ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

AN AGENT-BASED APPROACH TO ASSESS THE IMPACT OF ELECTRICITY GENERATION ON CARBON EMISSIONS

Ph.D. THESIS

Denizhan GÜVEN

Climate and Marine Sciences

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MARCH 2025

ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

BİR AJAN TEMELLİ YAKLAŞIM İLE ELEKTRİK ÜRETİMİNİN KARBON EMİSYONLARI ÜZERİNDEKİ ETKİSİNİN DEĞERLENDİRİLMESİ

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MART 2025

Denizhan GÜVEN, a Ph.D. student of İTU Graduate School student ID 601192002, successfully defended the dissertation entitled "AN AGENT-BASED APPROACH TO ASSESS THE IMPACT OF ELECTRICITY GENERATION ON CARBON EMISSIONS", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 12 February 2025
Date of Defense : 20 March 2025

To my family,

FOREWORD

The commitment to understanding the intricate relationship existing between climate change, energy systems, and sustainable technologies has been the hallmark of this PhD journey. It is a reflection of years of research work, well guided by the urge to make some contribution toward the global effort of mitigating climate change through innovative approaches in energy production. This would not have been possible without the continued support of my mentors, Prof. Dr. M. Özgür KAYALICA and Prof Dr. Ömer Lütfi ŞEN, whose encouragement and expertise have been of paramount importance in shaping the direction and depth of my studies. I am very grateful to my family and best friends who have shown immense patience with my grumpiness during this period. The presentation of these results herein is the hope that their contribution to new knowledge will positively affect the community's understanding regarding sustainable energy solutions and their huge potential for enabling positive environmental and societal impacts.

February 2025 Denizhan GÜVEN

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ABBREVIATIONS

ABM : Agent-Based Model
AHP : Analytical Hierarchical Process
ANN : Artificial Neural Network
ARIMA : Auto-Regressive Integrated Moving Average
BSA : Best Selection Anomaly
CDD : Cooling Degree Day
CEE : Climate-Energy-Economy
CET : Carbon Emission Trading
CH_4 : Methane
CMIP6 : Coupled Model Intercomparison Project Phase 6
CNN : Convolutional Neural Network
CO_2 : Carbon Dioxide
CR : Consistency Ratio
CRU : Climatic Research Unit
DNN : Deep Neural Network
DPRC : Daytime Passive Radiative Coolers
DSK : Dystopian Schumpeter Keynes
ELM : Extreme Learning Machine
ENS : Arithmetic Mean Ensemble
ETR : Extra Tree Regressor
GA : Genetic Algorithm
GBRT : Gradient Boosting Regression Tree
GCM : Global Climate Model
GDP : Gross Domestic Product
GHG : Greenhouse Gas
GWP : Global Warming Potential
IPCC : Intergovernmental Panel on Climate Change
IPP : Independent Power Producer
KGE : Kling-Gupta Efficiency
KNN : K-Nearest Neighbour

LCOE : Levelized Cost of Electricity

LSTM : Long-Short Term Memory

MAS : Multi-Agent Systems

MAUT : Multi-Attribute Utility Technique

MCDA : Multi-Criteria Decision Analysis

md : Modified Index of Agreement

MENR : Ministry of Energy and Natural Resources

ML : Machine Learning

MLP : Multilayer Perceptron

MLR : Multiple Linear Regression

MME : Multi-Model Ensemble

MR : Comprehensive Rating Metrics

N_2O : Nitrous Oxide

NEMR : North-East Monsoon Rainfall

nRMSE : Normalized Root Mean Square Error

NSE : Nash-Sutcliffe Efficiency

PV : Photovoltaic

QM : Quantile Mapping

RBF : Radial Basis Function

RCP : Representative Concentration Pathways

RES : Renewable Energy Sources

RF : Random Forest

RI : Random Index

RMSE : Root Mean Square Error

ROI : Return on Investment

RVM : Relevance Vector Machine

SCM : Simple Composite Method

SLR : Simple Linear Regression

SVM : Support Vector Machine

TSW : Thermochromic Smart Windows

XGBoost : Extreme Gradient Boosting Tree

SYMBOLS

$\mathbf{G_i}$	:	Simulated values derived from GCMs
$\mathbf{L}$	:	Loss function
$\bar{\mathbf{O}}$	:	Mean of the observed data
$\mathbf{O_i}$	:	Observed values extracted from the ERA5/CRU dataset
$\mathbf{R}$	:	Pearson correlation coefficient
$\mathbf{T_{ref}}$	:	Reference temperature
$\hat{y}_i^{XG}$	:	Outcome generated by the model
$\mathbf{z}$	:	Wind turbine hub height
$\mathbf{z_{ref}}$	:	GCM output height
α	:	Coefficient of the power law exponent
β_{ref}	:	Temperature coefficient
βt	:	Population correction coefficient
β_{WT}	:	Efficiency of the wind turbine
γ	:	Arrow-Pratt risk aversion coefficient
ε_i	:	Threshhold for the investment decision
η_c	:	PV panel conversion efficiency
η_{cd}	:	Temperature adjusted PV panel efficiency
η^{CDF}	:	Capital damage factor
η_{ref}	:	Standard PV efficiency at the reference temperature
η_{rr}	:	Reduction percentage of carbon emission permits
λ^c	:	Sensitivity coefficient for carbon tax
μ_G	:	Mean of the simulated values
μ_O	:	Mean of the observed values
Ω	:	Penalty parameter
ρ	:	Air density
σ_G	:	Standard deviation of simulations
σ_O	:	Standard deviation of observations
τ	:	Proportional coefficient reflecting price fluctuations
υ_{t-1}	:	Expected profit margin of IPP

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AN AGENT-BASED APPROACH TO ASSESS THE IMPACT OF ELECTRICITY GENERATION ON CARBON EMISSIONS

SUMMARY

The research addresses the complex interplay between climate change, energy production, and economic policies in general and the specific context of the electricity generation sector in Türkiye. This research will seek to respond to critical challenges related to CO_2 reduction, showing how different sources of energy can provide the country's energy mix and how future policies might influence these dynamics.

The main focus of this research is to study the interaction of energy, economic, and environmental policy in a complex way, showing its consequences for electricity demand and generation and CO_2 emissions in Türkiye, taking into account its specific geographical and climatic condition. The agent-based model (ABM) and Global Climate Model (GCM) data are used in this study to evaluate the influence of different future policies on framing electricity generation-based CO_2 emissions in a climate change regime. Some of the key objectives of this study include identifying the most accurate GCMs for Türkiye, assessing how climate change is going to influence future electricity production, projecting increased space cooling needs, assessing the effectiveness of different policies in reducing CO_2 emissions, and analyzing changes in the electricity mix of Türkiye and the generation capacity over time. These objectives, therefore, enable the study to provide strategic information on sustainable energy planning and policy development in Türkiye.

In the central place, a model of agent-based simulation will be developed, allowing for an experiment in greater detail with scenarios on different policies, such as carbon taxes and subsidies for renewable energy. Through this study, different policy outcomes can be simulated to provide information on the likely impacts on CO_2 emissions, and to help identify effective ways of reducing it while ensuring electricity reliability.

The research methodology involves several key steps. First, climate data from the CMIP6 experiment is collected and compared with observation-based data to identify the GCMs that best represent the climatic conditions in Türkiye. Those models are then used to predict future climate variables under a high-emission scenario, providing a basis for understanding how climate change might impact Türkiye's energy systems. In estimating the future values of climate variables, a machine learning approach using Extreme Gradient Boosting was utilized.

Another important aspect of this investigation is the evaluation of various energy policies and their consequences in terms of CO_2 emissions from generated electricity. The ABM will simulate the interaction of government, the Independent Power Producers (IPPs), and the market forces deep into the various policy scenarios that could influence energy production and its related emissions. This would permit the identification of the best strategies leading to sustainable electricity generation with the least environmental impact.

Turkey's electricity output forecast, while showing a high decline in solar power generation due to efficiency loss, it increases the effect of the rising temperature. The declines are projected to be highest in the Mediterranean and the Eastern Black Sea Regions. The least amount of solar potential is exhibited by the Eastern Black Sea Region, making this region economically unviable for photovoltaic solar power plants. This decrease in the Marmara and Southeastern Anatolia Regions is relatively less in percentage. It is observed that wind power production will increase, especially in the Thrace region and the north of Central Anatolia, where a decrease in wind power is observed in the Eastern Black Sea and Uşak-Kütahya-Eskişehir-Bolu region.

It is expected that global warming will elevate Cooling Degree Days (CDD) by almost two and a half times in the majority of Turkish cities-mostly Mediterranean as well as the southeastern part of the country. Changes in cooling requirements thus represent an overall increase of CDDs in the period 2020-2040, computed from the GCM's output, thus bringing to the fore the need for structural improvement in their cooling infrastructure.

This research covers a wide analysis of how various energy policy options impact the electricity sector of Türkiye concerning capacity expansion, electricity price, and CO_2 emissions. The study applies a scenario choice-based analysis with one basic scenario and nine peculiar policy scenarios in order to draw wide lessons regarding the role and potential of combining various policy measures to better meet the climate and energy challenge using renewable energy sources (RES).

The ABM used for the forecast of electricity demand is almost linear, reaching 456 TWh in 2030, 521 TWh in 2035, and 571 TWh in 2040. By 2040, industrial demand will be above 50% of total demand, outpacing the residential and commercial sectors. The projection from the ABM also gives insight into the future distribution of technologies in electricity generation, underlining the role of policy scenarios in shaping capacity expansion and emissions.

A drastic improvement in forecast installed capacity from the installed capacities under the base case of PV would amount to approximately 28.7 GW and 79.5 GW under the respective horizons 2030 and 2040, while similar action for reduction of corporate tax could lead up to an enhancement as huge as 94 GW of capacities through that sector in comparison to a modest augmentation witnessed for Wind powers' respective installations. Natural gas power plants are expected to grow, while coal power plant capacity is unchanged. Nuclear power, because of its base-load dependability, may decrease the dependence on natural gas power plants.

With the expansions in capacity, there will be a drop in prices of electricity up to 2029 and eventually stabilize. The most promising prices are forecasted when the two policies of carbon tax and renewable energy subsidy are executed. Without policy intervention, price increases may occur, particularly when nuclear power is integrated.

The cost for renewable technologies, such as PV and wind power, is seen to continuously decrease and become more economically feasible. It is expected that the investment costs of PV systems will decrease by more than 19% from 2023 to 2040, while those of wind power will decline by about 16%. Biomass and geothermal technologies will also become cheaper, although hydro-electric, natural gas, and coal-which are more traditional sources-will not see much change. These trends reinforce the movement toward cleaner, more sustainable energy systems.

The analysis yields a continuous extension of the capacity of solar and wind power plants in all alternatives. This growing extension of RES causes a threshold effect in the year 2032, so that CO_2 emissions during electricity generation pass their maximum to decline. Hereby, the drop is caused due to the continuing share of the energy mix expanded by RES; however, such a drop in carbon emissions depends also on the individual energy-climate policies.

The study recommends a combination of nuclear power deployment, carbon taxing, and subsidies for RES to achieve the greatest reduction in cumulative CO_2 emissions. It thus advises the government to provide inflation-indexed RES subsidies in conjunction with a carbon tax. An integrated approach drives the transition to a low-carbon energy system but improves the financial viability of renewable energy projects. In this regard, it is optimum to see the decline in over 11% CO_2 emission within the baseline projection for the years 2022 to 2040.

In total, the carbon tax can achieve a CO_2 emission reduction of 1.52% below the base case. On the other hand, the subsidy on RES will result in higher cuts, up to 4.14%. The sum effect will actually be more than 6%, showing a synergy effect above adding the effects from each policy, since both policies have been in place.

Nuclear power also plays an important role. Without additional policies, deploying nuclear power plants could decrease cumulative CO_2 emissions by approximately 5.3%. However, the wide dissemination of nuclear power plants involves high initial investment costs and public skepticism. Therefore, governmental support for the development of such infrastructure and changing of public opinion could be required.

On the price of electricity, the study foresees a further drop in prices up to 2029 amidst increased RES capacities, after which the price stabilizes. The prices are expected to stay between $25 to $31 per MWh for all scenarios. Concerning electricity prices, RES subsidies are important in that they allow RES power plants to bid lower, thus pulling down the overall market price. The best strategy to achieve low CO_2 emissions at the least electricity price appears to be using nuclear power together with RES subsidies; this offers the double advantage of being both an environmentally and economically sound policy option.

This research, therefore, underlines the need for a diversified and integrated approach to energy policy. Renewable energy expansion, nuclear power deployment, and targeted subsidies and taxes can help Türkiye effectively respond to the challenges of climate change and transition towards a sustainable and resilient energy future. The study provides actionable insights for policymakers to design effective energy-climate policies and achieve a more environmentally responsible and economically viable energy landscape.

BİR AJAN TEMELLİ YAKLAŞIM İLE ELEKTRİK ÜRETİMİNİN KARBON EMİSYONLARI ÜZERİNDEKİ ETKİSİNİN DEĞERLENDİRİLMESİ

ÖZET

Bu çalışma, iklim değişikliği, elektrik üretimi ve ekonomik politikalar arasındaki karmaşık ilişkiyi, özellikle Türkiye'nin elektrik üretim sektörü üzerinde yoğunlaşarak incelemektedir. Araştırma, çeşitli enerji kaynaklarının ülkenin elektrik karışımına katkısını ve gelecekteki politikaların bu dinamikleri nasıl etkileyebileceğini keşfederek karbondioksit (CO_2) emisyonlarını azaltma konusundaki kritik zorlukları ele almayı amaçlamaktadır.

Bu çalışmanın temel amacı, enerji, ekonomi ve çevre politikaları arasındaki karmaşık etkileşimi ve bunların Türkiye'deki elektrik talebi, üretimi ve CO_2 emisyonları üzerindeki etkisini incelemektir. Ülkenin özel coğrafi ve iklimsel koşullarını dikkate alarak, enerji-iklim politikalarının iklim değişikliği etkisi altındaki CO_2 emisyonlarını nasıl şekillendirebileceğini değerlendirmek için bir ajan tabanlı simülasyon modeli ve Küresel İklim Modelleri (KİM) verileri kullanılmaktadır. Çalışma, Türkiye için en doğru KİM'leri belirleme, iklim değişikliğinin gelecekteki elektrik üretimini nasıl etkileyeceğini değerlendirme, artan soğutma ihtiyaçlarını tahmin etme, farklı politikaların elektrik üretimi kaynaklı CO_2 emisyonlarını azaltmadaki etkinliğini değerlendirme ve Türkiye'nin elektrik karışımındaki ve üretim kapasitesindeki değişimleri analiz etme gibi birkaç temel hedef belirlemektedir. Bu hedefler aracılığıyla, çalışmanın Türkiye'deki sürdürülebilir enerji planlaması ve politika geliştirme için stratejik içgörüler sağlaması amaçlanmaktadır.

Çalışmanın merkezinde, KİM'lerden gelen gelecekteki iklim projeksiyonlarını entegre eden bir ajan tabanlı simülasyon modelinin geliştirilmesi bulunmaktadır. Bu model, karbon vergileri veya yenilenebilir enerji teşvikleri gibi çeşitli politika senaryoları ile detaylı deneyler yapma olanağı tanımaktadır. Çeşitli politika sonuçlarını simüle ederek, çalışmada elektrik üretimi kaynaklı CO_2 emisyonları üzerindeki potansiyel etkileri ve farklı stratejilerin emisyonları azaltma konusundaki etkinliğini belirlemeye yönelik değerli içgörüler sağlanmaktadır.

Araştırma metodolojisi birkaç ana adımı içermektedir. İlk olarak, CMIP6 deneyinden elde edilen iklim verileri toplanarak gözleme dayalı verilerle karşılaştırılmakta ve Türkiye'nin iklim koşullarını en doğru şekilde temsil eden KİM'ler belirlenmektedir. Bu modeller, yüksek emisyon senaryosunda gelecekteki iklim değişkenlerini tahmin etmek için kullanılmakta ve bu, iklim değişikliğinin Türkiye'nin enerji sistemleri üzerindeki etkilerini anlamak için bir temel sağlamaktadır. Gelecekteki iklim değişkenlerinin değerlerini tahmin etmek için Extreme Gradient Boosting makine öğrenme yöntemi kullanılmaktadır.

Bu makine öğrenme yaklaşımı, verilerdeki karmaşık ve doğrusal olmayan ilişkileri ele alma yeteneği nedeniyle tercih edilmiştir. Eğitim veri seti ile eğitilip test veri seti ile hata oranları en aza indirilen modeller, daha sonra SSP5-8.5 iklim senaryosu altında gelecekteki iklim değişkenlerini tahmin etmek için kullanılmakta ve bu, enerji

sistemleri üzerindeki potansiyel gelecekteki iklim etkilerini anlamak için sağlam bir temel sağlamaktadır.

İklim verileri işlendikten sonra, çalışma, Türkiye'deki enerji manzarasını değerlendirmek için kritik öneme sahip olan elektrik talebi, soğutma derece günleri (CDD) ve rüzgar ve güneş enerjisi sistemlerinden elektrik üretimi gibi temel enerji göstergelerini tahmin etmektedir. Ayrıca, teknoloji yatırım kararları için yarar fonksiyonu ağırlıkları Analitik Hiyerarşi Süreci ve Çok Kriterli Fayda Tekniği aracılığıyla belirlenmektedir. Bu yöntemler, çeşitli kriterleri ve paydaş tercihlerini dikkate alarak farklı enerji teknolojilerine yatırım önceliklerini belirlemek için sistematik bir yaklaşım sunmaktadır.

Çalışmanın önemli bir yönü, farklı enerji politikalarının elektrik üretimi kaynaklı CO_2 emisyonları üzerindeki etkilerinin değerlendirilmesidir. Ajan temelli model (ABM), hükümet, bağımsız enerji üreticileri (IPP'ler) ve piyasa güçleri arasındaki etkileşimleri simüle ederek çeşitli politika senaryolarının elektrik üretimi ve emisyonlar üzerindeki etkilerini derinlemesine analiz etmektedir. Bu yaklaşım, çevresel etkiyi asgariye indirerek sürdürülebilir enerji üretimi sağlamak için en etkili stratejilerin belirlenmesine olanak tanımaktadır.

Türkiye'nin elektrik üretim projeksiyonları, sıcaklık artışlarından kaynaklanan verimlilik kayıpları nedeniyle güneş enerjisi üretiminde önemli bir düşüş öngörmektedir. Akdeniz ve Doğu Karadeniz bölgelerinde en büyük azalmanın yaşanması beklenirken, Doğu Karadeniz Bölgesi'nin fotovoltaik güneş enerjisi santralleri için ekonomik olarak uygun olmadığı görülmektedir. Buna karşın, Marmara ve Güneydoğu Anadolu bölgelerinde güneşten elektrik üretiminde en az düşüş yaşanacağı öngörülmektedir. Rüzgar enerjisi üretiminin ise Trakya ve kuzey Orta Anadolu bölgelerinde artması, Doğu Karadeniz ve Uşak-Kütahya-Eskişehir-Bolu bölgelerinde ise azalması beklenmektedir.

Soğutma Derece Günleri (CDDs), soğutma enerji talebini tahmin etmede kullanılan bir metrik olarak çoğu şehirde, özellikle Akdeniz ve güneydoğu bölgelerde, önemli bir artış göstermektedir. KİM'lerin çıktıları, 2020'den 2040'a kadar genel bir artış göstermekte olup, büyüyen soğutma taleplerini yansıtmakta ve iyileştirilmiş soğutma altyapısının gerekliliğini vurgulamaktadır. 2031 ve 2032 yıllarında dikkate değer artışlar gözlemlenmektedir, ardından gelen yıllarda ise hafif düşüşler ve toparlanmalar yaşanmaktadır. Veriler, iklim değişikliğinin enerji tüketim desenleri üzerindeki etkisini öne çıkararak, sürdürülebilir enerji çözümleri ve iklim uyum stratejilerine olan ihtiyacı ortaya koymaktadır.

Bu çalışma, çeşitli enerji politikalarının kapasite genişlemeleri, elektrik fiyatları ve CO_2 emisyonları üzerindeki etkilerini kapsamlı bir şekilde değerlendirmektedir. Bir temel senaryo ve dokuz farklı politika senaryosunu inceleyerek, yenilenebilir enerji kaynaklarının (YEK) kritik rolünü ve farklı politika önlemlerinin iklim ve enerji sorunlarına nasıl yanıt verebileceğini vurgulamaktadır.

ABM çıktıları, elektrik talebini neredeyse doğrusal bir artış olarak göstermekte, talebin 2030'da 456 TWh, 2035'te 521 TWh ve 2040'ta 571 TWh seviyelerine ulaşması öngörülmektedir. Endüstriyel elektrik talebinin 2040'a kadar toplam talebin %50'sini aşması, konut ve ticari sektörleri geçmesi beklenmektedir. ABM'nin projeksiyonları ayrıca, elektrik üretim teknolojilerinin gelecekteki dağılımı hakkında içgörüler sunmakta ve politika senaryolarının kapasite genişlemesi ve emisyonlarla başa çıkmadaki önemini vurgulamaktadır.

Fotovoltaik (PV) güneş enerjisi kapasitesinin önemli ölçüde büyümesi öngörülmektedir; temel senaryoda 2030'da 28,7 GW ve 2040'ta 79,5 GW'a ulaşması beklenmektedir. Kurumlar vergisi oranlarını düşürme gibi politika önlemleri, PV kapasitesini 2040'a kadar 94 GW'a çıkarabilmektedir. Rüzgar enerjisi kapasitesinin de artması beklenmektedir, ancak bu artış PV'ye göre daha yavaş olacaktır. Doğalgaz santralleri genişlemesi beklenirken, kömür santralları kapasitesi büyük ölçüde değişmeyecektir. Nükleer enerji, temel yük güvenilirliği nedeniyle doğalgaz santralları ihtiyacını azaltabilir.

Elektrik fiyatlarının kapasite genişlemeleri nedeniyle 2029'a kadar düşmesi, sonrasında ise stabil hale gelmesi öngörülmektedir. En uygun fiyatların, hem karbon vergisi hem de yenilenebilir enerji teşvik politikaları uygulandığında elde edileceği projeksiyon edilmektedir. Ancak, politika müdahaleleri olmadan, fiyatların artması, özellikle nükleer enerjinin entegrasyonu ile birlikte olabilmektir.

Yenilenebilir teknolojilerin maliyet düşüşleri, PV ve rüzgar enerjisi dahil, devam etmesi beklenmektedir ve bu durum onları daha ekonomik hale getirecektir. PV sistemleri için yatırım maliyetlerinin 2023'ten 2040'a kadar %19'dan fazla düşmesi, rüzgar enerjisi maliyetlerinin ise yaklaşık %16 azalması öngörülmektedir. Biyokütle ve jeotermal teknolojiler de maliyet düşüşleri yaşayacak, ancak hidroelektrik, doğalgaz ve kömür gibi geleneksel kaynaklar minimal değişiklikler gösterecektir. Bu eğilimler, daha temiz ve sürdürülebilir enerji sistemlerine geçişi güçlendirmektedir.

Analiz, tüm senaryolar kapsamında güneş ve rüzgar enerjisi santrallerinin kapasitelerinde tutarlı bir artış göstermektedir. Bu YEK genişlemesi, 2032'de CO_2 emisyonlarının zirveye ulaşmasına ve ardından düşmeye başlamasına yol açmaktadır. Bu düşüş, enerji karışımındaki YEK'in artan payına atfedilmektedir. Ancak, CO_2 emisyonlarındaki azalma derecesi, uygulanan özel enerji-iklim politikalarına bağlı olarak değişiklik göstermektedir.

En yüksek CO_2 emisyonu azalmasını sağlamak için çalışma, nükleer enerji kullanımı, karbon vergisi ve enflasyona göre ayarlanmış YEK teşviklerinin kombinasyonunu önermektedir. Bu entegre yaklaşım, düşük karbonlu enerji sistemine geçişi hızlandırmakla kalmayıp, yenilenebilir enerji projelerinin finansal uygunluğunu da artırmaktadır. Bu optimal senaryoda, 2022'den 2040'a kadar CO_2 emisyonlarının %11'den fazla azaltılması mümkün olabilmektedir.

Nükleer enerjinin rolü de oldukça önemlidir. Ek bir politika olmaksızın nükleer enerji santrallerinin devreye alınması, toplam CO_2 emisyonlarını %5.3 oranında azaltabilir. Bu potansiyel faydalara rağmen, nükleer enerjinin yaygın olarak benimsenmesi yüksek başlangıç yatırım maliyetleri ve kamu şüpheciliği gibi zorluklarla karşı karşıyadır. Bu nedenle, hükümet müdahalesi, nükleer altyapı gelişimini desteklemek ve kamu endişelerini ele almak için gerekli olabilir.

Elektrik fiyatları açısından, çalışma, YEK kapasitelerindeki artış nedeniyle fiyatların 2029'a kadar düşmesini ve ardından bir istikrar dönemine girmesini öngörmektedir. Fiyatların tüm senaryolar arasında MWh başına 25 ila 31 dolar arasında dalgalanması beklenmektedir. YEK sübvansiyonları, YEK santrallerinin daha düşük teklifler sunmasını sağlayarak elektrik fiyatlarının genel olarak düşürülmesinde kritik bir rol oynamaktadır. Nükleer enerji ve YEK sübvansiyonlarının kombineli olarak uygulanması, hem CO_2 emisyonlarını hem de elektrik fiyatlarını minimize etmede en etkili strateji olarak ortaya çıkmakta ve çevresel ve ekonomik iyileşmelerin iki yönlü avantajını sunmaktadır.

Çalışma ayrıca YEK'lerin piyasa dinamikleri üzerindeki etkisini de vurgulamaktadır. Düşük marjinal maliyetlere sahip olan YEK'ler, "merit-order etkisi" olarak bilinen bir duruma yol açar; bu durum, daha yüksek maliyetli üretim yöntemlerinin yerini alarak genel piyasa fiyatlarının düşmesine neden olur. YEK kapasiteleri arttıkça, elektrik üretiminin ortalama marjinal maliyeti azalır ve bu da daha istikrarlı ve uygun maliyetli elektrik fiyatlarına katkıda bulunur.

