7.2 GW by 2035 and remain stable thereafter. Its inclusion in the energy mix enhances system reliability and enables higher shares of variable renewables without compromising supply security.

Moreover, the results emphasize the need for dynamic adjustments in generation planning based on consumption forecasts. Unlike earlier unadjusted models, aligning supply with anticipated demand ensures greater energy independence and reduces reliance on imported fuels. This adjustment mechanism proves essential in balancing the trade-off between affordability, reliability, and environmental impact.

Despite the positive outlook across all scenarios, there remains a gap between projected generation capacity and actual demand requirements by 2053. This suggests that additional investment in grid flexibility, demand-side management, and cross-border interconnection capacity will be necessary to maintain system resilience and avoid supply shortages during peak periods.

In summary, Türkiye is on a clear path toward a cleaner and more sustainable energy system. The combined effects of declining technology costs, supportive policies, and increasing domestic resource utilization position renewables as the leading components of the electricity generation mix. However, achieving the ambitious goal of net-zero emissions by 2053 will require consistent policy implementation, accelerated deployment of low-carbon technologies, and enhanced system flexibility through tools such as hydrogen, battery storage, and demand-side response mechanisms.

This study contributes to the growing body of literature on energy forecasting by offering a structured, data-driven approach to modeling Türkiye's electricity generation future. It supports strategic decision-making in the context of energy transition and provides insights into how different policy frameworks can shape the evolution of the energy system.

4.1.2. Societal Contribution and Alignment with the Sustainable Development Goals

This study makes a significant contribution to the global efforts toward sustainable energy transition by offering a structured forecasting framework that supports strategic planning in Türkiye's electricity generation sector. The findings indicate Türkiye's advancement in augmenting its renewable energy capacity and diminishing its reliance on fossil fuels, a progression that is congruent with numerous United Nations Sustainable Development Goals (SDGs). These include SDG 7, which pertains to affordable and clean energy; SDG 13, which addresses climate action; SDG 11, which concerns sustainable cities and communities; and SDG 8, which focuses on decent work and economic growth [7].

The extant research demonstrates that the transition from fossil fuels to renewable energy sources has the potential to mitigate environmental impact while concomitantly enhancing energy security, reducing greenhouse gas emissions, and stimulating job creation in clean energy sectors. The study employs historical data analysis and future trend projection under multiple scenarios to elucidate the potential

of policy interventions, technological advancements, and cost reductions to expedite this transformation. Moreover, the integration of nuclear energy and hydrogen-based flexibility mechanisms has been demonstrated to contribute to grid stability and long-term sustainability.

These contributions underscore the significance of evidence-based energy planning in achieving both national climate objectives and international commitments, including the Paris Agreement and the EU Green Deal alignment process. In essence, the study functions as a substantial reference point for policymakers seeking to implement strategies that support a fair and inclusive energy transition consistent with the principles of the SDGs.

4.1.3. *Future Prospects*

This study provides a comprehensive forecasting framework to analyze Türkiye's electricity generation transition under multiple policy and economic scenarios up to 2053. The results indicate that the share of renewable energy sources will continue to grow significantly, especially wind and solar technologies, while fossil fuel-based generation is expected to decline over time.

A key direction for future research involves source-specific modeling rather than treating all renewable energy sources as a single aggregated group. While this study grouped hydroelectric, wind, and solar power under a general “renewable energy” category, further work can separate these technologies to capture their unique technical and operational characteristics. For instance, hydroelectric plants offer dispatchable power with high-capacity factors but are limited by geographical constraints. Wind farms provide intermittent output with strong seasonal patterns, whereas solar PV systems exhibit daily variability based on weather conditions. Modeling each source independently will allow for more precise capacity planning and grid integration strategies, particularly in regions where resource availability varies significantly.

In addition to source-level disaggregation, regional energy modeling represents an important area for improvement. The current national-level approach assumes uniform expansion rates across the country, but Türkiye's diverse geography affects

the potential and efficiency of different energy technologies. For example, the Aegean and Mediterranean coasts offer higher solar irradiation levels, making them ideal locations for photovoltaic installations, while Central Anatolia and the Black Sea region have stronger wind resources, favoring wind farm deployment. Incorporating spatially resolved data into the forecasting models will enhance precision and support location-based investment decisions.

Another promising avenue lies in the development of cost-optimized decision-support systems. While this study used levelized cost of electricity (LCOE) values from IRENA reports to guide investment preferences, future work should integrate dynamic cost structures, including carbon pricing, battery storage costs, and hydrogen production expenses. These parameters can be included in a multi-objective optimization framework to identify the most economically viable long-term pathways for expanding clean energy infrastructure. Such a system would assist policymakers in determining the optimal mix of investments in renewables, storage technologies, and grid modernization projects.

Finally, incorporating real-time demand-side response mechanisms, advanced forecasting techniques such as machine learning–based load prediction, and flexibility indicators into the modeling framework could improve scenario realism. These enhancements can help assess the impact of demand-side management, smart grids, and distributed energy resources on overall energy security and system reliability.

These advancements will not only refine the accuracy of projections but also strengthen the practical applicability of the model in guiding Türkiye toward a sustainable and resilient electricity system.

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