Elektrik talebinin ABM kullanılarak hassas bir şekilde tahmin edilmesi, enerji verimliliğini artırma, talep tarafı yönetimini geliştirme ve şebeke optimizasyonu çabalarını ilerletme açısından kritik bir öneme sahiptir. ABM, sektör düzeyinde elektrik tüketimini yönlendiren faktörlere derinlemesine bakarak enerji israfını azaltma, yük desenlerini ince ayar yapma ve enerji verimli teknolojiler ve yöntemlerin benimsenmesini teşvik etme yollarını aydınlatmaktadır. Bu proaktif yaklaşım, kamu hizmetleri, şebeke işletmecileri ve politika yapıcılara talep yanıtı girişimleri, zaman dilimine bağlı fiyatlandırma stratejileri ve enerji verimliliği teşvikleri gibi özelleştirilmiş müdahaleleri uygulamak için eyleme dönük bilgiler sağlamaktadır. Bu önlemler, sadece sistem maliyetlerini azaltmayı değil, aynı zamanda enerji tüketimi spektrumunda genel enerji verimliliğini artırmayı da hedeflemektedir.

Sonuç olarak, bu araştırma, enerji politikasına yönelik çeşitlendirilmiş ve entegre bir yaklaşımın önemini vurgulamaktadır. Yenilenebilir enerji genişlemesi, nükleer enerji kullanımı ve hedeflenmiş sübvansiyonlar ile vergiler gibi stratejileri bir araya getirerek, Türkiye iklim değişikliği nedeniyle karşılaştığı zorlukları etkili bir şekilde aşabilir ve sürdürülebilir ve dirençli bir enerji geleceğine geçiş yapabilir. Çalışma, politika yapıcılara etkili enerji-iklim politikaları oluşturma ve çevresel olarak sorumlu ve ekonomik olarak uygulanabilir bir enerji manzarası elde etme konusunda uygulanabilir içgörüler sunmaktadır.

1. INTRODUCTION

1.1 Background

A comprehensive analysis of temperature records from the past century reveals a clear and consistent upward trend in global average temperatures. By combining direct measurements from weather stations, sea surface temperature data, and satellite observations, researchers have assembled extensive datasets that accurately track global temperature changes over time. These datasets, supported by paleoclimate evidence, indicate substantial planetary warming, especially in recent decades. Since the late 19th century, the global average temperature has increased by about 1.2°C, with the most rapid rises occurring after 1970 (Masson-Delmotte et al., 2021). As this is not a uniform warming, the higher latitudes (especially the Arctic region) have seen larger changes in temperature relative to the global average, causing increased rates of ice melt and thawing of permafrost. The data strongly suggest that human activities including the burning of fossil fuels, deforestation, and industrial processes are the most dominant causes of this warming trend.

One of the other evidences that support the rising global temperatures comes from many indicators and proxy records. Changes in ice core specimens, tree rings, and coral reefs are consistent with the instrumental temperature record and extend the view of the current warming trend over a longer period. The frequency and intensity of heatwaves and extreme weather events, such as hurricanes, droughts, and heavy precipitation, have also raised in a manner consistent with climate model predictions (Pachauri et al., 2014). These models, based on atmospheric dynamics and feedback mechanisms, project continued warming under different greenhouse gas emission scenarios. The Intergovernmental Panel on Climate Change (IPCC) highlights the urgent need to reduce emissions to limit future temperature rises and prevent the most severe impacts of climate change. Therefore, the analysis of temperature records not only underscores the significant warming over the past century but also emphasizes the critical need for comprehensive climate action.

In this context, Carbon dioxide (CO_2) emissions are pivotal in driving climate change due to their substantial role in the greenhouse effect. As one of the most prevalent greenhouse gases (GHGs) in the Earth's atmosphere, CO_2 is predominantly generated by human activities such as the combustion of fossil fuels (coal, oil, and natural gas), deforestation, and various industrial processes. Since the onset of the Industrial Revolution, atmospheric CO_2 levels have surged dramatically from approximately 280 parts per million (ppm) to over 425 ppm today (SIO, 2023; Ritchie et al., 2023). This sharp increase is mainly due to the extensive growth of industrial activities and the consequent rise in fossil fuel usage. The heightened CO_2 concentrations amplify the natural greenhouse effect, trapping additional heat in the atmosphere and resulting in global warming and related climate changes (See Figure 1.1).

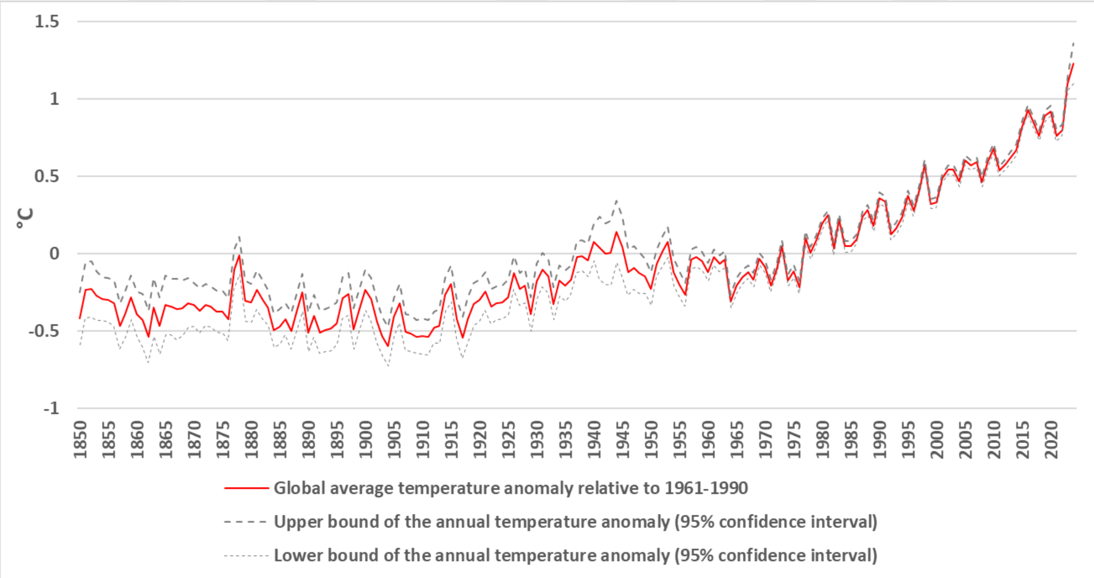

Figure 1.1 : Global average surface temperature anomaly relative to 1961-1990.

GHGs can be defined as the constituents of atmospheric composition that absorb infrared radiation, further re-emitting and causing the so-called 'greenhouse effect.' Key GHGs include carbon dioxide, CH_4 (methane), N_2O, and fluorinated gases. Each one has different GWP values and a span of time spent in the atmosphere; they are expected to impact climate change in an assortment of ways. While CO_2 is much more abundant than methane, for example, methane has a GWP about 28-36 times higher over a 100-year period, so its relatively short lifetime in the atmosphere still makes it an important factor in driving climate change. Nitrous oxide, for example, has a GWP about 298 times greater than CO_2 and stays in the atmosphere for more than a century.

Fluorinated gases, though present in smaller quantities, can have GWPs in the thousands and long atmospheric lifetimes, substantially contributing to long-term climate forcing (Masson-Delmotte et al., 2021).

It refers to the process whereby a layer of GHGs in the atmosphere can trap heat, thus maintaining the planet at a temperature which can support life. However, this effect has been highly enhanced by human activities increasing the concentration of GHGs. The solar radiation that reaches the Earth's surface is first absorbed then re-emitted as infrared radiation. Infrared radiation is absorbed by the GHGs in the atmosphere and re-emitted in all directions, including back to the Earth's surface, causing further warming. This enhanced greenhouse effect results in higher global temperatures, which then lead to climate change. As already mentioned, the consequences of this heating are wide-ranging, affecting weather patterns, sea levels, and ecosystems. Understanding the sources of GHG emissions is essential for elaborating effective mitigation strategies. Sources of GHG emissions are varied and include energy production, transport, industry, agriculture, and waste management. Each of these sectors has a different contribution to the general pattern of emissions, thus requiring a source-specific approach to reduction.

Figure 1.2 presents annual global GHG emissions from various sectors for the period 1990-2020. Emissions are split across ten sectors, including: other fuel combustion, bunker fuels, waste, buildings, industry, fugitive emissions from energy production, agriculture, manufacturing and construction, transport, and electricity and heat. A notable trend is the significant increase in GHG emissions from electricity and heat production, which consistently rose from 8.65 gigatonnes (Gt) of CO_2-eq. in 1990 to 15.18 $GtCO_2$-eq. in 2020. Transport emissions also saw a marked increase, nearly doubling from 4.73 $GtCO_2$-eq. to 7.29 $GtCO_2$-eq. over the same period (Ritchie et al., 2020).

Industrial emissions showed a steady rise, while emissions from manufacturing and construction exhibited more variability but an overall upward trend. Agricultural emissions remained relatively stable but consistently high, indicating the sector's substantial contribution to global GHG emissions. Emissions from waste, buildings, and other fuel combustion also increased, though at a slower rate compared to electricity and transport sectors.

Fugitive emissions from energy production, representing leaks during the extraction, processing, and transport of fossil fuels, showed a moderate increase over the decades. Bunker fuels, used for international shipping and aviation, demonstrated a gradual rise in emissions, reflecting the growing global transportation demands.

This sectoral breakdown highlights the critical areas for targeted GHG reduction strategies, with electricity and heat production, transport, and industry being key sectors where significant emission cuts could substantially impact global GHG levels.

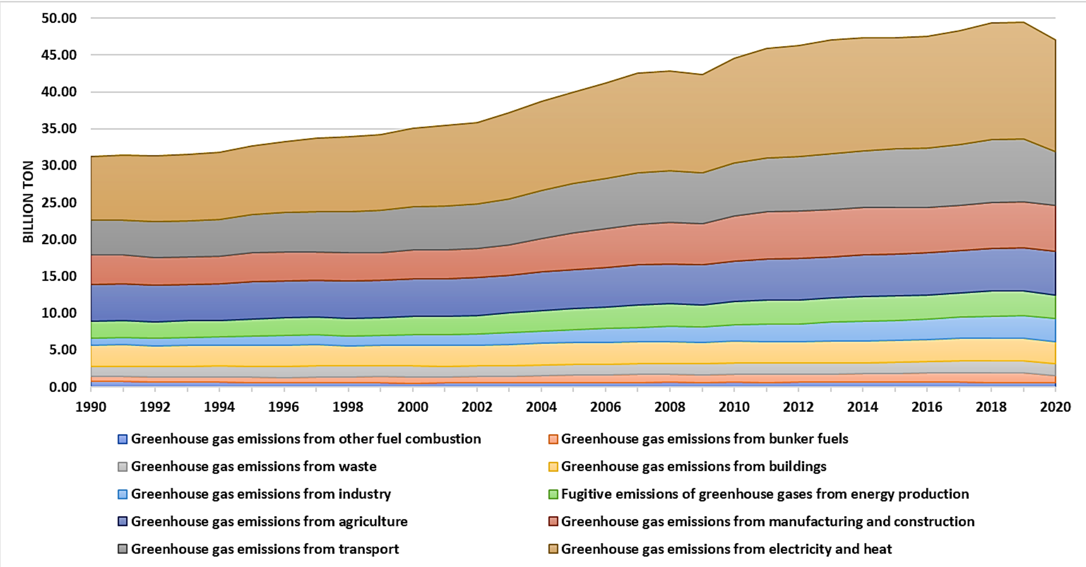

Figure 1.2 : Annual global GHG emissions by sector.

As given in Figure 1.2, electricity and heat production causes approximately one-third of the global GHG emissions due to their heavy reliance on fossil fuels, particularly coal, natural gas, and oil. These energy sources are carbon-intensive, releasing large quantities of CO_2 and other GHGs during combustion. High energy demand from industrial, residential, and commercial sectors exacerbates emissions, as power plants and heating systems must operate continuously to meet these needs. Additionally, inefficiencies in energy production and transmission lead to higher emissions, as older, less efficient plants often remain in use due to economic and infrastructural constraints. The combustion process emits not only CO_2 but also CH_4 and N_2O, which are potent GHGs with higher global warming potentials than CO_2. The growing global population and economic expansion further increase the demand for electricity and heat, especially in developing regions where energy infrastructure is rapidly expanding.

In an effort to supply the world with its ever-increasing demand for electricity, different types of power plants have been invested in and built across the globe. These have ranged from new constructions to renovations of already existing facilities, the purpose of which was to capture several energy sources. For a long time, coal, hydroelectric, and nuclear power plants have been used as the backbone of most countries in generating electricity. Coal plants are predominant due to their large capacity and established infrastructure. But all this has changed over time as tremendous investments have been made in renewable technologies of energy production. Solar and wind power recently had amazing growth spurts thanks to the changing technology and cost dynamics. Natural gas is also an important fossil fuel source considered to be cleaner than coal.

In this regard, Figure 1.3 and 1.4 show the global electricity mix from 1985 to 2023, with the breakdown of different energy sources that contribute to it. Initially, coal, hydro, and nuclear energy were the major sources of electricity generation. Coal has always maintained the highest share, from around 3748 TWh in 1985 and has been increasing year after year, peaking at 10468 TWh in 2023. Hydroelectric power has also been highly significant, rising from around 1979 TWh in 1985 to over 4211 TWh by 2023. Nuclear power also contributed greatly to it, as it rose steadily from 1489 TWh in 1985 and crossed 2686 TWh by 2023. These three have always been the significant ones in the electricity mix, giving a mirror reflection of their importance in global energy supply (Ritchie et al., 2024).

By contrast, the contributions from renewable energy sources-solar, wind, and bioenergy-have grown very fast, particularly from the early 2000s onwards. The contribution of solar energy was almost zero in the beginning, increasing to a whole new level. From 0.01 TWh in 1985, it surged to 1629.9 TWh in 2023. This position changed from 0.06 TWh in 1985 for wind to 2304.44 TWh in 2023. Bioenergy has also risen gradually to reach 678.74 TWh in 2023. This marks a global transition toward more sustainable and renewable sources of energy in efforts to address climate change and reduce reliance on fossil fuels. While natural gas also increased quite significantly from 1426 TWh in 1985 to 6623 TWh in 2023, this positions it as a transition fuel in the global energy mix. As Ritchie et al. (2024) note, even with these advances, the continued dominance of coal is indicative of how far the rest of the world is from moving toward a fully low-carbon energy system.

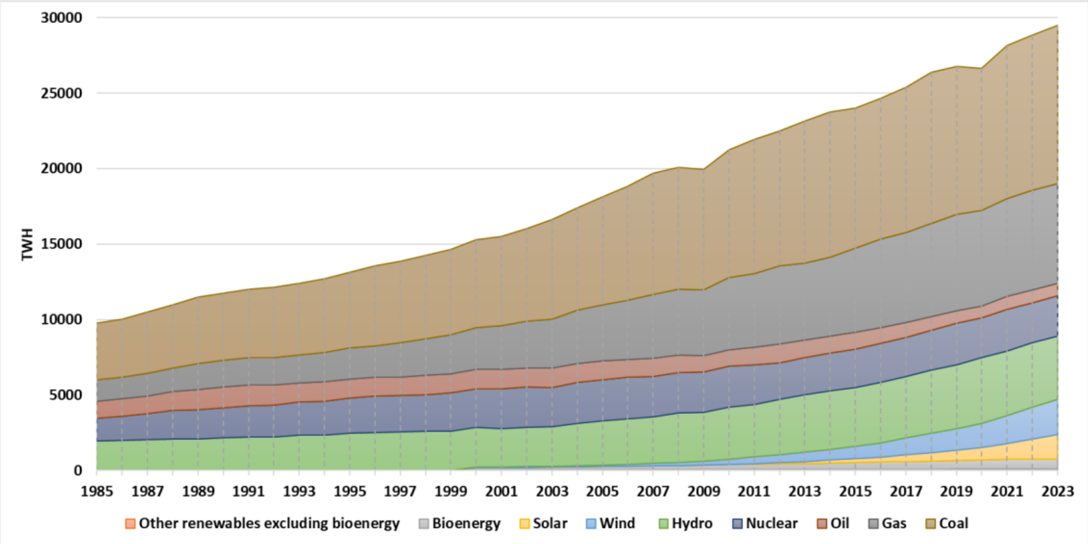

Figure 1.3 : Global electricity generation by source.

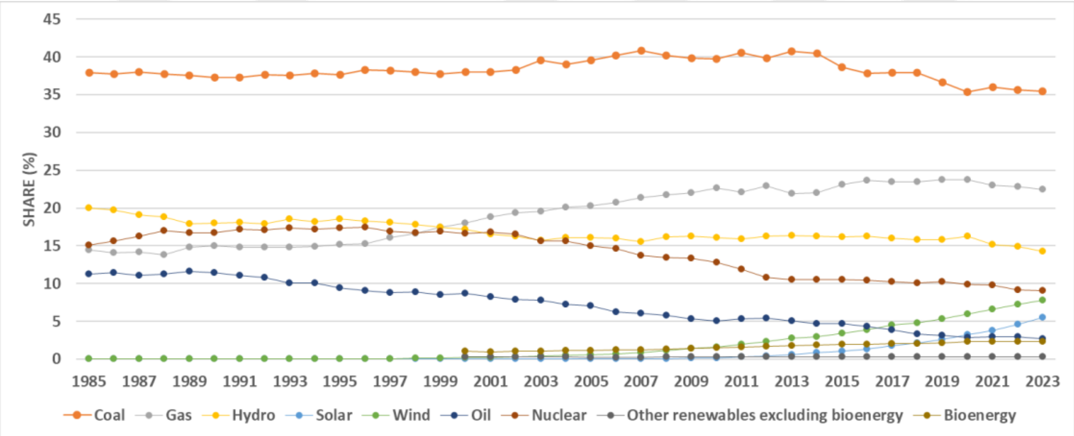

Figure 1.4 : Global electricity mix shares of generation technologies.

1.2 Research Significance

As a developing country, the demand for electricity in Türkiye is increasing day by day due to its growing population and expanding economy. The requirement for energy increases every year with more urbanization and industrialization. Improved living standards and increased usage of electronic gadgets increase the consumption of electricity. Besides, all strategic initiatives undertaken by the government of Türkiye for economic development and infrastructure building increase the demand for reliable sources of power.

Figure 1.5 below shows the country's electricity generation from 1985 to 2023. It illustrates graphically the changes in the country's sources of electricity over the years. In the earlier years-that is, starting in 1985 through the late 1990s, coal and hydroelectricity had been the two main sources of electricity, wherein coal's contribution to the country's total was consistently over 30%, while that of hydroelectric power ranges from 30% to 60%. (See Figure 1.6). During this period, natural gas and oil also dominated significantly, especially in the mid-1990s, when the country diversified its energy portfolio. The striking point here is that, over time, the share of oil declined considerably while natural gas consumption increased enormously and reached the highest in the early 2000s (Ritchie et al., 2024). This shows how Türkiye strategically changed track in terms of energy sources toward a more diverse but highly fossil fuel-based energy mix.

From the mid-2000s, there is quite an evident gradual shift in the use of renewable sources of energy, with solar and wind power leading the fray. Solar power started to appear in the energy mix around 2014 and has grown steadily to reach considerable contributions by 2023, while wind power also follows the same trend-from the early 2000s, one can notice it and then substantial in the mix by the 2010s. While there is a presence of bioenergy and other renewables from the early 1990s, more consistent and larger contributions happened recently (Ritchie et al., 2024). Such gradual but clear shifts towards renewable energy sources indicate efforts in Türkiye to reduce dependence on fossil fuels with the constraint on emissions. However, with coal and natural gas still major contributors, this indicates ongoing challenges in being able to make a full transition into a sustainable model of energy.

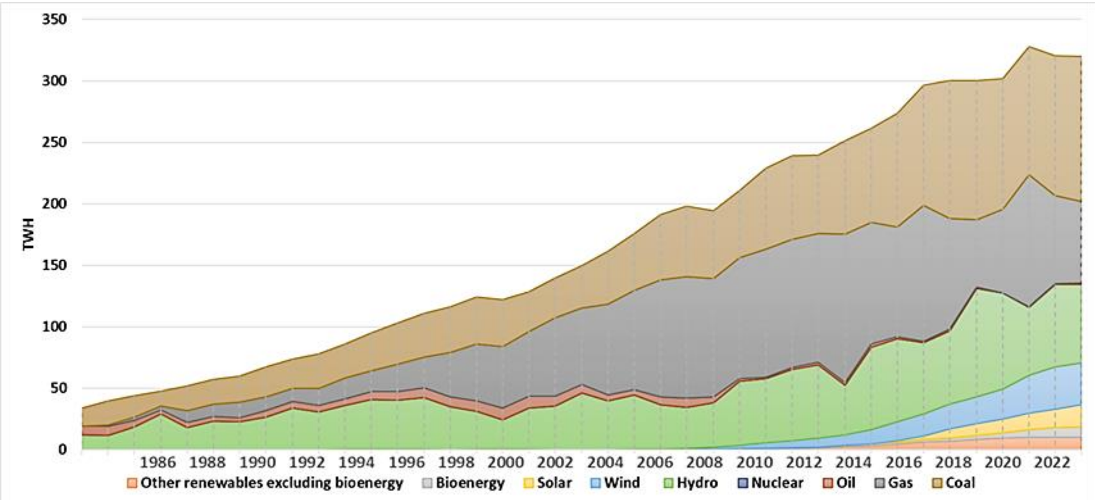

Figure 1.5 : Electricity generation by source in Türkiye.

As concerns about climate change and global warming continue to escalate, the transition towards green energy technologies is becoming increasingly crucial in shaping the future of electricity generation. In this context, Türkiye has made significant strides by heavily investing in renewable energy sources such as wind and solar. This commitment is driven by both environmental considerations and the desire to reduce dependency on finite resources. Over the past decade, Türkiye has achieved remarkable growth in renewable energy capacity, increasing the share of renewables (excluding hydro) in its total installed capacity from 3.5% to an impressive 22.96% as of 2023 (MENR, 2023). This shift underscores the importance of renewable energy in addressing climate challenges.

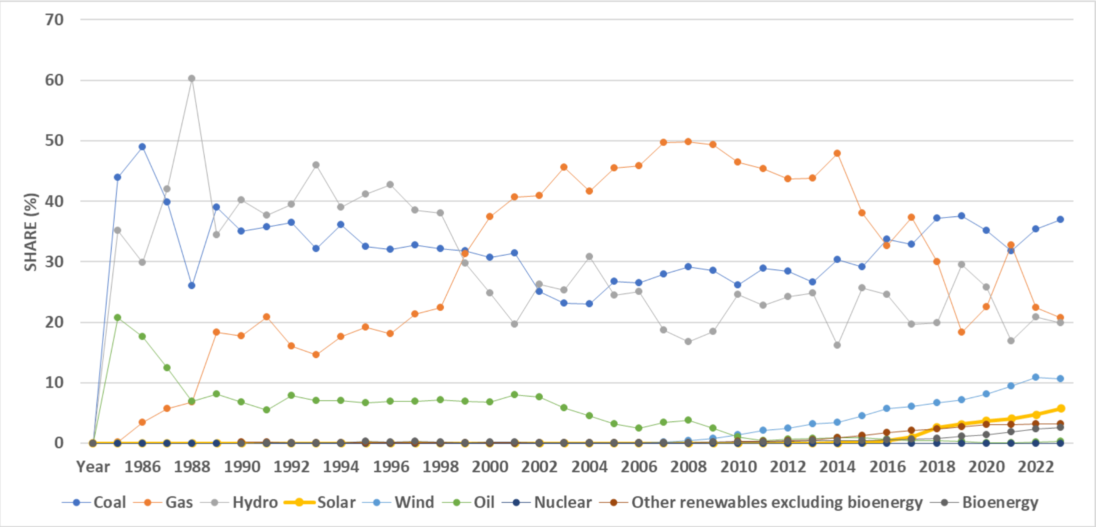

Figure 1.6 : Electricity mix shares of generation technologies in Türkiye.

However, the effectiveness of renewable energy production is largely contingent upon uncontrollable natural factors such as wind speed, temperature, and solar irradiance. These variables introduce uncertainty and make it difficult to generate electricity reliably from these renewable sources. In this regard, understanding and mitigation of these uncertainties form the basis of optimization and stability in renewable systems. The inherent variability in these energy sources requires strong modeling and forecasting to ensure that supply is made available without necessarily compromising stability.

This work investigates complex interactions of climate-energy-economy (CEE) through a novel agent-based model (ABM). Coupled with the future projections of Global Climate Models (GCMs), estimated through state-of-the-art machine learning techniques, the current study shows an advanced, complex analysis that identifies how the two most important climate variables would impact energy supply and demand. The ABM developed in this paper allows one to run in detail a whole variety of policy scenarios, ranging from imposing carbon taxes to providing subsidies. This makes it of tremendous value when modeling varied policy outcomes during the planning and optimization of long-term energy strategies.

The significance of the research is that it could project, based on different policy conditions in generating electricity, the amount of CO_2 that would be emitted. This way, policymakers can identify ways through which emission could be reduced with adequate and secure energy supply. Agent-based modeling, therefore, offers a useful tool in assessing the potential impacts of various policy measures to support decision-making for the transition to a more sustainable energy future.

This study has underlined the vital role of renewable energy in dealing with climate change and the importance of sophisticated modeling tools in managing the uncertainties associated with renewable energy production. The substantial investments of Türkiye in wind and solar energy mark the exemplary proactive steps that need to be taken in order to mitigate environmental impacts and reduce resource dependency. This research, via state-of-the-art simulation models and machine learning, provides relevant input to the CEE nexus, giving insights into the paths toward more efficient and sustainable energy policies.

1.3 Research Objectives

The overall objective of the study is to analyze complex interactions of energy-economic-environmental policy impacting electricity demand and production as well as the resulting CO_2 emissions, considering geographical and climatic conditions in the case of Türkiye. In this paper, an attempt is made to incorporate an agent-based simulation model with input data from GCMs in order to obtain a more accurate view of the impacts of different future energy and economic policies on CO_2 emissions from the electricity generation sector, considering the progression of climate change. The present research attempts to critically consider the following key objectives:

Identification of optimal GCMs for Türkiye: The first objective will be to identify the GCMs that best capture the climatic conditions relevant for the study area of Türkiye. This means different climate models have to be analyzed in order to estimate their performance in simulating temperature fluctuations, wind speeds, and solar irradiance for the specific climatic patterns in Türkiye. By choosing the most suitable

GCMs, evidence of their reliability and accuracy will be at hand for subsequent simulations and projections within the study.

Assessment of future electricity generation under climate change: The second objective gives the focus to study the impacts that might be induced from climate change on future electricity generation in Türkiye, including deep analysis of how changing environmental factors of wind speed, solar radiation, and temperature variation will shape the output of renewable energy sources. The dynamics understood, the study intends to project the changeable capacity and efficiency of wind, solar, and other renewable energy technologies over time due to climate change.

Projection of space cooling needs due to climate change: This third objective deals with analyzing how climate change will influence space cooling demands in Türkiye. This means increased temperatures are necessarily going to increase the demands for air conditioning and other technologies of cooling that, in turn, will be reflected in the demand for electricity. In this study, an attempt at quantification was done to incorporate changes into wider energy demand forecasts that provide a clear vision of the future energy needs and the related stress on the production systems.

Assessment of the impacts of policies on CO_2 emissions: The fourth objective probes how different energy and economic policies are going to affect CO_2 emissions from electricity generation in view of climate change. This involves simulating policy scenarios that include the introduction of carbon taxes, subsidy for renewable energy, among other regulatory measures. These would be intended to ascertain the extent these policies can succeed in reducing associated emissions and therefore indicate the best direction effective measures, which will be conducive to the achievement of environmental sustainability with reduced environmental damages or impacts on production.

Analysis of changes in electricity mix and generation capacity: The fifth objective is periodic projected changes in the mix of electricity and generation capacity in the view of climate change through government regulations or policy intervention. This will be done by devising scenarios of what the future composition of renewable energies, such as wind and solar, will look like, along with the necessary changes in overall generation capacity to meet future demands. By charting these trends, the study should yield strategic insights for the planning and development of Türkiye's energy infrastructure.

2. LITERATURE REVIEW

2.1 Agent Based Simulation Models

In the international literature, the impacts of government policies on energy demand and generation have been explored using various methods. Among the most effective approaches to investigate the effects of various policies, whether singular or in combination, on the energy sector is Agent-Based Simulation. In this context, Sopha et al. (2011) aim to identify potential interventions for the purchase of wood pellet heating in Norway using an agent-based model. The theoretically and empirically established model suggests that for a wood pellet market to succeed, financial support, stable wood pellet prices, and technical development, namely functional reliability improvement, need to be established simultaneously. In another study, Lee et al. (2014) present an innovative agent-based simulation model that integrates the behaviors of individual homeowners within a long-term domestic stock framework, specifically for energy policy analysis. Their findings highlight that current policies fall considerably short of the 80% target, suggesting a need to reassess the existing subsidy levels. The model reveals that the current subsidies overly benefit specific technologies, thereby hindering others with higher potential for energy savings. Policymakers can utilize this model to explore additional scenarios and develop more compelling policy alternatives.

Another study focusing on buildings' energy consumption, Liang et al. (2019), propose an agent-based model for formulating Energy Efficiency Enhancement policies. The model conceptualizes the government and homeowners as agents, applying principal-agent theory to simulate their decision-making processes. Subsequently, a platform grounded in this model is created, enabling the optimization of incentive policies under varying conditions. In this platform, the model's effectiveness is analyzed by considering three different policy scenarios from China. The results of this study show that the incentive policy deduced from this model performed best in satisfying the energy and financial criterion. In a related study on household behaviors, Hesselink and Chappin (2019) present a systematic review of agent-based modeling studies on the adoption of energy efficiency by households. They analyze the use of modeled technologies, simulated policies, and included decision-making theories and empirical data. The resulting analysis provides a general overview of the interrelation between technologies, barriers, and policies, which, using pre-existing models, gives basic policy recommendations. The review reveals that most studies primarily concentrate on various obstacles, including capital shortages, insufficient information, high initial costs, and a general lack of awareness.

More recently, Babatunde et al. (2023) utilized an ABM to carry out simulations encompassing various scenarios from 2015 to 2050, with the aim of examining the impact of renewable energy policies on emission reduction within Malaysia's energy sector. The results of these simulations indicate that the implementation of all renewable energy initiatives resulted in a 16 percent increase in the proportion of renewable energy usage, accompanied by a 26 percent decrease in emissions intensity compared to 2005 levels. However, this progress falls short of the government's target of a 45 percent reduction. These findings underscore that a single approach alone cannot attain the ambitious emission reduction objective.

In addition to the studies on energy policies, there are also studies in the literature under the same title focusing on the penetration of renewable energy sources using agent-based modeling. Karimi and Veaz-Zadeh (2021) propose a structure for ABM intended to evaluate sustainable policies of the electricity system and, particularly, integrated renewable energies. This type of policymaking is considered a multistage process entailing long-term dynamics, uncertainty, and complexity. The framework, proposed in their ABM model, identifies and categorizes all acting actors of energy systems and their unique rules, properties, and interactions. Accordingly, the model was applied to one representative system containing many well-known electricity generation technologies, including renewables, under various policy scenarios. The ABM-based evaluation has, therefore, indicated that badly fitted or unsustainable energy policy scenarios produce uncertain results and are likely to entail either long-run electricity shortages or environmental degradation.

On the other hand, Ernst and Briegel (2017) present an agent-based social simulation model, aimed at validating a dynamically enhanced psychological decision micro-theory through the introduction of negotiation-based decisions, social environment, and personal communication. A survey on psychological factors associated with the acceptation of green energy and sustainable lifestyles is complemented by experiments focused on information processing styles and communication networks. The experiment conducted within the model examines the influence of the frequency of personal communication about the technology and the influence of a significant media-covered event on the adoption of green energy. The results point to the potential of social simulation as a means to build and test dynamic psychological theories.

In another study, Palmer et al. (2015) develop an ABM to explore how modifications to the Italian Support Plan might influence the spread of photovoltaic (PV) solar systems among single-family and two-family households. The payback period is calculated by considering factors such as capital costs, zonal solar radiation levels, government incentives, gains from utilizing self-generated electricity against purchasing from the existing electricity grid, operational and maintenance expenses. Environmental benefits are assessed based on the reduction of CO_2 emissions. Household income reflects specific regional economic conditions and also accounts for the agent's age, education level, and household type. Lastly, the effect of communication is gauged by the number of connections with other households that have already adopted PV systems. The findings suggest that under Italy's new tariff guarantee program, local PV installations have moved beyond the initial expeditious expension stage. However, while further expansion is anticipated, it is expected to proceed at a much slower pace, illustrating the significant impact of policy changes on the spread of renewable energy systems.

In a similar article, Zhao et al. (2011) create a decision support system to evaluate the impact of regulations and incentives on the growth rate of distributed PV systems, aiming to prevent grid destabilization and sharp rises in electricity prices. The study utilizes both ABM and system dynamics approaches. The models, which are based on actual data from residential districts in two distinct regions of the United States, effectively illustrate how policies influence PV system growth across different locations.

Similarly, Wang et al. (2018) integrate a social network-based innovation diffusion model with anecdotal information exchange to analyze household perceptions of benefits in deciding to adopt residential PV systems. A case study is conducted for villages in Beijing, exploring different scenarios related to policies from both economic benefits and information dissemination in the social network. The study findings indicate that: 1) Providing free insurance against the harm caused by PV adoption can increase the adoption rate from 24% to as high as 62% (full insurance), and the cost of acquiring new adopters is only 36% of providing additional subsidy; 2) In cases where most households lack sufficient knowledge about PV systems, enhancing communication poses a barrier to the adoption of residential PV; and 3) Information campaigns and screening are both effective and necessary in reducing the negative effects resulting from strengthened communication in the initial phase of the residential PV market.

In their study, Ponta et al. (2018) investigate the economic effects of a tariff guarantee policy designed to encourage investments in renewable energy generation. To conduct this analysis, they use an enhanced form of the Eurace macroeconomic model, which integrates both fossil fuel-based and renewable energy sectors. The results show that the tariff guarantee policy effectively encourages the conversion of the energy sector towards sustainability and increases investment levels by positively impacting unemployment rates. Additionally, it is observed that costs of financing instruments did not impact government finances.

Meanwhile, Chen et al. (2018) develop an integrated ABM-Monte Carlo simulation to analyze how risk and adaptive technical choices of energy companies influence their decision-making processes, especially in assessing the impact of investment choices on the energy sector's development. The results indicate that risk aversion and adaptive technical preferences within the firm are of paramount importance in the transition toward a low-carbon electricity sector and create a synergistic effect. Risk aversion further stabilizes the transition process.

In addition to energy policies, although limited in the literature, carbon trading has also been analyzed using agent-based simulation methods. In this regard, Cong and Wei (2010) examine the potential effects of implementing a Carbon Emission Trading (CET) system on China's power sector and evaluates various options for allocating allowances. ABM represents a promising new approach that addresses limitations of traditional methods. They construct an ABM, called CETICEM (CET Introduced

China Electricity Market), to simulate the implementation of CET in China. CETICEM features six agent classes and two distinct markets. The key findings are as follows: i) CET internalizes environmental costs, causing a 12% rise in average electricity prices and transferring carbon price volatility to the electricity market, resulting in a 4% increase in electricity price volatility. ii) CET affects the cost competitiveness of various power production systems through carbon pricing, significantly enhancing the adoption of environmentally friendly systems; in particular, the uptake of expensive solar power generation increases by 14%. iii) Emission-based allocation results in higher electricity and carbon prices compared to output-based allocation, encouraging producers to adopt greener practices.

Tang et al. (2015) develop a multi-factor model to evaluate various CET concepts and determine the most suitable option for China. Their bottom-up model, incorporating major economic agents within a general equilibrium framework, reveals that CET can effectively lower carbon emissions, albeit with some negative economic impacts. The study finds that the historical allocation rule is less aggressive compared to the benchmark rule. Setting the carbon price at approximately 40 RMB/ton yields satisfactory emission reductions. Additionally, the penalty rate, economic growth, mitigation effects, and subsidies for energy technology improvements can further reduce emissions without significant economic drawbacks. The new model is deemed a promising tool for CET policy development.

In a follow-up study, Tang et al. (2017) propose a multi-factor ETS simulation model for carbon allocation auction design in China. This model includes the government and sector-specific firms as agents, interacting through three markets: the commodity market, primary carbon auction market, and secondary carbon trading market. Various auction designs are analyzed, with results showing that ETS positively impacts carbon reduction and energy structure improvement but poses economic challenges. Among auction formats, the single-price design is moderate, while the discriminatory price design leads to more pronounced economic and emission reduction outcomes.

The examination of policies related to climate and climate change using agent-based simulation methods holds significant importance in the literature, given that climate change ranks among today's most pressing global issues.

Among the pioneering works in this area, Nannen and van den Bergh (2010) illustrate the application of an evolutionary agent-based model to assess climate policies, taking into account the diverse strategies of individual agents. The model's distinctive aspect is that it evaluates the effectiveness of an economic strategy based on an agent's relative well-being compared to their immediate neighbors within a social network. This approach enables the analysis of policies that impact individuals' comparative standings. They propose two novel climate policies: one modifies relative welfare through direct incentives, while the other shapes social interaction networks via advertising. These policies are demonstrated using a simple global warming model where a source with negative environmental impact may be substituted for renewable energy, which is environmentally neutral but less cost-effective.

In another climate policy study, Gerst et al. (2013) introduce the ENGAGE multi-level model structure: an agent-based approach and relaxing some of the standard modeling assumptions. The framework incorporates local actors- including firms and households-into an evolutionary model representing economic development, energy generation systems, and climate change. It is thus set up to evaluate policies considering intermediary decision-making as well as social and technological evolution. Accordingly, the introduced model is used in order to explore the issue of reciprocal feedback between international agreements and local policy impacts.

Isley et al. (2015) introduce a new model that combines agent-based and game-theoretic approaches to explore how short-run policy choices affect the long-term trajectories of emission reduction. Their findings indicate that carbon pricing policies are designed by the main causes of long-term decarbonization outcomes. A related work, Chappin et al. (2017) present a modular and flexible ABM approach based on the toolkit of EMLab for the modeling of climate and energy policy in the European Union. Various challenges and methods concerned with energy transitions are discussed, including an agent-based investment model dealing with the issues of European energy policy. The model features a core framework with modules for carbon and renewable energy policies, capacity mechanisms, and intermittent renewable sources. They go on to discuss the relevance of the model through an overview of results, ongoing projects, and a case study on EU ETS reforms.

Furthermore, Lamberti et al. (2018) introduce the Dystopian Schumpeter Meeting Keynes (DSK) model-an agent-based integrated assessment model-developed in opposition to computable general equilibrium frameworks. Within the model, heterogeneous firms are interacting in the capital-good, consumption-good, and energy sectors, showing the way GHG emissions and changes in temperature will affect labor productivity, energy efficiency, and capital stock. The DSK model is able to match a wide range of empirical patterns on economic and climate dynamics.

Similar to previous study, Rengs et al. (2020) extend an already existing general-purpose macroeconomic ABM by investigating various climate policy options under different behavioral assumptions. Their model runs various policy scenarios, such as carbon taxation, labor tax reductions, subsidies for the adoption of greener technologies, and other measures, for their impact on carbon emissions and economic performance. The results suggest that carbon taxation could reduce emissions by a significant amount with no deterring effect on employment, while the subsidy for greener technology adoption may yield only limited emission reduction and potentially higher unemployment.

In a comparable investigation, Czupryna et al. (2020) suggest an ABM approach to investigate the trade-off between economic growth and environmental protection. The paper considers how individual decisions between economic growth and climate protection interact at the aggregate economic level. It is found that heterogeneity of agents, technology, and damage functions could yield slower GDP growth and higher climate damages than models with homogeneous agents.

There are also studies that compile existing literature on this subject. In this context, Balint et al. (2017) present a survey from a scientific perspective on the micro and macroeconomics of climate change and discussed the challenges ahead for this research line. As a result of the study, they identify four areas in which complex system models already generate valuable insights: 1) coalition formation and climate negotiations, 2) macroeconomic impacts of climate-related events, 3) energy markets, and 4) dissemination of climate-friendly technologies. Meanwhile, Hansen et al. (2019) conduct a systematic review of 62 studies to evaluate the potential of ABM in understanding energy transitions from a socio-scientific point of view. The results highlight that ABM's greatest potential lies in its application to policy and planning decisions. In a similar study, Castro et al. (2019) review 61 ABM studies focused on climate-energy policies aimed at reducing emissions, spreading technologies, and conserving energy. They cover a wide range of policy tools and recommend future research directions for ABMs to address overlooked policy questions. More recently, Yao et al. (2023) provide a systematic review of ABM and multi-agent system (MAS) applications from 2007 to 2021. They categorize studies based on agent implementations, examining MAS applications in building, district, and regional energy systems, as well as ABM applications in behavior simulation and policy-making. The review underscores the potential of ABM in energy transition research due to its flexible and decentralized decision-making capabilities.

Apart from the studies mentioned earlier, numerous other studies employ ABM to evaluate the effects of various policies on reducing emissions, disseminating technologies, and converting energy. Table 2.1 classifies these studies according to their application domains, while Table 2.2 categorizes them based on the policy instruments employed.

Table 2.1 : Classifications of ABM studies based on application.

Theme	Subcategory	Studies
Emission reduction	Carbon Market	Matsumoto (2008), Chappin and Dijkema (2009), Richstein et al. (2014), Tang et al. (2015), Isley et al. (2015), Lee and Han (2016), Zhu et al. (2016), Tang et al. (2017), Zhu et al. (2018)
	Electricity Market	Karimi and Vaez-Zadeh (2021), Veit et al. (2009), Chen et al. (2013), Beckendach et al. (2018), Li (2017), Li and Strachan (2017), Kraan et al. (2018), Wu et al. (2018), Czupryna et al. (2020)
	Macroeconomic Analysis	Gerst et al. (2013), Monasterolo and Raberto (2016), Lamperti et al. (2018), Monasterolo and Raberto (2018), Rengs et al. (2020), Niamir et al. (2020)
	Vehicle Market	Mueller and De Haan (2009), van der Vooren and Brouillat (2015), Hofer et al. (2018)
Product/Technology Diffusion	Electric Vehicles	Köhler et al. (2009), Eppstein et al. (2011), Natarjan et al. (2011), McCoy and Lyons (2014), Silvia and Krause (2016), Kangur et al. (2017), Ramsey et al. (2018), Klein et al. (2020), Buchmann et al. (2021), Zhuge et al. (2021)
	Renewable energy	Held (2010),Nannen and van den Bergh (2010), Ermst and Briegel (2017), Herrmann and Savin (2017), Safarzyńska and van den Bergh (2017), Chen et al. (2018), Ponta et al. (2018)
	Residential Solar Panel	Palmet et al. (2015), Rai and Robinson (2015), Wang et al. (2018), Al Irsyad et al. (2019), Stavrakas et al. (2019), Caprioli et al. (2020)
	Low Carbon/Energy Products	Bleda and Valente (2009), Desmarchelier et al. (2013), D'Orazio and Valente (2018)
	Heating Technologies	Sopha et al. (2011), Sopha et al. (2013)
Energy Conservation	Residential Buildings	Damiani and Sissa (2013), Lee et al. (2014), Hicks and Theis (2014), Hicks et al. (2015), Kowalska-Pyzalska (2016), Jensen and Chappin (2017), Walzberg et al. (2017), Moglia et al. (2018), Niamir et al. (2018), Wang et al. (2018)
	Office Buildings	Azar and Menassa (2011), Zhang et al. (2011), Zhao (2012), Lin et al. (2016), Jia et al. (2019)
	Transport	Schröder and Wolf (2017), Safarzyńska and van den Bergh (2018), Adenaw and Lienkamp (2021)
	Multi-Field	Allen et al. (2019)

Table 2.2 : Classifications of ABM studies based on policy instruments.

Theme	Policy Instrurement	Studies
Emission reduction	Tax	Isley et al. (2015), Karimi and Vaez-Zadeh (2021), Chen et al.(2013), Li (2017), Li and Strachan (2017), Kraan et al. (2018), Wu et al. (2018), Gerst et al. (2013), Monasterolo and Raberto (2016), Monasterolo and Raberto (2018), Rengs et al. (2020), Niamir et al. (2020), van der Vooren and Brouillat (2015)
	Emissions Trading	Matsumoto (2008), Chappin and Dijkema (2009), Richstein et al. (2014), Richstein et al. (2015), Tang et al. (2015), Isley et al. (2015), Lee and Han (2016), Zhu et al. (2016), Tang et al. (2017), Zhu et al. (2018), Beckenbach et al. (2018)
	Subsidy	Richstein et al. (2015), Tang et al. (2015), Beckenbach et al. (2018), Czupryna et al. (2020), Gerst et al. (2013), Rengs et al. (2020), Niamir et al. (2020)
	Command and Control	Beckenbach et al. (2018), van der Vooren and Brouillat (2015) , Hofer et al. (2018)
	Discount/Pricing	Mueller and De Haan (2009)), van der Vooren and Brouillat (2015)
	Financial instruments	Czupryna et al. (2020), Monasterolo and Raberto (2016), Monasterolo and Raberto (2018)
	Mixed Politics	van der Vooren and Brouillat (2015), Hofer et al. (2018)
	Other	Veit et al. (2009), Chen et al. (2013), Li and Strachan (2017), Hofer et al. (2018), Lamperti et al. (2018), Rengs et al. (2020)
Product/Technology Diffusion	Subsidy	Natarajan et al. (2011), Silvia and Krause (2016), Kangur et al. (2017), Herrmann and Savin (2017), Safarzyńska and van den Bergh (2017), Safarzyńska and van den Bergh (2018)
	Information Acquisition/Marketing	Nannen and van den Bergh (2010), Ernst and Briegel (2017), Wang et al. (2018), Bleda and Valente (2009), Desmarchelier et al. (2013) , Sopha et al. (2018)
	Tariff Guarantee	Herrmann and Savin (2017), Ponta et al. (2018), Palmer et al. (2015), Al Irsyad et al. (2019)
	Tax	Eppstein et al. (2011), Kangur et al. (2017), Nannen and van den Bergh (2010), Desmarchelier et al. (2013)
	Infrastructural Policies	Silvia and Krause (2016), Kangur et al. (2017)
	Discount/Pricing	Eppstein et al. (2011), Rai and Robinson (2015), Wang et al. (2018)
	Other Financial Incentives	Palmer et al. (2015), Al Irsyad et al. (2019)
	Financial instruments	Safarzyńska and van den Bergh (2017), Al Irsyad et al. (2019), D'Orazio and Valente (2018)
	Other	Köhler et al. (2009), Natarajan et al. (2011), McCoy and Lyons (2014), Silvia et al. (2016), Safarzyńska and van den Bergh (2017) , Chen et al. (2018), Wang et al. (2018), Desmarchelier et al. (2013), Sopha et al. (2011), Sopha et al. (2013)
Energy Conservation	Information Acquisition/Marketing	Kowalska-Pyzalska (2016), Jensen and Chappin (2017), Moglia et al. (2018), Azar and Menassa (2011), Zhang et al. (2011), Schröder and Wolf (2017)
	Incentives	Lee et al. (2014), Hicks and Theis (2014), Hicks et al. (2015), Moglia et al. (2018), Safarzyńska and van den Bergh (2018)
	Tax	Lee et al. (2014), Hicks et al. (2015)
	Other Financial Incentives	Moglia et al. (2018), Wang et al. (2018), Azar and Menassa (2011),
	Smart Measurement Systems	Damiani and Sissa (2013), Walzberg et al. (2017)
	Other	Lee et al. (2014), Moglia et al. (2018), Niamir et al. (2018), Zhang et al. (2011), Allen et al. (2019)

2.2 Climate Projections

The quantity of research examining the effectiveness of various techniques for ensembling GCMs is steadily rising. However, this section will primarily focus on reviewing papers that predominantly utilize Machine Learning (ML) methods among all the GCM ensemble approaches available.

Of these, the Random Forest (RF) algorithm is one of the in-use methods for GCM ensembling. In this context, Ahmed et al. (2019), first evaluate the performance of 36 CMIP5 (Coupled Model Intercomparison Project Phase 5) GCMs in capturing the precipitation and temperature variability over Pakistan. Further, they rank the performance of the best performing GCMs by multi-model ensemble analysis in both RF and simple mean methods. The current paper reports results showing that, in this regard, the RF method outperforms a simple mean. In another similar research, Homsi et al. (2020) project the likely precipitation change over Syria due to climate change. Using methods of symmetrical uncertainty (SU) and multi-criteria decision analysis (MCDA), it identifies an optimum GCM for precipitation projection. It then used a RF model to produce the multi-model ensemble of precipitation projections for the four RCPs.

To further assess the future changes in drought metrics, Prodhan et al. (2022) use the Deep Neural Network (DNN) and Gradient Boosting Regression Tree techniques for combining selected CMIP6 GCMs, along with the RF algorithm. It is found from the results that the proposed ensemble method presents higher performance compared to individual techniques.

The Support Vector Machine (SVM) technique has also been used in various researches for the ensembling of GCMs in literature. For instance, Ahmed et al. (2020) utilize several machine learning techniques, including SVM, to ensemble best models from a pool of 36 CMIP5 GCMs over Pakistan for precipitation and temperature prediction. The K-Nearest Neighbor (KNN) algorithm and Relevance Vector Machine (RVM) algorithms outperform Artificial Neural Network (ANN) and SVM algorithms. Thus, KNN and RVM methods are suggested to develop Multi Model Ensembles (MMEs) for temperature and precipitation. In a similar study, Dey et al. (2022) employ ANN, RF and SVM algorithms to ensemble top-5 GCMs for precipitation and temperature projection over the Damodar River basin in India. The results of this research indicate that both the SVM and RF methods outperform ANN and simple mean approaches. Wang et al. (2022) investigate extreme temperature indices in the North China Plain based on climate observations at 54 meteorological stations and projection data from seven CMIP6 GCMs. It investigates temporal and spatial variations in these indices during the past and future periods. The result suggests that the RMSE of the multi-GCM predictions regressed by SVM are smaller than those obtained by using the arithmetic mean approach.

ANN is generally considered an essential ensemble integration approach of GCMs along with the RF and SVM algorithms. Acharya et al. (2014) apply a nonlinear approach called the Extreme Learning Machine (ELM) to the outputs of GCM to estimate the MME of NEMR in southern part of India. In this study, the proposed technique is compared to other conventional MME methods, such as the simple arithmetic mean of GCMs and multiple linear regressions based on singular value decomposition. A wide variety of skill metrics, including spread distribution, multiplicative bias, and prediction errors, is utilized to evaluate the performance. Results show that ELM efficiently captures extremes compared to other MME methods. Recently, Yan et al. (2022) try applying an ANN approach to integrate multiple models using outputs from CMIP6, hence achieving better nonlinear and complex relationships between the climate models than the normally adopted approach of ensemble median. This improves the accuracy of predictions of the future precipitation patterns. Then, they analyze temporal changes and spatial distribution of the indices for several climate zones in China in three distinct time periods of the 21st century (2023 to 2100) and found that the application of multi-evaluation metrics outperforms the traditional ensemble median approach.

In addition to these studies, Kim et al. (2020) investigate the skill of various MME methods in enhancing the accuracy of 1-month lead seasonal forecast products. Seven MME methods are compared based on their hindcast performance for global 2-meter temperature and precipitation from 1983 to 2009. It is found that Genetic Algorithm (GA) emerged as the most effective MME method for predicting both global 2-meter temperature and precipitation across all seasons. In this work, Jose et al. (2022) use five different ML approaches, namely RF, SVM, Multiple Linear Regression (MLR), Extra Tree Regressor (ETR), and Long-Short Term Memory (LSTM), for the integration of temperature and precipitation information from 13 CMIP6 GCMs over

India. The results show that LSTM performs prominently better than others in the integration of the precipitation data, while RF and LSTM performed exceptionally well with the temperature data. Moreover, this study has shown that all the ML methods outperform the simple mean approach.

Sun et al. (2023) propose a Convolutional Neural Network (CNN) framework for MME of monthly precipitation over China from the CMIP6 models and, compared to 32 GCMs, quantile mapping (QM), and other in-widely used MME approaches such as Arithmetic Mean Ensemble (ENS), MLR, SVM, RF, and KNN, against in-situ measurements. CNN gives the best MR value of 0.96, outperforming KNN, RF, and MLR. While slightly trailing the top GCM, it surpasses other MME methods in capturing observed interannual variations and probability density functions, showing minimal sensitivity to changes in ensemble size. Lastly, Fu et al. (2023) introduce a regional downscaling model called stacking-MME, which combines multiple machine learning models through stacking. The model's performance is assessed in simulating precipitation, solar radiation, maximum temperature, and minimum temperature, and in predicting three future climate variable scenarios across near-term (2031–2040), medium-term (2051–2060), and long-term (2081–2090). Results indicate that Light Gradient Boosting Machine, Gradient Boosting Regressor, and RF demonstrate the most effective performances among the nine machine learning models evaluated.

Table 2.3 : Summary of GCM ensemble studies.

Reference	Study Area	Method	Variable
Acharya et al. (2014)	India	ANN	Precipitation
Wang et al. (2018)	Australia	RF, SVM, Bayesian Model Average	Temperature, Precipitation
Ahmed et al. (2019)	Pakistan	RF	Temperature, Precipitation
Yılmaz (2019)	Euphrates-Tigris Basin, Türkiye	Arithmetic mean	Temperature, Precipitation, Evapotranspiration
Xu et al. (2020)	Han River, China	Bayesian Model Average	Precipitation
Kim et al. (2020)	Several cities	MLR, ANN, Genetic Alg.	Temperature, Precipitation
Ahmed et al. (2020)	Pakistan	ANN, KNN, SVM, RVM	Temperature, Precipitation
Homsi et al. (2020)	Syria	RF	Precipitation
Carvalho et al. (2021)	Europe	Overlap percentage	Wind speed
Bağçacı et al. (2021)	Türkiye	Arithmetic mean	Temperature, Precipitation
Asadollah et al. (2021)	Iran	GBRT	Temperature, Precipitation
Dey et al. (2022)	India	ANN, RF, SVM	Temperature, Precipitation
Jose et al. (2022)	Netravati, India	SVM, ETR, MLR, RF, LSTM	Temperature, Precipitation
Prodhan et al. (2022)	South Asia	RF, GBRT, DNN	Temperature, Precipitation
Yan et al. (2022)	China	ANN	Precipitation
Zhang et al. (2022)	Global	OLS, DT, DNN	Temperature, Precipitation
Wang et al. (2022)	North China	SVM	Temperature, Precipitation

Table 2.3 (continued) : Summary of GCM ensemble studies.

Reference	Study Area	Method	Variable
Gholami et al. (2023)	Gharesu basin, Iran	Runoff Hybrid Approach	Precipitation
Guven (2023)	East Thrace, Türkiye	RF, GBRT, XGBoost	Temperature, Precipitation, Radiation, Wind Speed
Sun et al. (2023)	China	SVM, CNN, MLR, KNN, RF	Precipitation
Fu et al. (2023)	Zhongwei, China	9 ML algorithms	Temperature, Precipitation, Radiation
Zhao et al. (2023)	East China	Arithmetic mean	Precipitation
Present study	Türkiye	XGBoost	Temperature, Radiation, Wind Speed

3. METHODOLOGY AND MODEL

This study goes in for a structured and comprehensive methodology to analyze the impacts of energy, economic, and environmental policies on energy demand, production, and CO_2 emissions in Türkiye. Firstly, the study involves data collection and regridding of GCM-based climate data from the experiment CMIP6, and further compares these with observation-based data, ERA 5, which has been bias-corrected with CRU data, henceforth referred to as ERA5. These have been compared for the three skill measures: Kling-Gupta efficiency, normalized Root-Mean Squared Error, and a modified index of agreement. All that will be needed to further establish the appropriateness in providing accurate and reliable climate data for subsequent analysis.

Performances of GCMs are analyzed with the objective of selecting the four best models that could satisfactorily describe the climatic condition in Türkiye. Further, the top-ranked models will be trained using ERA5 via the Extreme Gradient Boosting Tree (XGBoost) method of machine learning. It is a technique well adapted for dealing with complicated nonlinear associations of variables given in Table 3.1. The resultant models, used for the future forecasting of climate variables under the SSP5-8.5 climate scenario, provide a strong base to understand the potential future climatic impacts on energy systems.

After the processing of climate data, the study estimates important energy indicators related to electricity demand, cooling-degree-days (CDD), and the generation of wind and solar power systems. The estimates are important to determine the future energy landscape of the country. Besides, the Analytical Hierarchical Process (AHP) and the Multi-Attribute Utility Technique (MAUT) are utilized to determine the utility function weights corresponding to the decisions of technology investment. These methods allow a systematic approach to prioritizing investments in various energy technologies, considering multiple criteria and stakeholder preferences.

Finally, one ABM is developed which is capable of simulating various policy scenarios. This model allows complex interactions of different agents such as Independent Power Producers (IPPs) and government within the energy system to be explored. The ABM shows the probable impacts of different policy preferences on energy demand, production, and CO_2 emissions under various simulation scenarios.

Figure 3.1 provides an overview of the proposed GCM-ABM framework structure with details on components and their linkages. In the presented framework, the integration of GCMs and ABM for simulating a set of policies regarding electricity demand, production, and related CO_2 emissions in the case of Türkiye is shown. Figure 3.1 facilitates an easier description of the methodology to be followed in this study by providing a clear visual display of the dynamic processes involved.

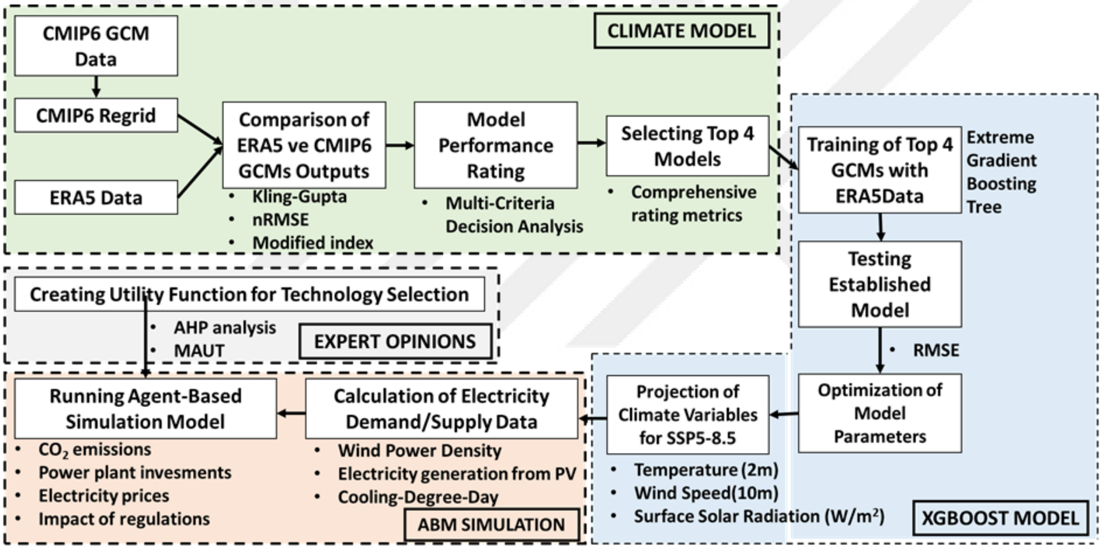

Figure 3.1 : Proposed model framework.

3.1 Climate Model

GCMs are the specialized tool applied by the scientist to know, understand, and predict Earth's climate system. Such models run simulation interactions between atmosphere, oceans, land surfaces, and ice by integrating physical, chemical, and biological processes. The major application of GCMs is projections on future climate conditions according to a wide range of GHG emission scenarios and, therefore, useful insights into potential impacts by researchers and policy makers in developing strategies for mitigation and adaptation.

GCMs are the result of several decades of research and are based on the fundamental principles of physics, representing processes such as atmospheric circulation, ocean currents, and energy exchanges through mathematical equations. Such models work for the whole globe, which is divided into some sort of grid system whereby the climate conditions for each cell in the grid are estimated and updated step by step in time. It enables GCMs to capture large-scale climate features such as El Niño events and monsoons, at the same time providing insights into regional climate changes.

The large increases in resolution and skill are the resultant consequences of large improvements in computational powers and data. The new models make full use of comprehensive observational databases derived from satellite observations, from weather stations, and from ocean buoys that have formed an important aspect in the processes of model simulation validation and enhancement. Equally, new algorithm and parameterizations that are at present being devised have enabled improved representations of complex procedures of cloud formation or land-atmosphere interaction.

GCMs have been a cornerstone in climate science, forming the basis for such major assessments as the reports done by the Intergovernmental Panel on Climate Change (IPCC). These models yield critical evidence supporting human influence over climate change and help identify probable future risks in the form of sea-level rise, extreme weather events, change in ecosystems, and agriculture. As the world grapples with the challenges of climate change, GCMs remain at the forefront of research in providing the essential knowledge to inform effective decision-making (Lee et al., 2023).

GCMs work by discretizing the surface of the Earth into a three-dimensional grid, with each cell having a unique geographical location. Within each model grid cell, atmosphere, ocean, land, and ice are simulated through mathematical equations driving physical processes that include fluid dynamics, thermodynamics, and radiation. Such a set of equations allows for variables in air temperature and pressure, wind speed, humidity, and the currents in the oceans. These models calculate the interactions among those components and simulate exchanges of energy and matter within and among grid cells through time. The time steps at which the model makes these calculations are from a few minutes to several hours, and projection of climate change on timescales from days and months to hundreds of years is enabled.

The performance of models in GCMs is directly related to the quality of the input data and algorithmic complexity. Observational data from a satellite, ground station, or buoy may be used as an initial condition for the model and constant verification. Advanced parameterization schemes are applied to represent processes that occur at scales smaller than the resolution of the grid, such as cloud formation, convection, and land-atmosphere interactions that are essential to capture the richness of the climate system (Lee et al., 2023). Thirdly, GCMs usually make several runs, referred to as ensembles, by having slightly different initial conditions or different settings of the parameters to represent uncertainties and natural variability. These ensembles help to bound the future climate possibilities and to identify signals that are most robustly projected.

Ensembling of GCMs is vital in climate studies due to the manifold benefits which this particular technique offers. This ensembling technique enhances the robustness and reliability of the climate projection by amalgamating outputs of various GCMs. This method decreases uncertainties in models compared to single model outputs, offering more comprehensive and closer-to-reality future climate scenarios. It is useful for ascertaining agreement among models using ensembling, hence displaying common trends and patterns despite model diversity. This enables the possibility to explore uncertainty ranges, which is crucial for making informed decisions on climate adaptation and mitigation. (Gholami et al., 2023). Besides, various ensembling techniques, including weighted averaging or machine learning algorithms, allow integrating various sources of information, such as different emission scenarios and model configurations, thus further enriching the scope and depth of climate projections. These ensembling methods involve different ways of combining outputs from different models with the view to enhancing predictive accuracy and reliability.

One such big way is by weighted averaging wherein the predictions are weighted in inverse proportion to a measure of the model's performance or their reliability. Thus, it would capitalize on strengths of each particular model while reducing a particular model's biases or inaccuracy. A weighted average allows much in simplicity, adaptability, and translucency-weights may even be tuned finer through empirical cross-validation and insights experted or otherwise. However, the technique may be sensitive to weight selection, which can introduce subjectivity or uncertainty unless done with careful calibration. It also assumes constant performance for each model over time, potentially overlooking temporal changes (Castaneda-Gonzalez et al., 2023).

Another emerging technique for ensembling involves machine learning algorithms that will incorporate multiple GCM outputs through data-driven modeling, such as neural networks or random forests. These algorithms capture the complex interactions and nonlinearities of the climate system that might further improve predictive performance. Machine learning-based ensembling automatically adapts and refines ensemble weights based on training data, hence limiting manual intervention. However, all those methods require really substantial computational resources. The mechanisms of the ensemble predictions are not so easy to understand and far from transparent; it is not easy to judge their reliability.

Each of these techniques has particular strengths-for instance, simple averaging is easy and tends to reduce random errors, while the more sophisticated techniques can account for model biases and uncertainties more accurately. They also have weaknesses, like the possibility of overfitting in the more complicated techniques and the computational intensity of large ensemble runs. Understanding such trade-offs is important for applying GCM ensembling effectively in climate projections.

Table 3.1 compares all the popular methods of ensembling, along with their respective pros and cons in detail. Weighted averaging adds the relative performance of each model together for its advantages to increase the accuracy in predictions. In ANN, while highlighting complex nonlinear data relationships, ANN can be very computational and suffer from overfitting issues. Random Forests, being the ensemble of many decision trees, provide robustness and interpretability but may face the problem of high variance. XGBoost has high predictive power and efficiency but may result in overfitting unless it is tuned correctly. SVM work very well for high-dimensional spaces but can be pretty slow when it comes to handling big datasets.

K-NN is simple and intuitive but computationally expensive and sensitive to noise. Decision Trees provide clear and interpretable models but can be unstable, overfitting easily. Naive Bayes Classifier is rather computationally effective for large sets of data and efficient, presupposing the independence of features. Gradient Boosting Machines are powerful predictors, correcting the errors of weak learners sequentially, but they can be prone to overfitting and require careful tuning. This comprehensive overview helps in selecting the appropriate ensembling method based on specific needs and constraints.

Table 3.1 : Advantages and disadvantages of the ensembling methods (adapted from Dineva and Atanasova, 2020).

Ensembling Technique	Description	Advantage	Disadvantage
Weighted Averaging	Combines outputs from multiple models by assigning weights based on performance or reliability.	Simplicity and flexibility Transparency in weight adjustment Straightforward interpretation of ensemble predictions Facilitates communication and decision-making in climate-related contexts	Sensitivity to weight selection, potentially introducing subjectivity or uncertainty Assumes constant model performance over time, may overlook temporal variations or model drift
Artificial Neural Networks (ANN)	Utilizes interconnected layers of nodes to learn complex relationships between input and output data.	Ability to capture nonlinear relationships in the data Flexible architecture capable of handling various input types and complexities	Require large amounts of data for training Vulnerable to overfitting if not properly regularized Training can be computationally intensive and time-consuming
Random Forests (RF)	Ensemble learning method that constructs multiple decision trees and then combines their predictions through averaging.	Robust against overfitting Less sensitive to noise and outliers in the data Can handle both numerical and categorical data	Less interpretable compared to individual decision trees Can be computationally expensive for large datasets and complex models May suffer from biases in class distributions if not properly balanced
Extreme Gradient Boosting (XGBoost)	Gradient boosting algorithm that sequentially trains weak learners and combines their predictions to improve accuracy.	High predictive performance Ability to handle missing data effectively Feature importance analysis for model interpretation	Prone to overfitting if hyperparameters are not tuned properly Sensitive to outliers and noisy data Training can be time-consuming for large datasets and complex models
Support Vector Machines (SVM)	It builds hyperplanes in high-dimensional space to classify data points.	Effective in high-dimensional spaces Versatile, as it can use different kernel functions for various data types Robust against overfitting	Memory-intensive for large datasets Can be sensitive to the choice of kernel function and hyperparameters Limited interpretability compared to simpler models

Table 3.1 (continued) : Advantages and disadvantages of the ensembling methods (adapted from Dineva and Atanasova, 2020).

Ensembling Technique	Description	Advantage	Disadvantage
k-Nearest Neighbors (k-NN)	Non-parametric method for classification and regression that predicts the output based on the majority vote or average of its k-nearest neighbors.	Simple and intuitive No training phase required Effective for small datasets with simple decision boundaries	Computational complexity increases with the size of the training dataset Sensitive to the choice of distance metric and value of k Can be inefficient for high-dimensional data
Decision Trees	A hierarchy of trees partitioning the space recursively, so decisions depend upon feature values at each level of the tree.	Easy to interpret and visualize Can handle both numerical and categorical data Robust to outliers and missing values	Prone to overfitting, especially with deep trees Instability, as small variations in the data can lead to different tree structures Limited expressiveness for capturing complex relationships
Naive Bayes Classifier	Probabilistic classifier based on Bayes' theorem, assuming independence between features.	Simple and computationally efficient Effective for text classification and spam filtering Can handle large feature spaces with sparse data	Strong independence assumption may not hold in real-world datasets Limited expressive power for capturing complex relationships
Gradient Boosting Machines	Ensemble learning method that builds models sequentially, each correcting errors of the previous ones.	High predictive accuracy Robust to outliers and noisy data Feature importance analysis for model interpretation	Sensitive to overfitting, especially with deep trees and large learning rates Prone to longer training times compared to simpler models
Logistic Regression	Linear regression model used for binary classification, estimating probabilities using the logistic function.	Simple and interpretable Efficient for large datasets with many features Outputs probabilities for class membership	Assumes linear relationship between features and log-odds of the outcome Limited flexibility compared to more complex models

3.1.1 Normalized root mean squared error (nRMSE)

nRMSE represents an important measure in many disciplines, such as engineering and data science, since it may reveal different characteristics in a model performance evaluation. It provides a very advantageous property for measuring the performance using the same scale of magnitude irrespective of data or the actual predictions (Chen and Liu, 2012). The normalization in the name of nRMSE means dividing the RMSE with a measure of observed data variability such as range or standard deviation. This is for a fair comparison; see equation 3.1.

$$nRMSE = \frac{\left[\frac{1}{N}\sum_{i=1}^{N}(G_i - O_i)^2\right]^{1/2}}{O_{max} - O_{min}} \tag{3.1}$$

Here, G_i represents the simulated values obtained from GCMs, while O_i represents observation values from ERA5/CRU. *N* is the total number of data used in the analysis.

nRMSE makes the interpretation of model performance easier because there is consistency and intuitiveness of results. Unlike the absolute error metrics like RMSE, which provides insight into the absolute magnitude of the prediction errors, nRMSE provides a dimensionless measure that is independent of the data scale. This is quite useful for comparing models that operate on different scales or datasets. Therefore, nRMSE is an indispensable tool for researchers, analysts, and practitioners seeking to benchmark and compare the accuracy of predictive models across different domains and datasets.

3.1.2 Modified index of agreement (md)

The modified index of agreement, md, is a statistical measure in general applications but finds its way into everyday usage in model performance analysis, especially in hydrology, climatology, and other environmental sciences. It provides full information on the agreement between observed and simulated values and thus gives useful insights into the accuracy and dependability of predictive models.

While the traditional measures involve either correlation coefficients or RMSE, the md considers the pattern and magnitude of errors in observed and simulated data points. The md hence reflects on timing and amplitude discrepancies, allowing a holistic view of model performance that will definitely enable researchers and practitioners to spot the areas of refinement in their models.

$$md = 1 - \frac{\sum_{i=1}^{N}|O_i - G_i|}{\sum_{i=1}^{N}(|G_i - \bar{O}| + |O_i - \bar{O}|)} \tag{3.2}$$

where $\bar{O}$ stands for the mean of the observed data.

md has a number of properties which are advantageous for model evaluation. Being dimensionless and ranging from 0 to 1, md offers an easily understandable measure of fit, with 1.0 indicating a perfect agreement between observed and simulated values. This is one of the reasons why it is so usable by stakeholders: they can discern the level of agreement between model predictions and observations (Willmott, 1981). Besides, md is resistant to outliers, hence resistant to extreme values and fluctuations in the dataset. Being able to present a balanced judgment about the events in terms of both timing and amplitude, md serves as a useful instrument for researchers and practitioners in many spheres, who strive for improving models predictive accuracy.

3.1.3 Kling-Gupta efficieny (KGE)

The Kling-Gupta Efficiency (KGE) is a metric that will crop up rather often in hydrological and environmental modeling. It's an overall indicator of model performance, integrating the main components: correlation, bias, and variability. Designed to be an improvement on more traditional indices, including the Nash-Sutcliffe Efficiency (NSE), KGE allows for a nuanced assessment of goodness of fit in regard to both simulated and observed values by means of their agreement in mean, variability, and correlation. This holistic approach allows for more accurate identification of model strengths and weaknesses, hence enhancing the reliability of model evaluations across different conditions and time scales (Liu, 2020; Quintero et al., 2020).

$$KGE = 1 - \sqrt{(R-1)^2 + \left(\frac{\sigma_G}{\sigma_O} - 1\right)^2 + \left(\frac{\mu_G}{\mu_O} - 1\right)^2} \tag{3.3}$$

Here, R represents the Pearson correlation coefficient calculated between the observed and simulated time series, σ_O stands for the standard deviation of observations, σ_G denotes the standard deviation of simulations, μ_G represents the mean of the simulated values, and μ_O indicates the mean of the observed values.

KGE is widely adopted in hydrological and environmental research due to its many advantageous characteristics. In formulation, KGE yields a dimensionless metric, bounded from negative infinity to 1, where 1 represents a perfect agreement. This standardized scale makes the model performance easy to interpret and compare across different studies and applications. Since KGE has the same sensitivity to systematic and random errors, it is a valued tool when it comes to the evaluation of complex hydrological processes and environmental systems.

3.1.4 Selection of GCMs

In evaluating the selected climate variables for each grid, data from GCMs will be compared with ERA5/CRU biased data using the above-described methods. Numerical values of each grid are ranked according to the performance of models. For the 13 selected GCMs (See Table A.1), the best-performing model in the selected grid takes the first rank, and the worst-performing one takes the 13th rank. In this ranking, the model with the lowest nRMSE will be considered the winner, while at the same time the model with the highest scores on the remaining two criteria will also be selected as a winner.

In this study, to rank the performance of GCMs for each climate variable in each grid, two different methods, namely Multiple-criteria Decision Analysis (MCDA) and Comprehensive rating metrics (MR), are employed consecutively.

3.1.4.1 Multiple-criteria decision analysis (MCDA)

MCDA has been found to be effective in ranking alternatives by aggregating information from diverse sources, as indicated by studies such as those by Homsi et al. (2020) and Salman et al. (2019). In this study, ranking of the GCMs will be done using scores obtained from an MCDA approach. This is done through the development of a payoff matrix, whereby the frequency of grid point numbers for a particular rank realized by a GCM is considered. For 13 GCMs under consideration, payoff matrix dimensions are 13 by 13, ranging between ranks 1 and 13. Model performance will be quantified based on the frequency of occurrence of each GCM across all grid points falling within Türkiye. The overall performance of a GCM over the study area will, therefore, be determined by its frequency of occurrence across different grid points. A higher frequency of occurrence attributes more weight to a particular model, resulting in a higher ranking compared to other models.

Following this approach, when a GCM attains rankings of 1, 2, 3, ..., n at grid points X_1, X_2, X_3, X_n, respectively, the MCDA score for the GCM is computed as follows:

$$MCDA\ Score = X_1 + X_2 \cdot (1/2) + X_3 \cdot (1/3) + \cdots + X_n \cdot (1/n) \quad (3.4)$$

For instance, a GCM will get n/1 points in case it ranks 1 (best performance) at all the n grid points. In the case of getting rank 2 at m grid points, the points are given as m/2, and so on. The total score is calculated by summing the points assigned to all the ranks obtained by a given GCM.

3.1.4.2 Comprehensive rating metrics (MR)

The MR approach, as extracted from the existing literature, was followed in this research to synthesize MCDA ranking results of models against all the performance criteria and climate variables into a single metric. MR can be mathematically defined as:

$$MR = 1 - \frac{1}{nm}\sum_{i=1}^{n} rank_i \quad (3.5)$$

Here, m and n denote the number of evaluation metrics and the number of GCMs, respectively; in this paper, m = 9 including 3 KGE, 3 md, and 3 nRMSE metrics, while n = 13. The higher the value of MR close to 1, the more powerful the GCM will be in reproducing the observed data.

3.2 Extreme Gradient Boosting Regression Tree

XGBoost is an ensemble machine learning algorithm with its foundation in decision trees and using gradient boosting techniques, established initially as part of a research project at the University of Washington in 2016. Renowned for its accomplishments in Kaggle competitions and its vital role in the latest industry applications, XGBoost receives considerable contributions from an active data science community (Niu et al., 2019).

XGBoost is recognized as an optimized gradient tree boosting technique that efficiently builds sequential decision trees, hence allowing for fast computation on a wide range of computing platforms. It has gained popularity due to its efficiency in modeling new features and classifying data points with high accuracy in tabular and structured datasets (Fan et al., 2018).

Evolved from a decision tree-based approach, XGBoost initially employed bagging-a collection meta-algorithm that took the predictions of multiple decision trees and combined them through majority voting. Further enhancements included reducing the margins of error in constructing sequential models with assistance from the gradient descent algorithm. Furthermore, XGBoost tackles overfitting and missing values through parallel processing for optimized gradient boosting by ways of tree pruning and parallelization, along with hardware optimization.

The implementation of the XGBoost algorithm proceeds as follows: Consider a dataset $S = \{(x_i, y_i); i = 1,2,\cdots,n; x_i \in R^m, y_i \in R\}$, where n denotes the number of observations, m signifies the number of features, and y represents the target variable. Let $\hat{y}_i^{XG}$ denote the outcome generated by the model

$$\hat{y}_i^{XG} = \phi(x_i) = \sum_{p=1}^{P} f_p\,(x_i) \tag{3.6}$$

f_p represents a decision tree, and $f_p(x_i)$ signifies the score for the pth tree for the i^{th} observation. To select the function f_p, it is necessary to minimize the regularized objective function, expressed as:

$$f_p = \sum_i L\left(y_i, \hat{y}_i^{XG}\right) + \sum_p \Omega\left(f_p\right) \tag{3.7}$$

incorporating both the loss function L and a penalty parameter Ω to mitigate the model's complexity.

$$\Omega\left(f_p\right) = \alpha T + \frac{1}{2}\lambda\|w\|^2 \tag{3.8}$$

Here, α and λ represent the parameters regulating the penalty for the leaves T and the leaf weight w respectively. The inclusion of $\Omega(f_p)$ serves to prevent overfitting and streamline the models generated by the algorithm.

XGBoost employs a unique algorithm in tree construction, utilizing the Similarity Score and Gain to pinpoint the most effective node divisions.

$$Similarity\ Score = \frac{\left(\sum_{i=1}^{n} Residual_i\right)^2}{\sum_{i=1}^{n}[Previous\ Probability_i \times (1 - Previous\ Probability_i)] - \lambda} \tag{3.9}$$

The concept of "prior probability" denotes the probability of an outcome estimated in a preceding step. At the outset, a probability of 0.5 is allocated to all observations to formulate the initial tree. Later, with the construction of other trees, this a priori probability gets updated, combining for the first prediction and all the predictions gathered from previous trees. The λ is a regularisation parameter. After calculating the Similarity Score of each leaf node, the Gain could be worked out in the following step:

$$Gain = Left\ leaf_{similarity} + Right\ leaf_{similarity} - Root_{similarity} \tag{3.10}$$

The greatest Gain signifies the optimal point for dividing the tree.

XGBoost has many parameters, all of which are very influential in the behavior and predictive performance of this algorithm. These include a learning rate that controls the contribution of each tree in the overall model, the maximum depth of each tree, regularization terms to prevent overfitting, and the number of trees in the ensemble.

- Learning Rate: Better known as the "eta" parameter, the learning rate controls the contribution of each tree to the global model: where a lower learning rate increases the robustness of the model by decreasing the influence a single tree would have, a higher learning rate allows for faster learning but might increase the risk of overfitting.
- Maximum Depth: Sometimes referred to as "max_depth," this parameter defines the deepest level to which trees in an ensemble can expand. In this regard, while deeper trees can capture even more complex data relationships, they are typically more subject to overfitting. Finding the right maximum depth thus finds a sweet spot between model complexity and generalization performance.
- Regularization Terms: Preventing overfitting, XGBoost contains several regularization terms: "gamma"-the minimum loss reduction required to create further partitioning of leaf nodes, and "lambda" ("alpha") is the L1 (Lasso) and L2 (Ridge) regularization on leaf weights, respectively. These penalize overly complex models to give ultimately better generalization performance.
- Number of Trees: This is often referred to as "n_estimators," which is the total number of boosting rounds or iterations during model training. Increasing the number of trees can improve model performance up to a point but may increase training time and lead to overfitting if not tuned properly.

The optimization of these parameters involves finding that combination of values from which the model achieves the highest predictive power with minimal overfitting. This can be done by grid search, randomized search, or more intelligent optimization techniques that can systematically explore this parameter space and identify the best configuration of a given dataset and objective.

Finally, the algorithm is trained and evaluated on the validation set or by using cross-validation for every possible combination of parameter values. Further, the optimal value of the parameters is determined regarding the performance metric-performance score on the validation set-which might be accuracy or mean squared error.

In this study, the XGBoost algorithm is used to ensemble the top four CGMs for the prediction of future values of climate variables in each grid. Prior to ensembling and forecasting, the datasets-both top four GCMs and ERA5/CRU-are split into two parts: namely, the train dataset and the test dataset. The training dataset consists of data over the years from 2010 to 2013, while the test dataset includes data from the year 2014 only.

In every grid, climate variables are forecasted for the future until 2040 using a grid search technique to find the best combination of parameters that minimize the RMSE.

3.3 Analytical Hierarchical Process (AHP)

The AHP was developed by Saaty in 1980 as an advanced decision-analysis technique that embodies both psychological and mathematical elements. According to Saaty (2001), it is a structured technique for analyzing complex problems that include knowledge and judgments.

From the day it was discovered, AHP has been a vital tool for the analyst and researcher. It has gained widespread acceptance as one of the most important methods in multiple criteria decision-making. Several major publications have appeared, expressing the wide-ranging applications that AHP has in the broad fields of optimization, alternative selection, efficient distribution of resources, and much more, to name a few (Vaidya and Kumar, 2006).

Basically, AHP works by setting priorities of the alternatives and the criteria on which such alternatives are based. Relevant criteria are selected by decision makers into the hierarchy to be considered, while irrelevant ones are discarded. The criteria could also range from well-defined and measurable criteria such as weight and length to intangible ones that do not have pre-defined scales.

In general, the priorities for each alternative's performance on every criterion are determined through pairwise comparisons of judgment or ratios of scale measurements, wherever possible. Such prioritization allows a resolution of the difficulty with disparate scales by interpreting their significance relative to user values.

Finally, a process of weighting and aggregation is used to deduce overall priorities for the alternatives about their contributions to the goal. This process parallels the arithmetic used in the past combination of alternatives evaluated under multiple criteria using a common scale for an aggregate result - normally monetary. Using the AHP, a multidimensional scaling problem is reduced to a unidimensional scaling problem (Saaty, 2001).

To assess the significance of variables, it's necessary to establish a pairwise comparison matrix A belonging to the real space $R^{n \times n}$. Moreover, this matrix must adhere to the following criteria:

- $a_{i,j} > 0$;
- $a_{i,i} = 1$;
- $a_{i,j} = 1/a_{j,i}$ for all i,j=1,2,…,n.

The pairwise comparison matrices are constructed utilizing Saaty's suggested 1-9 importance scale. Particularly, when a study's findings have broad implications across a significant population, researchers frequently aggregate opinions from multiple individuals to formulate these decision matrices. Furthermore, many researchers adopt the geometric mean method during consolidation to ensure the reliability of the pairwise comparison matrices. Table 3.2 provides an explanation of the importance scale values and their corresponding interpretations.

Table 3.2 : Importance scale values

Intensity of Importance	Definition	Interpretation
1	Equal importance	*i* and *j equally important*
2	Weak	
3	Moderate importance	*i* slightly more important than *j*
4	Moderate plus	
5	Strong importance	*i* more important than *j*
6	Strong plus	
7	Very strong importance	*i* very strongly more important than *j*
8	Very, very strong	
9	Extreme importance	*i* extremely more important than *j*

Normalization of a pairwise comparison matrix involves the division of each element by the sum of its column (3.11). Once the normalized pairwise comparison matrix is obtained, the normalized principal eigenvector corresponding to each row can be calculated by averaging the values in that row (3.12).

$$\bar{a}_{i,j} = \frac{a_{i,j}}{\sum_{i=1}^{n} a_{i,j}} \tag{3.11}$$

$$w_i = \frac{\sum_{j=1}^{n} \bar{a}_{i,j}}{n} \tag{3.12}$$

In this context, w_i, $\bar{a}_{i,j}$ and n represent the normalized principal eigenvector for row i, the elements of the normalized pairwise comparison matrix A_{norm}, and the number of factors, respectively.

Evaluating the model's consistency requires deriving the principal eigenvector (λ_{max}) using equation 3.13.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{w_i}{\sum_{i=1}^{n} a_{i,j}} \tag{3.13}$$

After calculating λ_{max}, the consistency index (CI) can be determined using the following equation:

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{3.14}$$

Finally, the consistency rate (CR) is expressed as follows:

$$CR = {}^{CI}/_{RI} \tag{3.15}$$

Table 3.3 presents the value of RI (Random Index) utilized in equation 3.15.

Table 3.3 : Random Index values based on the number of variable**.**

n:	2	3	4	5	6	7	8	9	10
RI:	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.51

3.4 Multi-Attribute Utility Technique (MAUT)

Multi-Attribute Utility Technique (MAUT) embeds psychological measurement models and scaling techniques appropriate for evaluating alternatives with more than one relevant attribute. Moreover, MAUT can be used as a decision aid since it decomposes complex evaluation tasks into more easily managed subtasks (Winterfeldt and Fischer, 1975).

It basically aims at valuing and comparing alternatives in respect to a pre-defined set of attributes or criteria. MAUT is strategically designed to support the decision-maker in making an informed decision, especially in cases when complicated multi-criteria considerations come into view. A utility score of 1.0 shall be assigned for the most favored option, with 0.0 assigned for the least favored choice. Next, experts choose a midpoint value that has a utility score of 0.5, which is exactly halfway between the most and least preferred alternatives. Experts then identify a "quarter point" value with a utility score of 0.25, positioned halfway between the midpoint and the least preferred alternatives. Finally, experts determine a value function with a utility score of 0.75, representing a point halfway between the most preferred and the midpoint values. (Doczy and AbdelRazig, 2017). In this regard, the framework of MAUT is given in Figure 3.2.

For criteria requiring maximization (i.e., higher marginal utility scores are preferable):

$$g_{ij} = \frac{c_j a_i - Min_j[c_j a_i]}{Max_j[c_j a_i] - Min_j[c_j a_i]} \tag{3.16}$$

For criteria necessitating minimization (i.e., lower marginal utility scores are preferable):

$$g_{ij} = \frac{Max_j[c_j a_i] - c_j a_i}{Max_j[c_j a_i] - Min_j[c_j a_i]} \tag{3.17}$$

Where a_i represents alternative i; c_j represents criteria j; g_{ij} denotes the normalized score for a_i in c_j, where $0 \leq g_{ij} \leq 1$; $c_j(a_i)$ indicates the performance score of a_i in c_j;

$Max_j[c_j(a_i)]$ and $Min_j[c_j(a_i)]$ represent the maximum and minimum elements in the column vectors c_j, respectively.

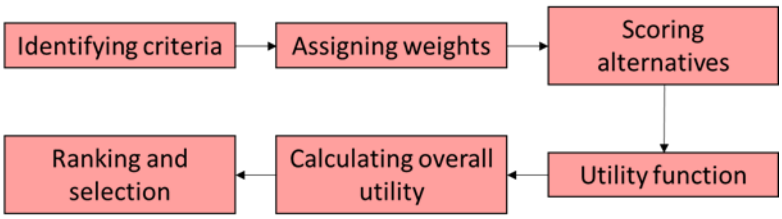

Figure 3.2 : Framework of MAUT.

3.5 Auto-Regressive Integrated Moving Average (ARIMA)

The Auto-Regressive Integrated Moving Average (ARIMA) model, is a method employed in time-series forecasting to predict the future value of a variable based on its historical values. It integrates auto-regression and moving averages while also employing differencing to eliminate trends and/or seasonality. The model can be represented by the following equation:

$$\acute{y}_t = c + \phi_1 \acute{y}_{t-1} + \cdots + \phi_p \acute{y}_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{3.18}$$

Here, $\acute{y}_t$ represents the differenced series and is computed by considering both the lagged values of y and the lagged errors.

The ARIMA model is defined by three parameters: *p, d,* and *q*. The p parameter dictates the number of lagged periods in the autoregressive component of the model. For example, with p=4, the model utilizes data from the past four periods to make predictions. The d-parameter indicates the numbers of differencing steps necessary for the time series to become stationary, removing thereby trends and seasonality-meaning constant mean and variance over time-which forms a necessary prerequisite for any ARIMA-modelling. It simply means the q parameter represents how many lags exist in the moving average part, dealing with the error or residual of that time series variable explained neither by the autoregressive and nor by differencing features. The two combined finally boost an added ARIMA model which can better estimate future values given one's past variation.

3.6 Agent Based Model

ABM is a way of computational modeling of complex systems that involves the simulation of individual entities, called agents, and their interaction within an environment. Each independent agent has behaviors, decision-making processes, and interactions with other agents and the surrounding environment. Such agents can model any entity from the individual in society to components involved in a manufacturing process (Macal and North, 2005).

The significant underpinning of agent-based modeling and simulation is the emergent capabilities in the interactional processes across independent agents. By simulating the behaviors of each agent, a researcher would visually observe their collective interactions over time to gain insight into the general dynamics of such a system. ABM is of particular value when studying systems for which analytical methods are inadequate, such as determining the flow of traffic in cities, analyzing the spread of diseases, or simulating economic markets (Macal and North, 2005).

The advantage of the agent-based modeling technique can be considered its potential to grasp a complex and diverse world that, by nature, represents real systems. Agents in ABM exhibit heterogeneous characteristics and adaptive behaviors based on local interactions. That gives them much more realistic capabilities of description compared with the traditional aggregate models for complex systems study (Khodabandelu and Park, 2021). Further, ABM allows analysts to conduct scenario analyses simply by changing the behavior of agents or environmental parameters. In that respect, ABM becomes a versatile tool for decision-making and policy evaluations. Apart from the features of the individual agent, ABM has a number of distinctive qualities giving it uniqueness and some advantages against other widely used simulation methods, notably Discrete-Event Simulation (DES) and System Dynamics (SD).

One of the key distinguishing features of ABM is that it recognizes agent heterogeneity. While other methods of simulation tend to represent a system in a homogeneous form, assigning similar properties to all agents within one group and regulating similar interaction protocols among them, ABM allows modeling agents to have a heterogeneous approach, differentiating each agent individually even from those within the same group (Macal and North, 2005). This perspective of heterogeneity facilitates the accurate modeling and enhances the collective behavior of the overall model. This is beneficial in many scenarios, as the oversimplification entailed in a homogeneous approach may overlook the individual differences among agents and thus can result in misleading deviations from reality (Lu et al., 2016).

A further important characteristic of ABM is its ability to handle problems with multiple options quite efficiently. The fact that each individual agent can be unique in ABM leads to the creation of almost all possible scenarios (Zhang et al., 2019). Even though this is often highly computational, it also raises the possibility of finding better options than the other simulation methods. DES and SD use a top-down approach. They start by building the system at a high, macro level, then propose hypotheses and test their validity, often relying on empirical data for analysis (Lu et al., 2016). Contrarily, ABM is a bottom-up approach in which characteristics and the interaction of the agents at an individual level are defined; emergent outcomes are produced at the macro-level of the system. This micro-level agent modeling makes ABM well-suited for exploring various what-if questions without heavy reliance on empirical analyses, excessive assumptions, or biased, preconceived model directions. Additionally, micro-level agent modeling allows ABM to investigate the likelihood of different scenarios occurring, including those that are rare but could significantly impact system outcomes (Tah, 2005).

Considering these capabilities and advantages of this method, ABM is one of the most proper methods to accurately simulate the proposed model. Thus, the following ABM structure is utilized in this study (Figure 3.3).

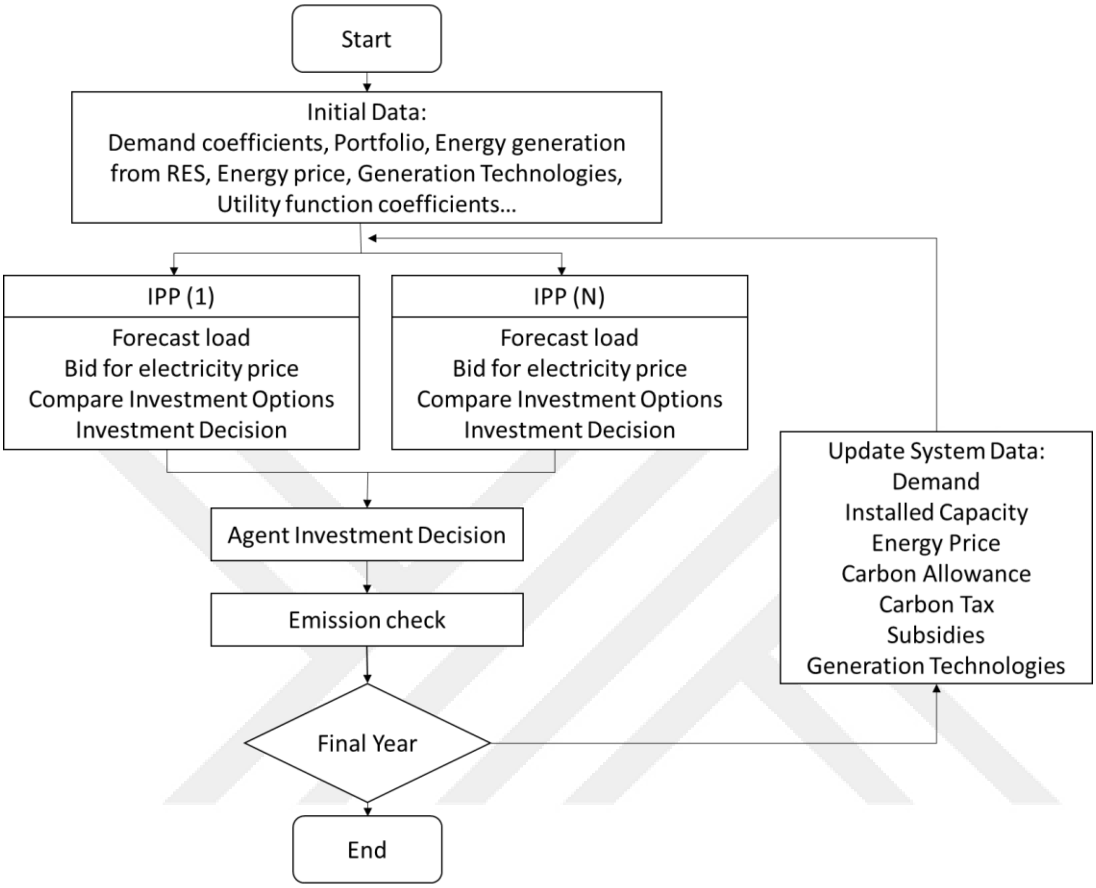

Figure 3.3 : Structure of the proposed ABM.

The proposed model includes three different agent types, namely government, independent power producers (IPP), and market maker. Government agent is responsible for the setting carbon tax, carbon allowance, and subsidies, while market maker agent stands for the collecting bids and determining the electricity prices. IPP agents represent the electricty producers which have different portfolios and profit margin expectations, and they give bids for each electricity generation technology in their portfolios.

To simulate the proposed ABM, this study employs four modules:

- Electiricty demand module
- Electricity generation module
- Capacity addition/shut-down module
- Carbon module

3.6.1 Electricity demand module

Considerig the electricity consumption of Türkiye, three major sector which constitute more than 93 percent of total electricity demand of Türkiye are analysed in this study (TEDC, 2023). These are i) residential buildings, ii) commercial buildings, and iii) industry. Electricty demand of each sector shows different sensitivities for changes in electricity prices, income levels, population, and temperature.

Based on these sensivities, equations 3.19, 3.20, and 3.21 show the electricity demand of residential sector, commercial sector, and industry, respectively.

$$\begin{aligned}\mathrm{ECA}_{\mathrm{t}}^{\mathrm{res}} = \mathrm{ECA}_{\mathrm{t-1}}^{\mathrm{res}} \cdot \left[1 + \left(\frac{Y_t}{Y_{t-1}} - 1\right) \cdot \rho_{gdp}^{res}\right] \cdot \left[1 + \left(\frac{P_{t-1}^{elec.cons.res}}{P_{t-2}^{elec.cons.res}} - 1\right) \cdot \rho_p^{res}\right] \\ \cdot \left[1 + \left(\frac{CDD_t}{CDD_{t-1}} - 1\right) \cdot \rho_{cdd}^{res}\right] \cdot \left[1 + \left(\frac{Pop_t}{Pop_{t-1}} - 1\right) \cdot \rho_{pop}\right]\end{aligned} \quad (3.19)$$

$$\begin{aligned}\mathrm{ECA}_{\mathrm{t}}^{\mathrm{com}} = \mathrm{ECA}_{\mathrm{t-1}}^{\mathrm{com}} \cdot \left[1 + \left(\frac{Y_t}{Y_{t-1}} - 1\right) \cdot \rho_{gdp}^{com}\right] \cdot \left[1 + \left(\frac{P_{t-1}^{elec.cons.com}}{P_{t-2}^{elec.cons.com}} - 1\right) \cdot \rho_p^{com}\right] \\ \cdot \left[1 + \left(\frac{CDD_t}{CDD_{t-1}} - 1\right) \cdot \rho_{cdd}^{com}\right] \cdot \left[1 + \left(\frac{Pop_t}{Pop_{t-1}} - 1\right) \cdot \rho_{pop}\right]\end{aligned} \quad (3.20)$$

$$\begin{aligned}\mathrm{ECA}_{\mathrm{t}}^{\mathrm{ind}} = \mathrm{ECA}_{\mathrm{t-1}}^{\mathrm{ind}} \cdot \left[1 + \left(\frac{Y_t}{Y_{t-1}} - 1\right) \cdot \rho_{gdp}^{ind}\right] \cdot \left[1 + \left(\frac{P_{t-1}^{elec.cons.ind}}{P_{t-2}^{elec.cons.ind}} - 1\right) \cdot \rho_p^{ind}\right] \\ \cdot \left[1 + \left(\frac{CDD_t}{CDD_{t-1}} - 1\right) \cdot \rho_{cdd}^{ind}\right] \cdot \left[1 + \left(\frac{Pop_t}{Pop_{t-1}} - 1\right) \cdot \rho_{pop}\right]\end{aligned} \quad (3.21)$$

Equation 3.22 stands for the calculation changes in real Gross Domestic Product (GDP) per capita in year *t* compared to the previous year considering the real GDP per capita potential growth rate (η_t^Y) in year *t* and capital damage factor (η^{CDF}) for natural disasters in response to rising temperatures.

$$\frac{Y_t}{Y_{t-1}} = (1 + \eta_t^Y) \cdot (1 - \eta^{CDF} \cdot (T_t^{POP} - T_0^{POP})) \quad (3.22)$$

T_t^{POP} is the population-weighted average temperature of Türkiye, and it is calculated as

$$T_t^{POP} = \frac{\sum_{i=1}^{81} Pop_{i,t} \cdot T_{i,t}}{\sum_{i=1}^{81} Pop_{i,t}} \quad (3.23)$$

where $Pop_{i,t}$ and $T_{i,t}$ represent the population and annual average temperature of i^{th} city in year *t*. T_0^{POP}, which is the population-weighted aveage temperature of Türkiye for the base year 2020, is calculated as 285.43K based on the established climate models.

$$Pop_{i,t} = \gamma_i \cdot Pop_{i,t-1} \cdot \beta_t \quad (3.24)$$

$$\beta_t = \frac{\sum_{i=1}^{81} Pop_{i,t}}{Pop_t^{TS}} \quad (3.25)$$

where β_t is the population correction coefficient in year t, and Pop_t^{TS} is the total population of Turkey projected by TurkStat (2017b).

Table 3.4 displays the variables employed for computing electricity demand across each sector, along with their respective descriptions and values sourced from the literature.

Table 3.4 : Variables of electricity demand calculations.

Variable	Description	Value	Reference
ρ_{gdp}^{res}	Income elasticity of residential electricity demand	0.227	Guven et al. (2021)
ρ_{p}^{res}	Price elasticity of residential electricity demand	-0.126	
ρ_{cdd}^{res}	CDD elasticity of residential electricity demand	5.397	
ρ_{gdp}^{com}	Income elasticity of commercial electricity demand	0.219	
ρ_{p}^{com}	Price elasticity of commercial electricity demand	-0.147	
ρ_{cdd}^{com}	CDD elasticity of r commercial electricity demand	4.55	
ρ_{gdp}^{ind}	Income elasticity of industrial electricity demand	0.548	
ρ_{p}^{ind}	Price elasticity of industrial electricity demand	-0.145	
ρ_{cdd}^{ind}	CDD elasticity of industrial electricity demand	3.25	
ρ_{pop}	Population elasticity of electricity demand	5.198	Sağlam et al. (2023)
η_t^{Y}	Real GDP per capita potential growth rate		OECD (2021)
η^{CDF}	Capital damage factor for natural disasters	0.061%	Czupryna et al. (2020)
$Pop_{i,t}$	Projected population of cities		Author's calculation based on TurkStat (2017a, b) data

3.6.2 Electricity generation module

This study utilizes actual portfolios of IPPs in Türkiye, where company names will be anonymized and replaced with codes. The analysis focuses on the top 50 power generation enterprises and treats the collective installed capacity of the remaining facilities in Türkiye, constituting the 51st power generation enterprise, as a single entity. Comprising 21.1% of the total capacity, these smaller enterprises are relatively small-scale and are more likely to adjust to market conditions based on industry-wide behavior patterns, particularly in terms of technology preferences, risk assessment, and investment thresholds (Chen et al., 2013). Given that the GCM outputs provide climate variables only, these data need to be integrated into various mathematical equations to relate them to energy production within the ABM before calculating electricity production from wind and solar.

Initially, wind speeds derived from the model represent speeds at a height of 10 meters above the surface. However, modern wind turbine towers often exceed 150 meters in height, necessitating adjustments to wind speeds based on altitude. For this study, an average wind turbine hub height of 100 meters was assumed, and wind speed was recalculated using the following equation:

$$wspd(z) = wspd(z_{ref})\left(\frac{z}{z_{ref}}\right)^{\alpha} \quad (3.26)$$

where z and z_{ref} denote the hub height of the wind turbine (100 m) and the GCM output height (10 m), respectively. wspd(z_{ref}) is the wind speed at z_{ref} and α =1/7 is the coefficient of the power law exponent, taken as suitable in open areas as indicated by earlier studies (e.g., Carvalho et al., 2021; Guven, 2023; Sawadogo et al., 2019).

Wind Power Density (WPD) generally stands for assessing the wind power generation potential and is widely being used as an indicative measure expressed by the following formula:

$$WPD = \frac{1}{2} \cdot \rho \cdot wspd(z)^3 \quad (3.27)$$

Here, ρ represents air density (1.225 kg/m^3). The main point can be drawn from the above formulation that WPD varies with cube of wind speed; hence small changes in the speed of winds would drastically impact the yield from wind.

The performance of a PV system hinges on the downward surface solar radiation it receives and the efficiency of the PV modules. Notably, PV system efficiency varies with ambient temperature (Dutta et al., 2022). To evaluate PV efficiency in relation to temperature, this study employs the Evans-Florschuetz PV efficiency correlation coefficients (Dubey et al., 2013).

$$\eta_c = \eta_{ref}\left[1 - \beta_{ref}\left(T_c - T_{ref}\right)\right] \quad (3.28)$$

Where η_{ref} and β_{ref} denote the defined PV efficiency (0.20) at the reference temperature (T_{ref}=25°C) and the temperature coefficient (0.0045), respectively.

The temperature T_c is defined by the equation:

$$T_c = c_1 + c_2 tas + c_3 rsds + c_4 wspd \tag{3.29}$$

Here, c_1=4.3°C, c_2=0.943, c_3=0.028°C m^{2}W^{-1}, and c_4=−1.528°C m^{-1} (Jerez et al., 2015).

The energy obtainable from the PV panel depends on solar radiation and panel efficiency, given by the equation:

$$E_{PV} = Radiation \left(\frac{W}{m2}\right) \times \eta_c \tag{3.30}$$

Each company is unique concerning the portfolio and capacity of production facilities. The production of electricity from photovoltaic panels depends on the shortwave radiation that reaches the surface and the panel efficiency, which is modified according to temperature and wind speed, as shown before. Then, the amount of produced electricity coming from a 1m^2 PV panel during year t is given by

$$Q_{i,PV,j,t} = \sum_{d=1}^{365} \eta_{c_d} \times rsds_d \times 24 \text{ [kWh/m}^2\text{]} \tag{3.31}$$

In this context, i denotes the IPP number, j represents a specific plant within the selected IPP portfolio, and $rsds_d$ stands for the average surface incident shortwave solar radiation on day d.

Likewise, electricity generation from the wind turbine is determined based on the following equation, which relies on the wind power density.

$$Q_{i,WT,j,t} = \sum_{d=1}^{365} \pi \times R^2 \times \beta_{WT} \times WPD_d \times 24 \text{ [kWh]} \tag{3.32}$$

The equation for calculating energy production from a wind turbine involves the radius R of the rotor and the efficiency β_{WT} of the wind turbine. In this study, the turbine efficiency was set at 0.4 based on literature sources (Rehman et al., 2023).

Following the calculation of energy production from renewable resources, which varies depending on the climate, the initial step in the process is to compute "residual generation." This term refers to the disparity between the total electricity demand (D_t^{total}) and the energy generated from renewable sources. The deficit represented by residual generation will be fulfilled by fossil fuel-based power plants (such as coal or natural gas) or high-availability plants (including hydroelectric, biogas, biomass, nuclear, and geothermal facilities).

$$Residual\ Generation = Electricity\ Demand - Generation_{PV\&WT} \quad (3.33)$$

As the first step, IPPs conduct annual production planning ($G^{planned}_{i,tech,j,t}$) for each power plant within their portfolio, taking into account the capacity and capacity factor of each plant.

$$G^{planned}_{i,tech,j,t} = 8760 \times CF_{tech} \times Cap_{i,tech,j} \quad (3.34)$$

Then, they formulate an annual electricity sales price offer ($bid_{i,tech,j,t}$) for each plant in their portfolio using the following equation.

$$bid_{i,tech,j,t} = \Big\{\big[P^{fuel}_{tech,t} \cdot G^{actual}_{i,tech,j,t-1} \cdot f^{consumption}_{tech} + (G^{actual}_{i,tech,j,t-1} \cdot f_{tech} - C^{allowance}_{i,techj,t}) \cdot tax^{carbon}_{t} + OPEX_{i,techj,t} + Depr_{i,techj,t}\big] \times \left(1 + \frac{\vartheta_{t-1}}{1 - tax_{tech,t}}\right) / G^{actual}_{i,techj,t-1}\Big\} - subs_{i,tech,j,t} \quad (3.35)$$

The descriptions of parameters used in equation 3.35 are presented in Table 3.5.

Table 3.5 : Parameters of bidding calculation.

Parameter	Description
$P^{fuel}_{tech,t}$	Fuel price
$G^{actual}_{i,tech,j,t-1}$	Actual generation of previous year
$f^{consumption}_{tech}$	Unit fuel consumption of power plant
f_{tech}	Unit carbon emission of power plant
$C^{allowance}_{i,techj,t}$	Carbon allowance of power plant
tax^{carbon}_{t}	Carbon tax (\$/ton CO_2)
$OPEX_{i,techj,t}$	OPEX of power plant
$Depr_{i,techj,t}$	Depreciation of power plant
ϑ_{t-1}	Expected profit margin of IPP
$tax_{tech,t}$	Corporation Tax
$subs_{i,tech,j,t}$	Government subsidy

Following the derivation of equations 3.34 and 3.35 for each power plant, the average electricity sales price offer (bid^{avg}_{t}) is computed using equation 3.36.

$$bid_t^{avg} = \frac{\sum_i \sum_{tech} \sum_j G_{i,tech,j,t}^{planned} \times bid_{i,tech,j,t}}{\sum_i \sum_{tech} \sum_j G_{i,tech,j,t}^{planned}} \tag{3.36}$$

For renewable energy power plants, actual generation matches planned generation. However, for power plants using fossil resources, the actual production ($G_{i,tech,j,t}^{actual}$) is determined by equation 3.37.

$$G_{i,tech,j,t}^{actual} = \begin{cases} G_{i,tech,j,t}^{planned}, tech: PV, WT, \ldots \\ G_{i,tech,j,t}^{planned} \times \frac{D_t^{total} - \sum G_{i,PV+WT,j,t}}{\sum_{tech} \sum_i \sum_j G_{i,tech,j,t}^{planned}}, tech: Coal,\ Natural\ Gas \end{cases} \tag{3.37}$$

Ultimately, the electricity sales price offered by the market maker agent is defined by equation 3.38.

$$P_t^{elec} = bid_t^{avg} e^{\left[\tau\left(\frac{D_t^{total} - \sum_i \sum_{tech} \sum_j G_{i,tech,j,t}^{planned}}{\sum_i \sum_{tech} \sum_j G_{i,tech,j,t}^{planned}}\right)\right]} \tag{3.38}$$

Here, τ represents a proportional coefficient that reflects price fluctuations resulting from imbalances between supply and demand, set at 0.001 according to Cong and Wei (2010).

3.6.3 Capacity addition/shut-down module

Anticipating future demand for electricity, IPPs may invest in new power plants. To begin, each producer of electricity must forecast electricity demand and supply in the future. It is pressumed each IPP employs an ARIMA algorithm to predict demand for year t+3 ($D_{i,t+3}^{pred.total}$):

$$\frac{D_{i,t+3}^{pred.total}}{Q_t^{serv.} + Q_t^{constr.} - Q_t^{ret.}} > \varepsilon_i \tag{3.39}$$

Here, $Q_t^{serv.}$ denotes the generation capacity in service, $Q_t^{constr.}$ indicates the power plants under construction, and $Q_t^{ret.}$ represents the power plant capacity expected to reach the end of their lifespans before year t+3.

Once the investment decision is taken, capacity of newly built power plants is determined, using estimations on electricity deficits and share of a producer on the electricity market, with equation 3.40.

$$Q_{i,t}^{inv.} = \left(\frac{D_{i,t+3}^{pre.total}}{\varepsilon_i} + Q_t^{ret.} - Q_t^{serv.} - Q_t^{constr.}\right) \cdot \frac{\sum_{tech} \sum_j G_{i,tech,j,t}^{actual}}{\sum_i \sum_{tech} \sum_j G_{i,tech,j,t}^{actual}} \tag{3.40}$$

Once capacity of newly built power plants is determined, the suitability of different power plant technologies is evaluated, considering their return on investment and related risks, as well as preferences about risks, public acceptance, environmental impact -assessed as Global Warming Potential (GWP) in the life cycle- and technology. The utility function equation used in this study is presented in equation 3.41.

$$U_{i,tech,j,t}^{inv.} = (\omega_{tech}^{eco}\theta_{i,tech,j,t}^{eco} + \omega_{tech}^{soc}\theta_{tech}^{soc} + \omega_{tech}^{env}\theta_{tech}^{env}) \cdot \varphi_{i,tech,t} \tag{3.41}$$

Here, ω represents the weight of the criteria determined through the AHP analysis, while θ denotes the environmental, economic, and social utility score of the technology In this regard, Table 3.6 presents social acceptance percentages and environmental impacts for various technologies (Baur et al., 2022; Chatzimouratidis and Pilavachi, 2008; Marashli et al., 2022).

Table 3.6 : Social acceptance percentages and environmental impacts of technologies.

Technology	Social Acceptance (%)	Environmental Impact (g CO_2-eq/kWh)
Wind	23.1	13.45
Geothermal	19.89	37.4
PV	18.44	38.8
Hydro	10.73	22.7
Biomass	8.47	62.4
CCGT	7.02	502
Coal	3.01	936
Nuclear	1.76	26.9

The economic utility function for energy investments is expressed as follows (Chen et al., 2018):

$$\theta_{i,tech,j,t}^{eco} = \left(1 - e^{-\gamma_i \cdot W_{i,tech,j,t}^{inv.}}\right) \tag{3.42}$$

$W_{i,tech,j,t}^{inv.}$ here is the discounted investment return rate, (3.43), and γ_i is the Arrow–Pratt risk aversion coefficient, influencing the attitude of an IPP towards risk: a positive γ_i characterizes risk-averse attitudes, and the stronger the aversion to risk, the higher is the value of $\phi_{i,tech,t}$ defines the share of this technology in the portfolio of an enterprise and its contribution to the total national contribution of the identical technology.

$$w_{i,tech,j,t}^{inv.} = \frac{\sum_{\acute{t}=t}^{T_{tech}+t} \left\{ \frac{(Q_{i,t}^{inv.} \cdot 8760 \cdot CF_{tech} \cdot P_t^{elec.avg}) - (Q_{i,t}^{inv.} \cdot 8760 \cdot CF_{tech} \cdot f_{tech} - C_{new.i,tech j,t}^{allowance}) \cdot tax_t^{carbon} + subs_{tech,t} \cdot Q_{i,t}^{inv.} - P_{tech,t}^{fuel} \cdot Q_{i,t}^{inv.} \cdot f_{i,tech,j,t}^{consumption} - OPEX_{i,tech j,t}}{(1+r)^{\acute{t}-t}} \right\}}{Inv_{new.i,tech,j,t}} + Decom_{tech} \tag{3.43}$$

Moreover, if a power plant has continuous losses for five consecutive years or reaches the end of its useful life, the generation company will dismantle it.

Considering the limited resources for low-carbon resources, environmental constraints also put a limit on their excessive use, as expressed in equation 3.44. Once the overall installed capacity of a specific technology reaches its resource threshold, further investment in that technology is not allowed, unless some power plants using the same technology are dismantled.

$$\sum_i \sum_j Q_{i,tech,j} \leq Cap_{tech}^{limit} \tag{3.44}$$

With ongoing technological advancements and economies of scale, the cost of energy generation technologies is decreasing year by year. Equation 3.45 illustrates the future average investment cost of a specific technology using a learning-by-doing model.

$$\ln(Inv_{tech,t}^{avg}) = \ln(Inv_{tech,t_0}^{avg}) - \sigma_{tech} \cdot \ln\left(\frac{(\sum_i \sum_j Q_{i,tech,j})_t}{(\sum_i \sum_j Q_{i,tech,j})_{t_0}}\right) \tag{3.45}$$

where σ_{tech} stands for the experience index for the technology *tech* (See Table 3.7).

Table 3.7 : Experience indexes of technologies (adapted from Wesseh Jr and Lin, 2016; Rubin et al., 2015; Chen et al., 2018).

Technology	σ_{tech}
Wind	0.15
Geothermal	0.1
PV	0.15
Hydro	0.03
Biomass	0.1
CCGT	0.03
Coal	0.07
Nuclear	0.3

3.6.4 Carbon Module

For any given year, the government would have apportioned carbon quotas to all the fossil-based power plants for that coming year as well as specified the subsidy policy during that time. According to Chen et al. (2018), at the very outset, the government would calculate carbon emission allowances of each power plant for the upcoming year using the grandfathering allocation mechanism:

$$C_{i,tech,j,t+1}^{allowance} = (1 - \eta_{rr}) \cdot G_{i,tech,j,t}^{actual} \cdot f_{i,tech,j,t} \cdot (1 - reservedrate) \tag{3.46}$$

The government provides subsidies to businesses involved in solar, wind, or biomass generation and evaluates the potential discontinuation of the subsidy scheme. Subsidies for renewable generation from solar, wind, or biomass cease once the levelized cost of electricity (LCOE) for these sources matches that of natural gas power plants.

This study assumes that the prevailing carbon tax rate is influenced by cumulative quotas and emissions from the preceding period. The current carbon tax rate can be approximated as (Cong and Wei, 2010):

$$tax_t^{carbon} = tax_{t-1}^{carbon} \cdot e^{(\lambda^{c} \cdot (Total\ emissions_{t-1} - Total\ allowance_t))} \cdot (1 + \epsilon_t) \sim N(0, 0.01^2) \tag{3.47}$$

λ_c denotes a proportional coefficient, set at 0.005 (Cong and Wei, 2010). Additionally, a random disturbance represented by ϵ_t is incorporated to accommodate various unforeseen factors. The initial value for the carbon tax rate, denoted as $tax_{t=0}^{carbon}$, is set at $75 per ton of CO_2-equivalent, aligning with the average carbon tax rate in Europe as of March 2024 (EU Carbon Permits, 2024).

3.7 Data

To implement the proposed model efficiently, a wide-ranging dataset is assembled from various sources. This procedure entails consolidating information from numerous channels to guarantee precision and dependability. The upcoming Table 3.8 functions as a succinct repository, presenting the compiled data alongside their corresponding origins.

3.8 Assumptions

In this study, it is hypothesized that Türkiye's CO_2 emissions, accounting for approximately 1.5% of the global total, exert a negligible influence on the global climate. Within the context of renewable energy advancement, IPPs are assumed to strategically invest in PV and wind energy projects, focusing on regions with optimal efficiency. Consequently, estimating power generation from these sources relies on calculations derived from the average output of the most efficient locations, utilizing capacity factors projected from future GCMs predictions.

Furthermore, it is assumed that Türkiye has reached its full capacity for hydropower plants, thereby limiting IPPs' ability to establish new facilities in this sector. Additionally, IPPs are expected to face obstacles in pursuing offshore wind turbine projects, further complicating Türkiye's transition to renewable energy sources. Despite these assumptions, IPPs are anticipated to persist in their efforts to advance renewable energy solutions within Türkiye's energy landscape.

Table 3.8 : Technical parameters of technologies.

	PV	Wind	Hydro	Geothermal	Biomass	Coal	NG	Nuclear	Reference
Fuel Consumption (ton/MWh)	-	-	-	-	-	0.4	0.26	0.08	
CAPEX (M$/MW)	0.92	1.1	2.574	5.3875	4.332	4.9	0.975	11.2	LAZARD (2023),
Variable OPEX ($/MWh)	-	-	-	16.375	5.8	4.25	3.75	4.5	NREL (2023)
Fixed OPEX (k$/MW-year)	10.5	27.5	64	14.5	150.85	65.375	13.5	142	
Carbon emission (gCO_2/kWh)	-	-	-	-	-	900	460	-	IPCC (2014)
Experience index	0.15	0.15	0.03	0.1	0.1	0.07	0.03	0.3	Chen et
Construction time (year)	1	1	4	3	2	4	2	6	al. (2018)
Life span (year)	30	30	100	30	45	30	30	60	NREL (2023)

In alignment with the aforementioned assumptions, the deployment of electricity generation technologies encounters specific capacity limitations. Specifically, it is proposed that the maximum capacity for PV systems in Türkiye is 387 GW, as reported by Kilickaplan et al. (2017). Similarly, the capacity cap for wind energy systems is estimated at 83 GW (Oğulata, 2003). Moreover, it is assumed that the capacity threshold for geothermal systems in Türkiye is approximately 5 GW (Url-1), while the capacity restriction for biomass energy systems is projected to be 9.5 GW (Ozcan et al., 2015).

Besides these assumptions, one base scenario and nine policy scenarios will be evaluated with the purpose to see the impact of energy policies on capacity additions, electricity prices and CO_2 emissions resulting from electricity generation. The features of the scenarios are presented in Table 3.9. The nuclear power plant capacity is taken as 4800 MW by considering the installment of the existing nuclear power plant in Akkuyu, Mersin.

Table 3.9 : Features of policy scenarios.

Scenario	Carbon Tax	Renewable Subsidy	Corporation Tax Reduction for RES	Nuclear Power Plant
Base	-	-	-	-
1	-	5 $/MWh (escalated with inflation rate) at t=0	-	-
2	75 $/ton $CO_{2\text{-}eq}$ at t=0	-	-	-
3	75 $/ton $CO_{2\text{-}eq}$ at t=0	5 $/MWh (escalated with inflation rate) at t=0	-	-
4	-	-	10% reduction	-
5	-	-	40% reduction	-
6	-	-	-	4800 MW t=3
7	-	5 $/MWh (escalated with inflation rate) at t=0	-	4800 MW t=3
8	75 $/ton $CO_{2\text{-}eq}$ at t=0	5 $/MWh (escalated with inflation rate) at t=0	-	4800 MW t=3
9	75 $/ton $CO_{2\text{-}eq}$ at t=0	Transfer of half of the carbon tax revenue as a subsidy for RES	-	4800 MW t=3

However, for comparison purposes, a carbon tax of US$75 per ton of CO_2 can be justified for matching with the average carbon price prevailing within the EU market dynamics and hence essentially covering the full environmental cost of carbon emissions. This benchmark will allow a relative analysis of how such a policy might have influenced Turkey's electricity prices and emissions reduction, therefore allowing some insight into how things could change. Adopting this rate allows for a consistent evaluation of economic and environmental impacts, ensuring a relevant comparison despite Türkiye's non-EU status. Moreover, Table 3.10 presents the technical parameters of electricity generation technologies.

Table 3.10 : Technical parameters of electricity generation technologies.

	PV	Wind	Hydro	Geothermal	Biomass	Coal	Natural Gas	Nuclear
Fuel Consumption (ton/MWh)	-	-	-	-	-	0.4	0.26	0.08
Carbon emission (gCO_2/kWh)	-	-	-	-	-	900	460	-
Experience index	0.15	0.15	0.03	0.1	0.1	0.07	0.03	0.3
CAPEX (M$/MW)	0.92	1.1	2.574	5.3875	4.332	4.9	0.975	11.2
Variable OPEX ($/MWh)	-	-	-	16.375	5.8	4.25	3.75	4.5
Fixed OPEX (k$/MW-year)	10.5	27.5	64	14.5	150.85	65.375	13.5	142
Life span (year)	30	30	100	30	45	30	30	60
Construction time (year)	1	1	4	3	2	4	2	6

4. RESULTS AND DISCUSSION

4.1 Climate Projections

As given in Section 1.3, the first objective of this study is to identify the most accurate GCMs that can simulate Türkiye's unique climate conditions. To detect the top four GCMs, outputs of CGMs for each climate variable were compared with ERA5/CRU data in 120 grids using three different methods, namely, Kling-Gupta efficiency, normalised Root Mean Squared Error, and modified index of agreement.

Following the calculation of these values for evergy grid, Multi-Criteria Decision Analysis (MCDA) method was applied to determine the performance of GCMs. The results of MCDA and rankings are given in Table 4.1 and Table 4.2, respesctively.

Table 4.1: MCDA results for each climate variable.

		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
RSDS	KGE	37.9	38.6	9.8	18.4	14.8	11.4	16.6	42.0	67.7	52.4	14.7	33.4	17.5
	md	40.3	33.8	14.8	14.9	12.3	13.0	13.1	45.1	73.0	47.0	14.8	42.2	11.2
	nRMSE	44.9	41.9	10.0	14.8	12.1	13.9	15.7	40.7	76.6	44.5	13.9	31.5	14.8
TAS	KGE	25.8	34.2	34.9	31.7	29.4	41.9	32.3	9.7	28.4	41.9	25.6	20.4	19.1
	md	36.2	54.2	30.4	29.5	36.2	27.6	16.9	28.1	29.3	35.4	12.7	26.0	13.0
	nRMSE	32.7	42.6	45.4	27.8	34.3	29.0	24.8	9.6	29.8	39.6	12.0	33.2	14.5
SFCWIND	KGE	61.2	29.5	9.1	27.7	29.7	13.9	56.6	15.2	30.6	26.7	25.8	14.5	34.7
	md	75.6	24.9	9.2	24.5	25.7	13.3	60.1	13.7	25.7	23.3	25.3	12.3	41.7
	nRMSE	52.4	21.4	9.1	30.8	27.6	14.1	59.6	14.0	36.5	34.3	19.9	11.4	44.1

Table 4.2: Rankings of GCMs for each climate variable.

		M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
RSDS	KGE	5	4	13	7	10	12	9	3	1	2	11	6	8
	md	5	6	9	7	12	11	10	3	1	2	8	4	13
	nRMSE	2	4	13	8	12	11	7	5	1	3	10	6	9
TAS	KGE	9	4	3	6	7	2	5	13	8	1	10	11	12
	md	3	1	5	6	2	9	11	8	7	4	13	10	12
	nRMSE	6	2	1	9	4	8	10	13	7	3	12	5	11
SFCWIND	KGE	1	6	13	7	5	12	2	10	4	8	9	11	3
	md	1	7	13	8	4	11	2	10	5	9	6	12	3
	nRMSE	2	8	13	6	7	10	1	11	4	5	9	12	3

After determining performance of each GCM utilizing MCDA, the comprehensive ranking metric (MR) method was employed to amalgamate the MCDA ranking outcomes of the models into a unified metric across all performance criteria and climate variables.

Table 4.3: The most successful GCMs for simulating Türkiye's climate conditions.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13
MR	0.709	0.641	0.291	0.453	0.462	0.265	0.513	0.350	0.675	0.684	0.248	0.342	0.368
Rank	1	4	11	7	6	12	5	9	3	2	13	10	8

The values in the Table 4.3 represent the performance scores of each model with respect to the MR. For instance, Model 1 (M1) has a score of 0.709, indicating it performs well according to the MR criterion. Model 2 (M2) has a score of 0.641, ranking it lower compared to Model 1 but still relatively high among the models. Model 11 (M11) has the lowest score of 0.368, indicating poorer performance according to the MR criterion. The second row labeled "Rank" shows the ranking of each model based on their scores for the MR criterion. Model 1 (M1) has the highest score and therefore ranks first, while Model 11 (M11) has the lowest score and ranks last.

As a result of these analyses, within the range of 13 GCMs, ACCESS-CM2, INM-CM5–0, INM-CM4–8, and ACCESS-ESM-1-5 emerged as the most promising options. Hence, they were chosen for forecasting Türkiye's future climate.

As the next step, the XGBoost ML algorithm was employed to ensemble the outputs of these GCMs due to the advantages of ensemling process provided in the Methodology Section. The future projections for each grid and climate variable are generated by combining the SSP5.85 scenario data from the chosen climate models. Projections were conducted for the years 2023-2040.

As a consequence of this projection, the alterations in future projections relative to historical data were determined by applying equations 3.26-3.30 . Figure 4.1 illustrates the variations in the averages of the periods 2025-2030, 2031-2035, and 2036-2040 compared to the average energy potentials from 1985 to 2014, expressed as percentages for each grid.

The forecast indicates an anticipated decline in the electricity output from solar power plants across Turkey, attributed to efficiency losses exacerbated by rising temperatures. Foremost among the regions expected to experience the most significant decrease are the Mediterranean and Eastern Black Sea Regions. However, despite the projected decline, the Eastern Black Sea Region presently exhibits relatively low solar potential, rendering it economically unfavorable for the installation of photovoltaic solar power plants. This study's findings corroborate the unsuitability of this region for such installations in the future. Conversely, the Marmara Region (particularly Thrace) and the Southeastern Anatolia Region are anticipated to undergo the least reduction in electricity production from photovoltaic solar power plants. Remarkably, these outcomes align with existing literature, as reported by Ha et al. (2023) and Jerez et al. (2015).

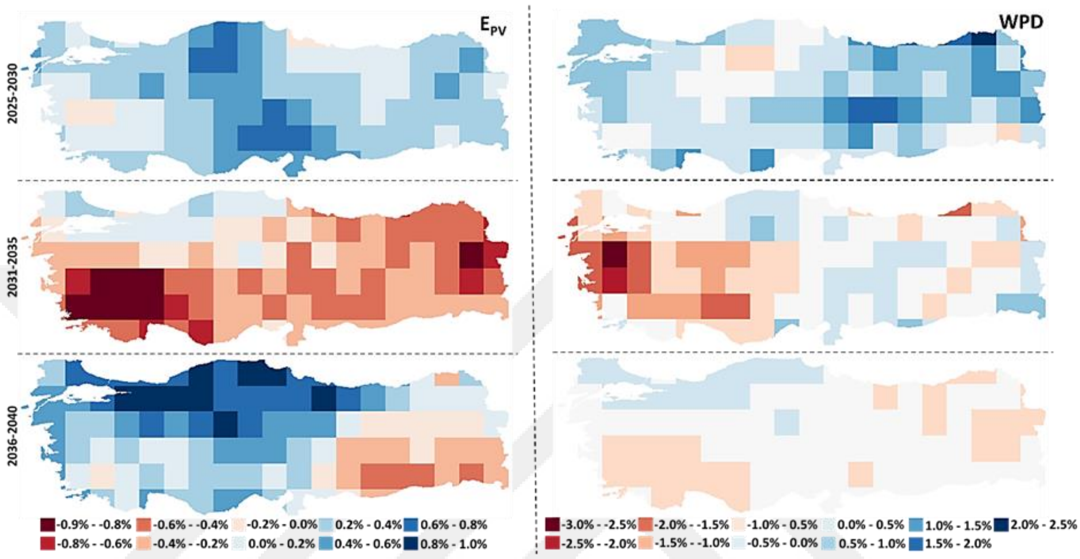

Figure 4.1 : Change in energy production as percentages for different time horizons.

Upon examining electricity generation from wind turbines, an uptick in wind power production is projected, notably in Thrace and the northern reaches of Central Anatolia (near Çorum and Tokat). Conversely, a downturn in wind power potential is anticipated in the Eastern Black Sea, and Uşak-Kütahya-Eskişehir-Bolu regions. Notably, these findings echo earlier research in the literature, as documented by Çetin (2023).

Furthermore, the mean CDDs for every city in Turkey are calculated over three specific time periods, employing temperature projections derived from GCM forecasts (Refer to Figure 4.2). It becomes conspicuously apparent that the average CDDs are expected to undergo a substantial increase across most cities, notably within the Mediterranean region and the southeastern sector of Turkey, as a consequence of the influences of global warming. These observations align with existing literature, as evidenced by studies such as those conducted by Lionello and Scarascia (2018) and Batibeniz et al. (2023).

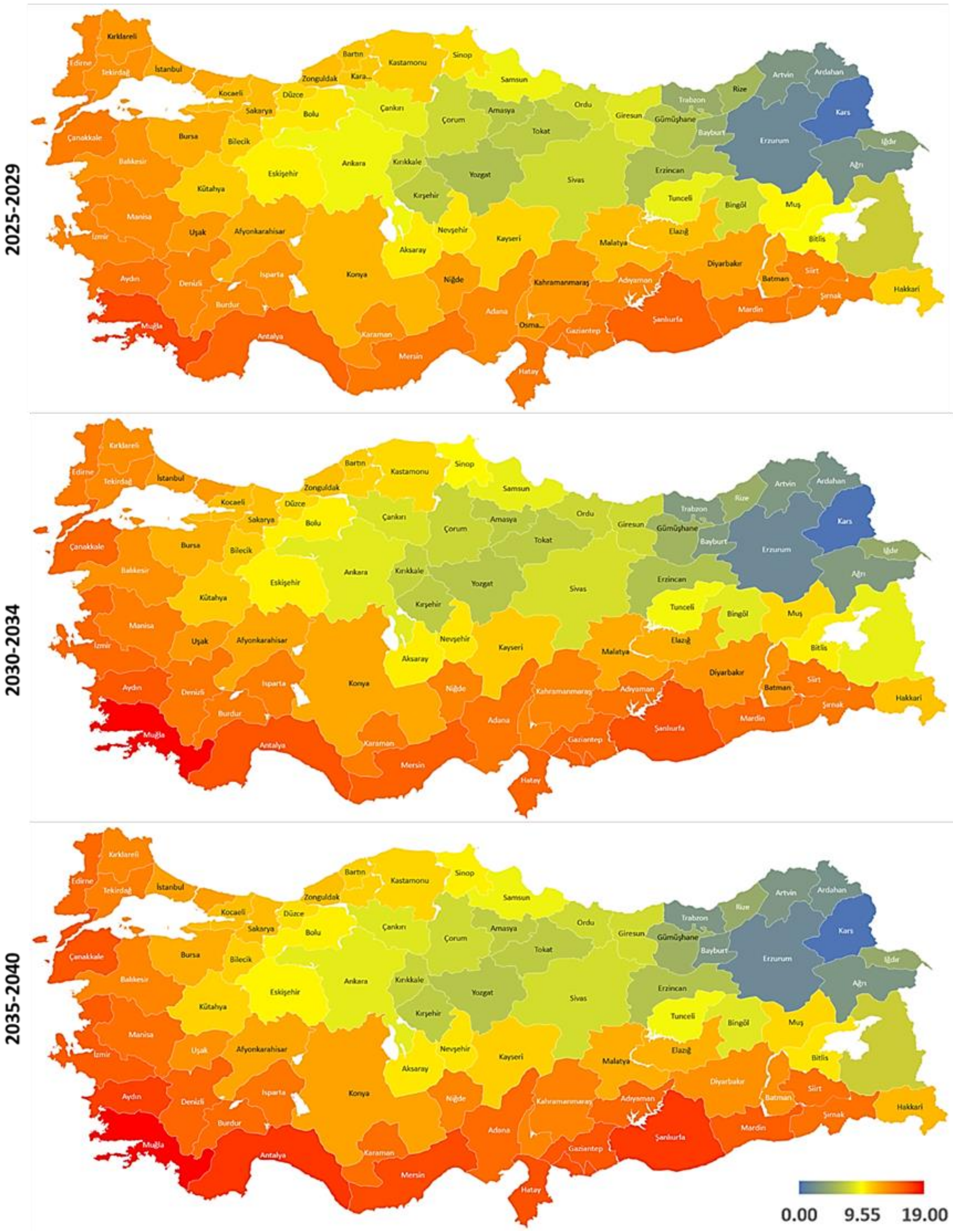

Figure 4.2 : Change in CDDs of cities based on time horizons.

Table 4.3 illustrates the annual population-weighted CDDs from 2020 to 2040. CDDs are a metric used to estimate the demand for energy needed to cool buildings; they increase with rising temperatures. The data shows a general upward trend over the two decades, suggesting an increase in cooling requirements over time, which may be indicative of a warming climate or changing population distribution towards warmer areas.

Notable increases are seen in the years 2031 (127.06) and 2032 (129.31), with slight dips and recoveries in subsequent years. This pattern reflects an overall increase in cooling demand, highlighting the importance of planning for enhanced cooling infrastructure and energy resources to manage the growing need effectively. The data underscores the impact of climate change on energy consumption patterns, emphasizing the need for sustainable energy solutions and climate adaptation strategies.

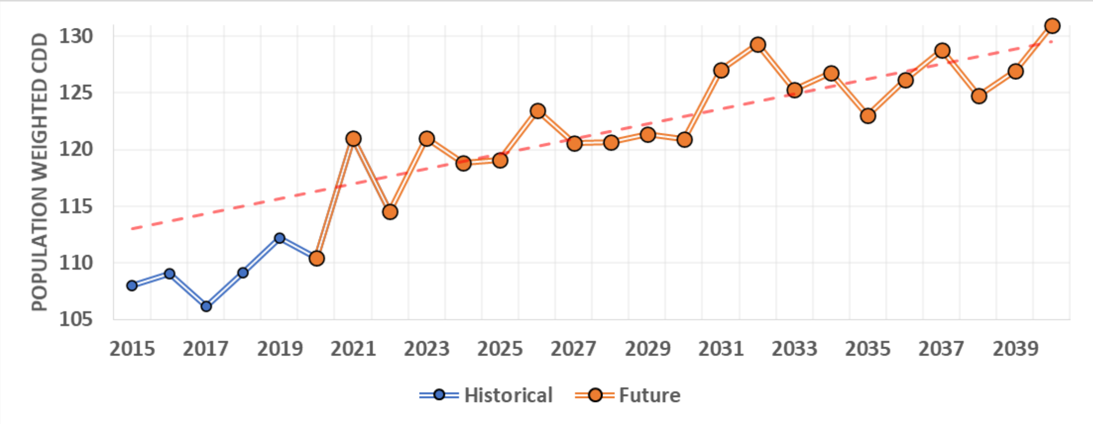

Figure 4.3 : Population weighted CDD of Türkiye.

4.2 AHP and Utility Function

In this study, an AHP analysis was conducted to determine the weights of utility function components given in equation 3.41. The weights of utility function components given in equation 3.41 were determined through an AHP analysis. The AHP analysis involved gathering comparative values provided by 11 experts from academia specializing in energy and environment, as well as the private sector focusing on energy and finance. After the survey values were collected, the pairwise comparison matrix was created as the first step of the AHP (See Table 4.4).

Table 4.4: Pairwise comparison matrix.

	W1	W2	W3
W1	1	6.590817	6.473262
W2	0.151726	1	1.995506
W3	0.154482	0.501126	1
Sum	1.306208	8.091943	9.468768

Following the pairwise comparison matrix, a normalized pairwise comparison matrix was created by applying equation 3.12 (See Table 4.5). The AHP analysis resulted in determining the weights of environmental, economic, and social utility scores as 0.095, 0.15, and 0.755, respectively.

Table 4.5: Normalized pairwise comparison matrix.

	W1	W2	W3	Criteria Weight
W1	0.765575	0.814491	0.683644	0.755
W2	0.116158	0.12358	0.210746	0.150
W3	0.118267	0.061929	0.10561	0.095

Moreover, since the Consistency Ratio (CR) with the value of 0.088 is lower than the threshold value (0.1) given by Saaty (1980), it can be concluded that the result of the AHP analysis is reliable.

Taking into account the MAUT, experts determine utility scores based on the ranges and units of utility functions related to environmental impact and social acceptance. Table 4.6 outlines these utility scores, while Figure 4.4 depicts the utility curves.

Table 4.6: Utility scores for each quartile.

Criteria/Score	Range	0	0.25	0.5	0.75	1.0
Environmental	13.45-936	13.45	290.12	420.21	520.34	936
Social acceptance	1.76-23.21	1.76	7.02	11.42	17.42	23.21

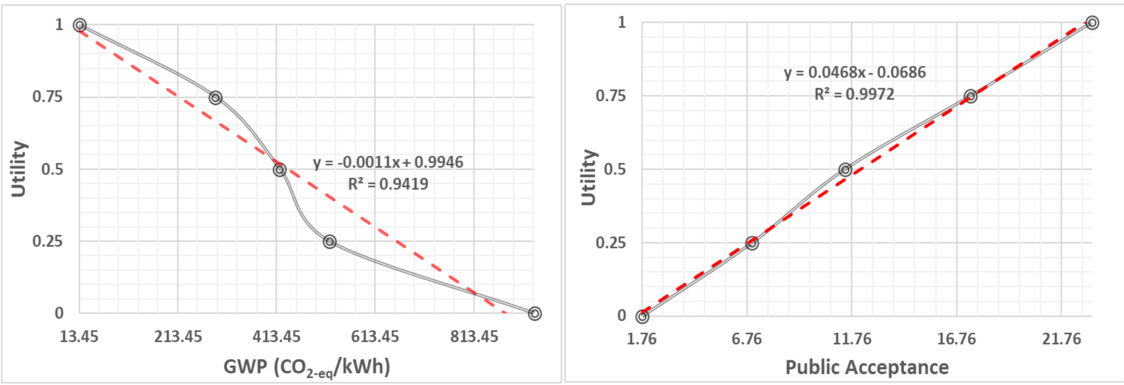

Figure 4.4 : Utility function of a) Environmental impact, and b) Social acceptance for electricity generation technologies.

Table 4.7 presents the combined utility scores for environmental impact and social acceptance of each electricity generation technology, derived from utility curves established using the MAUT and weights determined through AHP analysis. These scores are calculated in accordance with equation 4.1, which is a component of equation 3.41.

$$0.150(0.0468x_{soc} - 0.0686) + 0.095(-0.0011x_{env} + 0.9946) \qquad (4.1)$$

where x_{soc} and x_{env} are scores of environmental impact and social acceptance given in Table 4.7, respectively.

Table 4.7: Combined utility scores of electricity generation technologies.

Technology	Combined Utility
Wind	0.245
Geothermal	0.220
PV	0.210
Hydro	0.157
Biomass	0.137
CCGT	0.081
Coal	0.008
Nuclear	0.094

4.3 Agent Based Simulation

The outcomes of 10 distinct energy-climate policy scenarios, executed through a mathematically described agent-based simulation model detailed in Section 3.6, are outlined in the subsequent section.

The outputs of ABM are caterogized under five titles; i) electricity demand, ii) capacity additions, iii) carbon emissions, iv) electricity prices, and v) changes in technology costs.

Before executing the scenarios, the model is validated using data from 2020 to 2022. The outputs of the ABM, specifically electricity prices, emissions, and electricity demand, are compared with actual data from this period. Table 4.8 presents a comparison between the real data and the model outputs for 2020-2022. The results indicate that the model's outputs closely align with the observed data, confirming that the model is suitable for forecasting future values.

Table 4.8: Comparison of real data and model outputs for validation.

	Year	Price	Demand	Emission
Real Data	2020	40.92	262.7	128.8
	2021	55.6	288.8	143.7
	2022	147.5	296.6	145.2
Model Output	2020	41.1	264.2	129.4
	2021	54.4	286.7	144.1
	2022	149.2	299.1	145.9

4.3.1 Electricity demand

As outlined in the electricity demand module (Section 3.6.1), the demand for electricity is greatly influenced by shifts in income levels, electricity prices, temperature, and population.

Precise prediction of electricity demand using ABM holds pivotal significance in advancing energy efficiency, demand-side management, and grid optimization endeavors. By delving into the factors driving electricity consumption at the level of sectors, the ABM illuminates pathways for curbing energy wastage, fine-tuning load patterns, and fostering the uptake of energy-efficient technologies and methodologies. This proactive stance toward demand forecasting equips utilities, grid operators, and policymakers with actionable insights to deploy tailored interventions, including demand response initiatives, time-of-use pricing strategies, and incentives for energy efficiency. These measures are geared towards not only reducing system costs but also bolstering overall energy efficiency across the spectrum of energy consumption.

Illustrated in Figure 4.5, the projected electricity demand for Türkiye under the base scenario exhibits an almost linear trajectory. Projections suggest that by 2030, 2035, and 2040, electricity demand is anticipated to reach 456 TWh, 521 TWh, and 571 TWh, respectively.

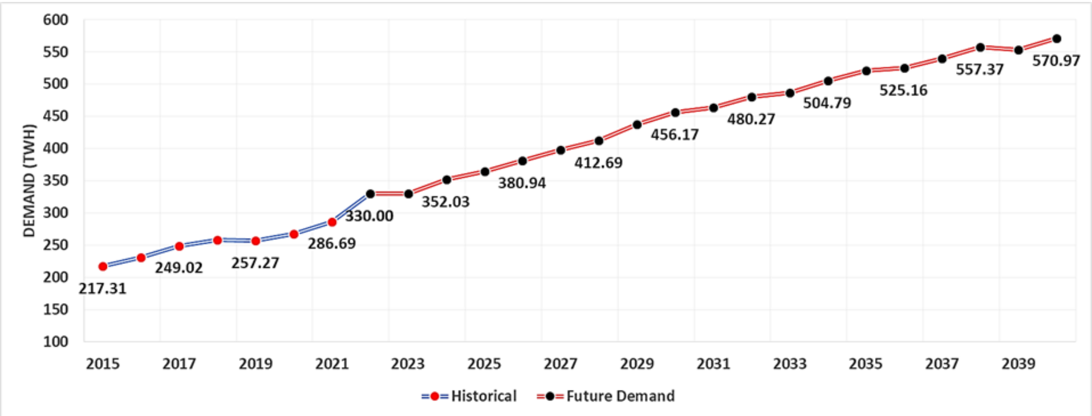

Figure 4.5 : Electricity demand of Türkiye.

Figure 6 illustrates Türkiye's annual sectoral electricity demand. With the projected rise in industrial electricity consumption, the industrial sector's share of total electricity demand is anticipated to exceed 50%, reaching 54% by 2040. Conversely, the growth rates of residential and commercial electricity demand are expected to be comparatively lower than that of industrial electricity demand. Forecasts indicate that residential and commercial electricity demand will reach 124.7 TWh and 138 TWh, respectively, by 2040, while industrial electricity demand is poised to surpass 308 TWh.

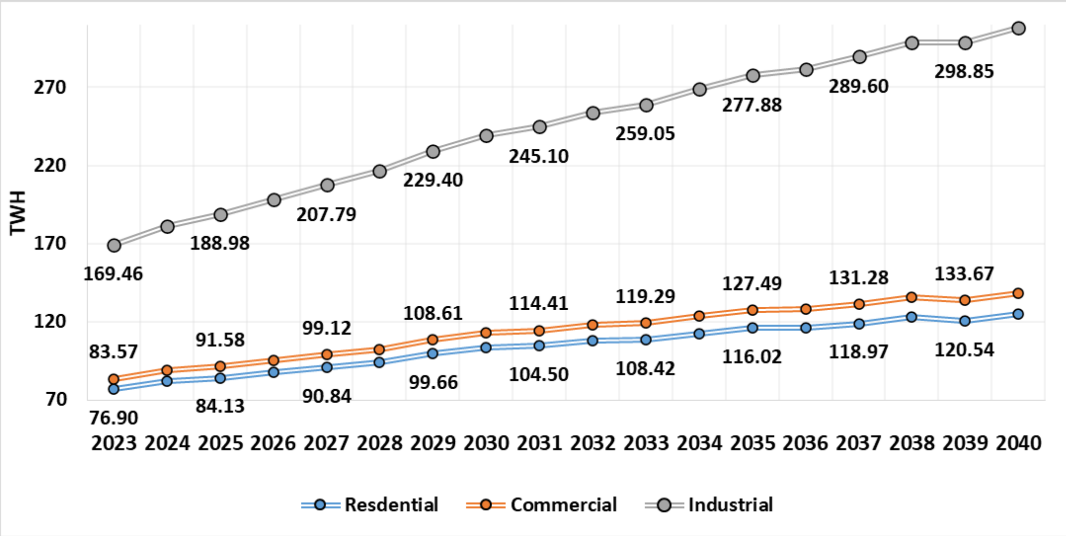

Figure 4.6 : Sectoral electricity demand.

4.3.2 Capacity additions

One significant outcome of the implemented ABM lies in its ability to project the installed capacity of electricity generation technologies, a factor heavily contingent upon policy scenarios. The distribution of installed capacity holds significant sway over not only emissions but also electricity prices. By simulating various policy scenarios, the ABM provides insights into how different regulatory frameworks and market conditions can shape the future landscape of electricity generation, facilitating informed decision-making processes aimed at achieving environmental sustainability and economic efficiency in the energy sector.

The installed capacity projections derived from ABM emerge as a fundamental tool for the long-term strategic identification of policymakers, energy strategists, and all concerned stakeholders. It is also essential that the probable development and deployment of different electricity generation technologies over time provide significant information for the determination of decision-makers about the future infrastructural requirements, avenue identification of investments, and resiliency of energy policy, thereby acting in tune with overall socio-economic objectives. Moreover, factoring in variables like technological advancement, fuel availability, environmental regulations, and market dynamics, the installed capacity projections using ABM will let stakeholders foresee upcoming challenges and opportunities for transitioning to a more sustainable and resilient energy paradigm.

Additionally, ABM is good at modeling the distribution of installed capacity across a suite of electricity generation technologies that enable the assessment of system reliability, resilience, and adaptability under a range of future scenarios. The ABM allows stakeholders to test whether available capacity will meet reliably future electricity demands without compromising grid stability or leading to potential shortages by simulating such a complex interaction between supply and demand dynamics, fluctuating renewable generation, and demand patterns. It views capacity planning in a holistic way that builds comprehension of complex dynamics inside energy systems; this, in turn, enhances strategy development to reinforce energy security while minimizing risks during the efficient integration of renewable sources into the grid.

Figures 4.7 and 4.8 depict the installed capacities and their respective shares needed to meet Türkiye's electricity demand across various policy scenarios. In the base scenario, installed PV capacity is projected to reach 28.7 GW by 2030, 50.7 GW by 2035, and 79.5 GW by 2040. This projection represents an almost tenfold increase in current installed PV capacity by 2040. Across all policy scenarios, PV technology emerges as the most favored choice for IPPs.

The policy identified as having the most significant impact on increasing installed PV capacity is the reduction of corporate tax rates. Under this policy, installed PV capacity could potentially reach 94 GW by 2040. However, it is important to recognize that the full utilization of this installed capacity is not guaranteed, as it depends on actual electricity demand and market prices. As illustrated in Figure 4.9, the share of RES in the electricity mix is 72 percent in Scenarios 4 and 5, which are the lowest among all scenarios. This indicates that IPPs have overinvested in PV systems, leading to a substantial amount of idle capacity. Consequently, while tax reductions can significantly boost PV installations, careful consideration must be given to aligning capacity expansion with realistic demand forecasts and economic conditions to avoid inefficiencies and underutilization of resources.

Wind power capacity is also expected to grow significantly in all scenarios. The installed wind power capacity is projected to increase by 1.5-fold every five years.

These trends suggest that solar and wind power systems will be the cornerstone of future electricity generation investments. In contrast, biomass, hydroelectric, and geothermal power plants show limited expansion potential compared to PV and wind systems due to capacity constraints.

In the base scenario, installed wind power capacity is projected to reach 20 GW by 2030, 31 GW by 2035, and 46.7 GW by 2040. While the reduction of corporate tax rates also stimulates an increase in wind power installations, this effect is relatively modest compared to the surge in PV capacity additions. Despite the positive impact of tax incentives, wind power does not experience the same dramatic growth as PV, reflecting different dynamics and investment incentives between these renewable technologies. Nevertheless, wind power remains a crucial component of the future energy mix, contributing significantly to the overall increase in renewable energy capacity. The strategic expansion of wind power, albeit at a slower pace than PV, underscores its vital role in complementing solar energy and ensuring a balanced and sustainable energy transition.

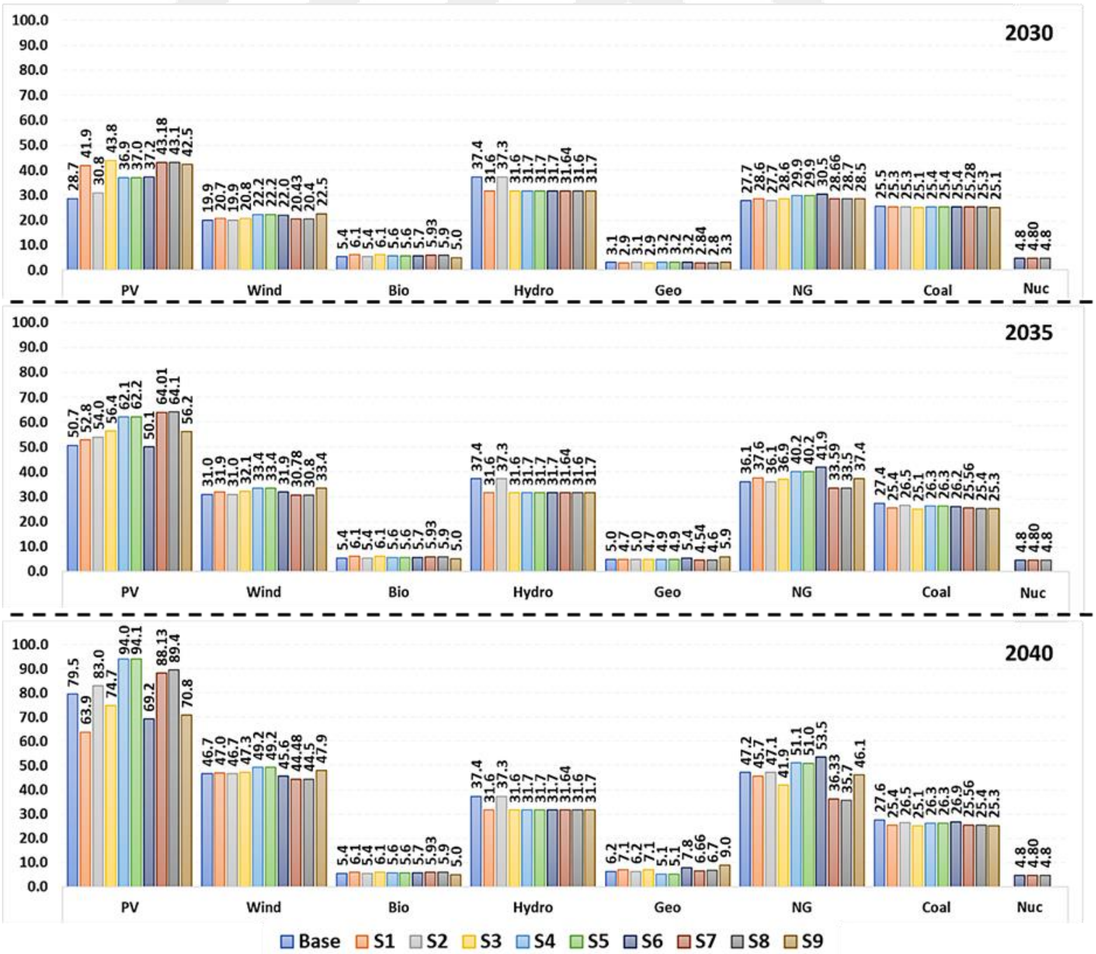

Figure 4.7 : Installed capacities of technologies in 2030, 2035, and 2040.

In the case of fossil fuel-based power plants, natural gas power plants are anticipated to grow more than coal. Under the base scenario, the installed capacity of natural gas power plants is expected to reach 27.7 GW by 2030, 36.1 GW by 2035, and 47.2 GW by 2040, while that of coal power plants would remain largely the same beyond 2030. This reflects a strategic shift in the energy mix, driven by the need for more flexible and responsive solutions for power generation.

This increased interest in natural gas-powered electrical plants has come primarily because of the efficiency at which such a facility could provide both load-following and peak-load operation. Natural gas plants, unlike coal-fired plants that supply base loads since their power output is stable and steady, can easily ramp up and down to meet increased and decreased output requirements caused by demand fluctuations. This flexibility is, however, important in a power grid that has a large share of intermittent and variable sources of energy like wind and solar. The greater the share of renewable energy sources in the energy mix, the more vital this becomes for quick scaling up or down of production to maintain grid stability and reliability.

Besides, the expansion in natural gas capacity is also driven by increasing variability from RES on the grid. The output of wind and solar generation varies with meteorological conditions and time of day, making the operation of natural gas-fired power plants necessary as a backup to maintain a reliable supply of electricity. Such plants can compensate for dips in renewable generation quickly in order to avoid blackouts and ensure demand for electricity at all times.

Natural gas, therefore, is an essential complement to the transition process in order to balance out the intermittency of RES and ensure the reliability of the overall electricity grid. This makes natural gas particularly crucial in this context: enabling further integration of intermittent renewable sources by offering flexible and responsive supply.

On the other hand, it is revealed that the installation of nuclear power plants can reduce investments in natural gas power plants due to the significant advantages nuclear energy provides for base-load power generation. Nuclear plants offer a consistent and reliable electricity output, operating at high capacity factors and delivering a continuous energy supply, which lessens the need for additional natural gas plants to meet base-load demands. Additionally, once built, nuclear power plants have lower operating costs and produce no greenhouse gas emissions during operation, making them appealing for countries focused on reducing carbon emissions while maintaining a stable energy supply. As nuclear energy can satisfy a substantial portion of base-load requirements, the demand for natural gas plants, particularly those intended for base-load generation, decreases.

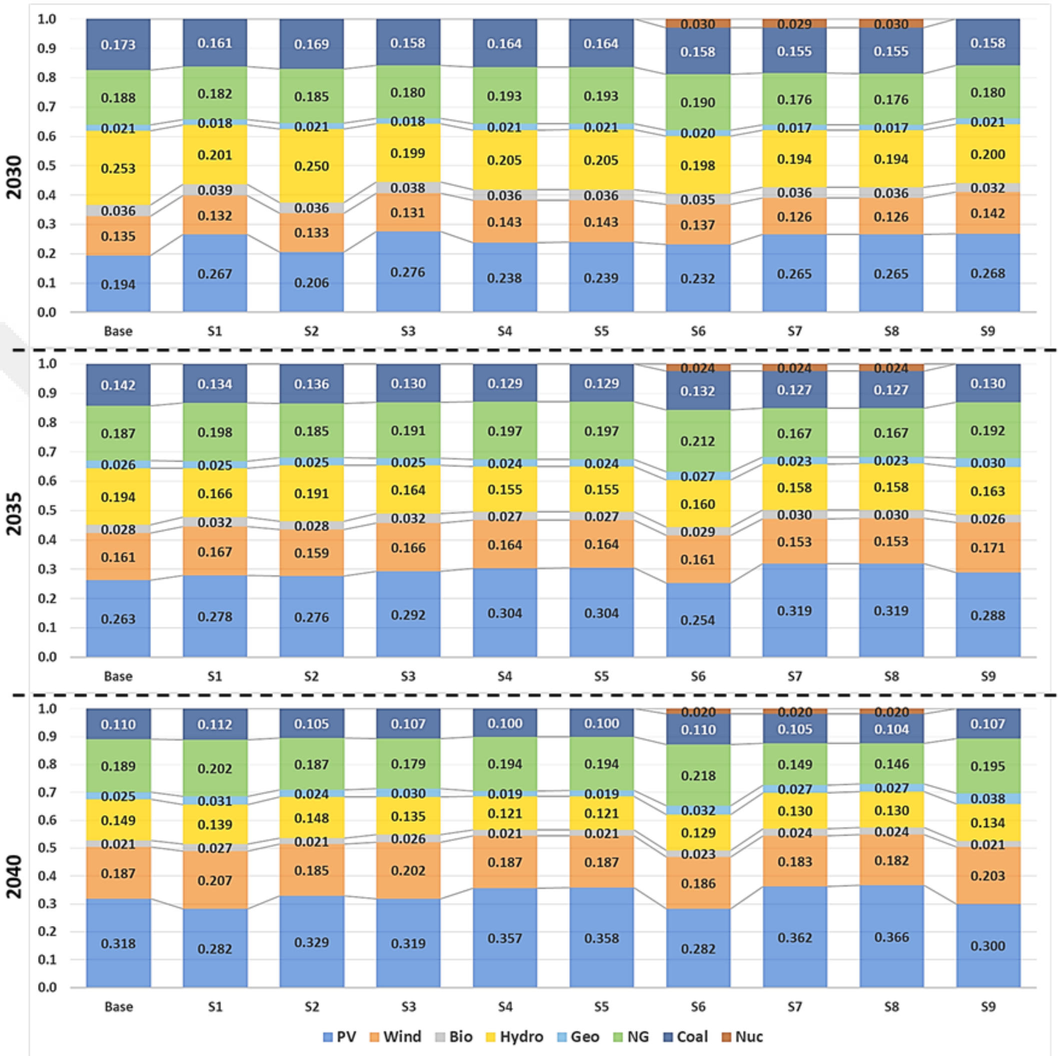

Figure 4.8 : Capacity shares of technologies in 2030, 2035, and 2040.

As illustrated in Figure 4.8, in the absence of governmental policy interventions in the electricity market, projections indicate that wind and solar power plants will collectively constitute half of Türkiye's total installed capacity by 2040. Each governmental policy uniquely impacts capacity development over different timeframes. Renewable energy subsidies significantly enhance capacity additions for wind and solar power plants in the short to medium term. However, their influence wanes in the long term. Conversely, carbon tax systems promote a more steady and sustained growth for wind and solar power plants over time.

Despite these differing impacts of policies, the share of RES in the total installed capacity is projected to remain below 71 percent in all scenarios. This suggests that while policies can drive considerable growth in renewable energy capacities, other factors may limit their ultimate share in Türkiye's energy mix.

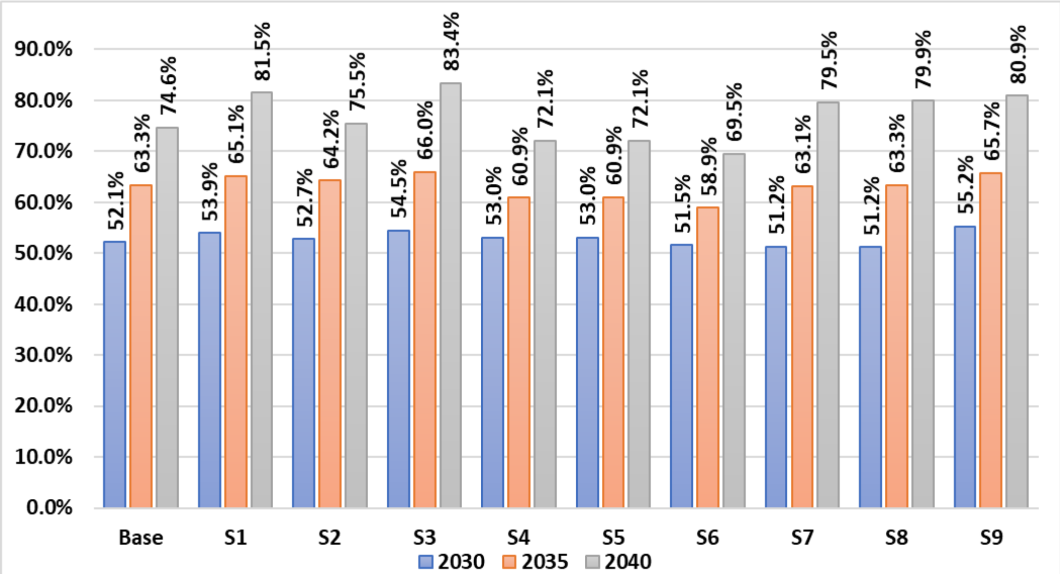

Figure 4.9 : Share of RES in electricity mix in 2030, 2035, and 2040.

4.3.3 Carbon emissions

Carbon taxing within the energy sector functions as a market-driven strategy aimed at reducing carbon emissions by imposing taxes on the carbon content of fossil fuels used in energy generation. This approach incentivizes energy producers to lower their carbon output by making fossil fuel consumption more expensive and thus less attractive compared to cleaner alternatives. Figure 4.10 illustrates the trajectory of carbon taxes under Scenarios 3, 4, and 9, highlighting how these taxes evolve over time to promote a shift towards more sustainable energy sources.

Projections indicate that by 2040, the carbon tax could exceed $271.1 per ton of CO_2 if implemented independently, without the integration of other policy measures. This scenario reflects a substantial increase in costs associated with carbon emissions, encouraging significant reductions in fossil fuel use. However, if carbon taxing is combined with other policy instruments, such as renewable energy subsidies or regulatory mandates, the carbon tax is anticipated to reach a slightly lower peak of $257.3 per ton of CO_2. This suggests that complementary policies can achieve similar environmental objectives with a less aggressive carbon tax rate, potentially easing the economic burden on energy producers while still fostering a transition to cleaner energy sources.

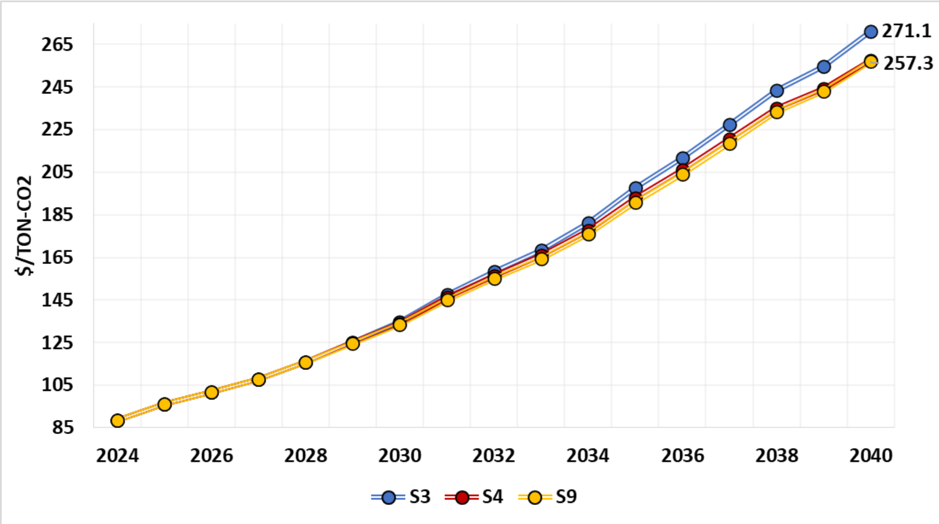

Figure 4.10 : Progression of carbon taxes.

The different paths of annual and cumulative electricity generation-based CO_2 emissions, considering capacity installations and energy-climate policies, are shown in Figure 4.11. In the baseline scenario, assuming no new policies are implemented, annual CO_2 emissions are set to peak at 174.6 million tons in 2032. This peak is expected to occur as a result of continued dependence on fossil fuels for energy generation. Following this peak, a decline in annual emissions is anticipated due to the increasing capacity of RES. By 2040, even without policy interventions, annual CO_2 emissions are expected to decrease to 118 million tons, indicating a natural shift towards cleaner energy driven by market and technological factors.

The influence of energy-climate policies on CO_2 emissions, however, is unmistakable. Various policy measures, such as carbon taxes and renewable energy subsidies, can significantly alter the emissions trajectory. Through the implementation of these policies, there is a clear potential to accelerate the reduction in CO_2 emissions. The analysis shows that with appropriate policies in place, cumulative CO_2 emissions for the period of 2022-2040 could be reduced by more than 11% compared to the baseline scenario. This reduction underscores the effectiveness of targeted policy interventions in mitigating climate change and promoting sustainable energy practices. These findings also highlight the critical role of government policies in shaping the future of energy and emissions. While market forces and technological advancements will naturally drive some reduction in CO_2 emissions, policy measures are essential for achieving more substantial and timely reductions.

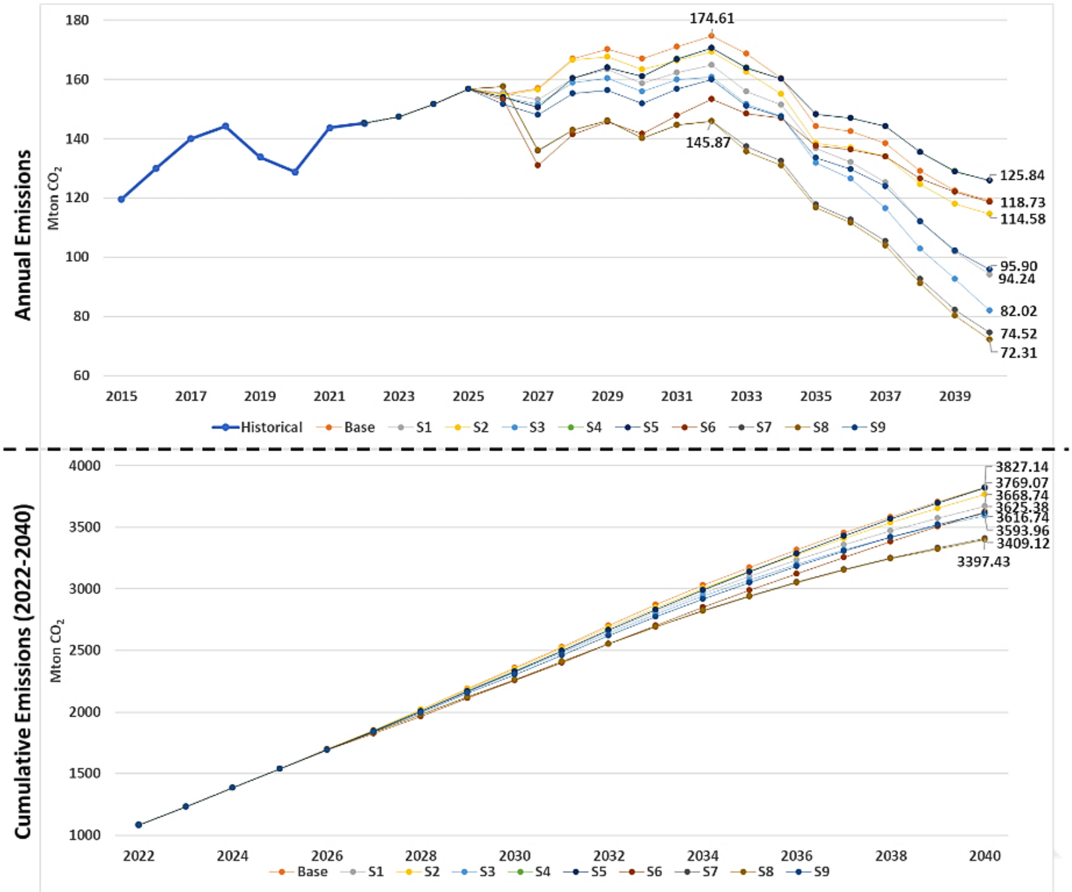

Figure 4.11 : Annual and cumulative electricity generation-based CO_2 emissions.

As the ABM operates only until 2040, the emissions outputs are extrapolated based on their trends to assess the effectiveness of the policies in achieving the net-zero target by 2053 (See Figure 4.12). The base scenario, which lacks any policy intervention, shows a gradual decline in emissions but fails to reach net-zero by 2053, indicating that without policy measures, decarbonization efforts will be insufficient to meet the target.

Scenarios involving a carbon tax (S2, S3, S8, S9) show a more significant reduction in emissions compared to those without such a tax. For instance, Scenario 2, which implements a carbon tax of \$75/ton$CO_{2\text{-eq.}}$ at t=0, results in a notable decrease in emissions, although it does not fully achieve net-zero by 2053. The combination of a carbon tax with renewable energy subsidies, as seen in Scenarios 3 and 8, accelerates the decline in emissions, pushing them closer to the net-zero target.

Renewable energy subsidies alone, as in Scenario 1, contribute to emission reductions but are less effective than scenarios incorporating a carbon tax. However, when combined with the introduction of new nuclear power capacity (Scenario 7), the subsidy shows an enhanced impact, nearly achieving net-zero emissions. Scenario 9, which integrates a carbon tax, a transfer of half the carbon tax revenue as a subsidy for renewable energy, and the addition of nuclear power, is the most effective strategy. It not only reduces emissions at a faster rate but also comes closest to or potentially achieves net-zero emissions by 2053.

These results suggest that the multi-faceted approach, combining carbon pricing, subsidies for renewable energy, and the expansion of nuclear power, works best to meet the 2053 net-zero emissions goal in electricity generation. The integration of financial incentives and diversified energy sources significantly amplifies the effectiveness of policy measures.

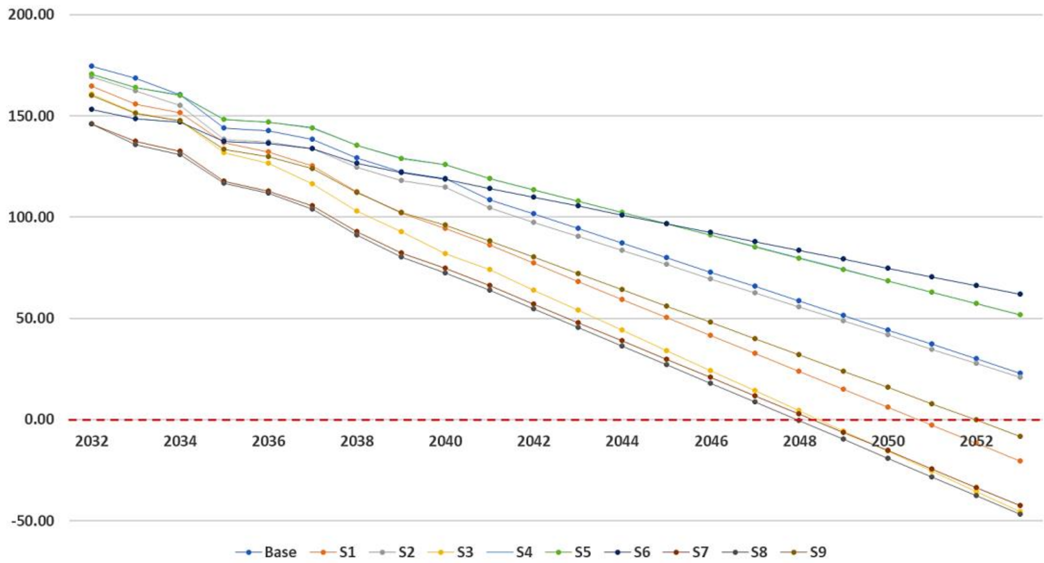

Figure 4.12 : Extrapolated emissions based on their trends.

4.3.4 Electricity prices

Understanding the future trends of electricity prices is important both for policymakers and consumers. Several factors, such as capacity expansions and policy interventions, influence the projected changes in these prices. This analysis considers the expected trends in electricity pricing up to the end of the forecast period, emphasizing the impact of different scenarios on price stabilization. This overview tries to put into perspective the expected impacts of capacity growth and certain energy policies, such as carbon taxes and subsidies for renewable energies, on the cost of electricity and wider energy market implications.

As seen in Figure 4.13, electricity prices are set to decline significantly up to 2029 due to capacity expansion. Beyond this initial decline, prices are set to stabilize across all scenarios for the rest of the forecast period. This decline is attributed to increased supply and efficiency brought on by these expansions in capacity. This stabilization infers a balancing in the supply and demand of electricity in the market, allowing both consumers and business entities to budget properly.

The most desirable rates of electricity are expected when carbon tax and renewable energy subsidy policies operate. Such policy measures encourage cleaner energy sources, hence driving down the costs. In contrast, in Scenario 6, with no policy interventions except integration of a nuclear power plant in the grid, the highest prices of electricity are seen. This example further shows how different policy decisions greatly affect energy prices and signifies the importance of a holistic approach to policy-making in order to better manage electricity cost and sustainable energy practices.

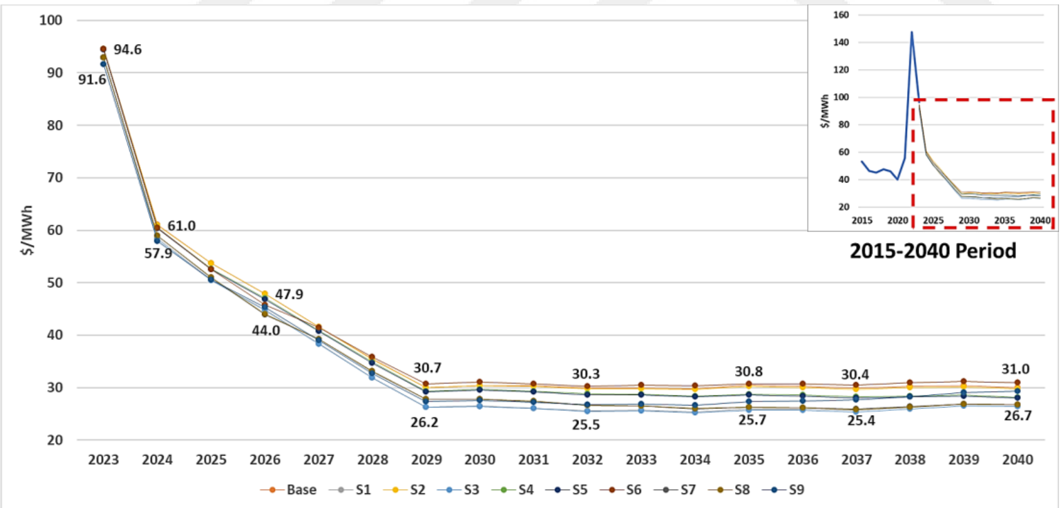

Figure 4.13 : Electricity prices.

4.3.5 Changes in technology costs

As technology continues to advance and economies of scale are realized, the cost of energy generation technologies is steadily decreasing each year. Innovations in renewable energy sources such as solar and wind power have led to more efficient and cost-effective solutions. Additionally, increased investment in research and development has accelerated the pace of technological improvements, further driving down costs. This trend is not only making clean energy more accessible and affordable but also fostering a competitive market that encourages further advancements and sustainable practices in the energy sector.

As illustrated in Equation 3.45, the investment costs of electricity generation technologies vary with installed capacity and the experience index. Accordingly, Figure 4.14 shows the projected changes in investment costs for 2030, 2035, and 2040 for each generation technology under the base scenario.

Figure 4.14 : Changes in cost of electricity generation technologies.

The most substantial cost reduction is anticipated in PV system installations. This technology is projected to see a decrease of over 19 percent in costs from 2023 to 2040. Wind power systems are also expected to experience significant cost reductions, with an estimated decline of approximately 16 percent over the same period. These reductions are driven by advancements in technology, increased manufacturing efficiencies, and economies of scale. As a result, both PV and wind power systems are becoming more economically viable, contributing to the broader adoption of renewable energy sources.

In addition to the anticipated cost reductions in PV and wind power systems, biomass technology is expected to see a 10.5 percent decrease in costs by 2030. After this initial reduction, the investment costs for biomass technology are projected to stabilize, remaining constant until 2040. Meanwhile, geothermal electricity generation technology is forecasted to undergo a continuous cost reduction of over 11.5 percent from 2023 to 2040. Conversely, only minimal cost reductions are anticipated for the well-established electricity generation technologies such as hydro-electric, natural gas, and coal. This marginal decrease reflects the maturity and established nature of these technologies, which have already undergone significant optimization. As a result, the potential for further cost savings is limited compared to newer, rapidly evolving renewable technologies. The modest cost changes in these traditional energy sources highlight the increasing economic competitiveness of emerging renewable options, reinforcing the shift towards cleaner, more sustainable energy systems.

4.4 Discussion

This study explores the potential impact of climate-energy policies on various aspects of the electricity sector in Türkiye, including electricity demand, renewable electricity generation, capacity expansions, electricity prices, and CO_2 emissions from electricity generation. It also considers the influence of future climate change on these factors. The research begins by identifying the top four GCMs that can accurately simulate Türkiye's unique climate conditions. This identification is achieved using three methods: normalized Root Mean Square Error, Kling-Gupta Efficiency, and modified index of agreement.

Among all the GCMs evaluated, the most promising ones were ACCESS-CM2, INM-CM5-0, INM-CM4-8, and ACCESS-ESM-1-5. These models are further used to project the future climate of the nation, Türkiye, under the SSP5-8.5 scenario, which is rather pessimistic and often referred to as Business-as-Usual. By applying such models, the study offers an integrated approach that can point out how climate changes could affect the projected future of the electricity sector in Türkiye by formulating applicable climate-energy policies that may offset adverse impacts and foster sustainable energy practices.

In the future climatic conditions of Türkiye, it is evident that rising temperatures due to climate change will strongly affect electricity demand for space cooling, especially in the Mediterranean and southeastern parts of the country. With the rise in temperatures, the need for air conditioning also increases, thus increasing the consumption of electricity. This causes some pressure on the energy infrastructure and requires one to take proactive steps to mitigate such effects.

The government can use various strategies to address the increasing demand for space cooling. First, there is a need to promote energy-efficient building practices that ensure new constructions are by default designed in ways that minimize cooling needs. Another approach is through incentives for the adoption of sustainable cooling technologies, which may encourage households and businesses to invest in efficient systems. Furthermore, awareness of efficient cooling behavior-for instance, optimal settings of the thermostat and maintenance of cooling equipment-will have the potential to pay rich dividends for decreasing consumption.

Besides that, the integration of passive thermal management systems (PTMS) such as thermochromic smart windows (TSW) and daytime passive radiative coolers (DPRC) will greatly reduce electricity consumption due to air conditioning. These advanced technologies also help regulate heat absorption and its dissipation within comfortable indoor temperature ranges, exempting buildings from active cooling requirements. According to Lin et al. (2021), the installations of these systems can save up to 17% of the electricity that is constantly utilized for air-conditioning. Therefore, it will be easy for Türkiye to respond to heightened demand for cooling with the rise in sustainable energy development.

The present study has examined one base case scenario and nine policy scenarios in evaluating the capacities of different energy policies for capacity expansion, electricity price, and CO_2 emissions from generation. It is observed in all these policy scenarios that capacity expansion in solar and wind power plants has increased considerably.This expansion in RES leads to a pivotal moment in 2032, where CO_2 emissions from electricity generation peak and then begin to decline in all scenarios. However, the degree of impact on CO_2 emissions varies with each specific energy-climate policy implemented.

To achieve the greatest reduction in cumulative CO_2 emissions, the study recommends the deployment of nuclear power plants in conjunction with both carbon taxing and subsidies for renewable energy sources by the government. In this optimal scenario, the government would provide a subsidy adjusted for inflation, alongside the carbon tax, to incentivize the adoption of clean energy technologies. This combined approach not only accelerates the transition to a low-carbon energy system but also ensures the financial viability of renewable energy projects. By strategically implementing these measures, Türkiye can effectively manage the growth in energy demand while significantly reducing its carbon footprint, paving the way for a sustainable and environmentally responsible energy future.

While carbon taxing alone has the potential to reduce cumulative CO_2 emissions by 1.52% compared to the base scenario, RES subsidies may achieve a more substantial reduction of 4.14%. If implemented together, the reduction in CO_2 could be more than 6% due to a synergistic effect greater than that of either policy in isolation. Such a combined approach would exploit the interaction between economic incentives and regulatory measures in providing major emission reductions.

Moreover, in synergy with the nuclear power plants deployment, such policies could further raise the cumulative CO_2 emission reduction to over 11% during the projection period. This is a far-reaching approach that points to the importance of a diversified approach to energy policy-where various measures reinforce each other to maximize environmental benefits. In contrast, the effect of reducing corporation taxes for RES on CO_2 emissions is marginal. Thus, if the main goal set by the government is to minimize CO_2 emissions in the short run, carbon taxing, RES subsidies, and deployment of nuclear power would be far more effective than to introduce corporation tax reductions for RES.

The nuclear power installed in the absence of any climate-energy policy would achieve a far-from-negligible reduction of 5.3% in cumulative CO_2 emissions, underlining the crucial role that nuclear energy could play in the mitigation of emissions. However, nuclear power plants are not very attractive for widespread adoption due to significant initial investment costs and public skepticism about the operation of plants. This may, therefore, create the need for the government's intervention in leading investments in and operating nuclear power plants.

In the absence of adequate enthusiasm by the IPPs regarding investment in nuclear energy, the gap between theoretical benefits of nuclear power and the practical challenges has to be filled by government intervention. A proactive role played by the government in financing and overseeing the development of nuclear infrastructure may help shape a cleaner, more sustainable energy future. Additionally, concerted efforts to address public concerns and enhance transparency regarding nuclear energy's safety and efficacy are essential for garnering broader societal acceptance and support for nuclear power initiatives.

Another important result of this study refers to the forecast of electricity prices, considering the influence of energy-climate policies. With the continuous increase in capacity additions, especially in RES, the electricity price is expected to drop significantly until 2029 and then remain relatively stable. During this stable phase, the prices are expected to range between 25-31 $/MWh for all scenarios. The introduction of RES subsidies will have substantial price-reduction effects, especially because the current cuts in corporation taxes for RES reduce the prices slightly. The impact is high since RES power plants, while operating under the auspices of subsidies, are in a position to present bids that can pull down the prices on average.

The combination of deploying nuclear power plants with the inflation-adjusted RES subsidy scheme is the best policy for reaching both minimum CO_2 emissions and minimum electricity prices. This option creates a synergy between the strong points of nuclear energy in the emission reduction process and the cost-reduction impact of RES subsidies. In this way, by using these two options, it would be possible for the country to achieve two goals simultaneously: a reduction in the GHG emission rate and keeping electricity prices at low levels for consumers.

This will also form an important link between the stabilization of electricity prices and the marginal generation cost of RES in electricity price stabilization. Generally, most RES have low marginal costs of electricity production and therefore are influential in market dynamics. With their very minimal ongoing operational costs, once the initial infrastructural investments are made, the price of electricity is therefore depressed. This is, in particular, the case in electricity markets, where power plants are dispatched according to their marginal costs, and often RES, due to their low operational expenses, have priority in the merit order. Because of this "merit order effect," more expensive generation methods are displaced, which reduces the overall market price for electricity. This interplay of low marginal costs of RES and their prominence in the energy mix is an important contributor to price stabilization.

Furthermore, the RES penetration alters the very nature of the cost structure of electricity production. With increasing shares of RES, the average marginal cost of electricity production falls, and the market price is correspondingly affected. The marginal cost falls especially strongly when the generation of low-cost electricity is high, such as on sunny or windy days. This means that greater availability of inexpensive electricity not only satisfies demand at a lower cost but also promotes more stable electricity prices over time.

Any results obtained from any study can only be made valid by comparing them with other studies or governmental projections. A comparison between the results of this study and the National Energy Plans issued by the Ministry of Energy and Natural Resources (MENR) in 2022 sheds light on very important data. While this study estimates total installed capacities in the range of 147.6-162.8 GW in 2030 and 190.2-204.3 GW in 2035, according to MENR, total capacities will amount to 149.1 GW and 189.7 GW for the same periods, respectively. The detailed capacity comparison between the results of this study and the National Energy Plans regarding 2035 is given in Table 4.9. It is obvious that the results from ABM and projections by MENR are very close, which shows the strength of the developed GCM-ABM framework in estimating capacity additions, taking into consideration future electricity demand and projections from wind and solar power plants.

This agreement underlines the robustness of the GCM-ABM framework for capturing plausible future scenarios accurately and therefore enhances confidence in the projections made by this study. Furthermore, it demonstrates the capabilities of the model in providing valuable insights into the potential impacts of various energy-climate policies on key aspects such as electricity prices, capacity expansions, and CO_2 emissions from electricity generation. This therefore makes the model very important for policymakers and other stakeholders as they consider the efficiency of various policy interventions that will finally shape the course of sustainability and resilience in the energy landscape of the Turkish economy. The robustness and accuracy revealed by the model form the ground on which further alternative policy scenarios can be explored, and what these may potentially mean for Türkiye's energy transition trajectory.

Table 4.9: Comparison of capacity projections for 2035 (GW).

Scenario	Solar	Wind	Hydro	Other	Natural	Coal	Nuclear	Total
Base	50.67	31.04	37.35	10.34	36.14	27.41	0	192.96
1	52.85	31.85	31.64	10.84	37.63	25.43	0	190.24
2	53.98	31.03	37.35	10.34	36.09	26.46	0	195.24
3	56..38	32.12	31.64	10.85	36.93	25.13	0	193.06
4	62.07	33.45	31.72	10.5	40.21	26.34	0	204.28
5	62.17	33.45	31.72	10.5	41.87	26.34	0	204.28
6	50.11	31.89	31.72	11.09	41.87	26.16	4.8	197.63
7	64.01	30.78	31.64	10.47	33.59	25.56	4.8	200.84
8	64.11	30.75	31.64	10.5	33.47	25.42	4.8	200.71
9	56.21	33.4	31.72	10.93	37.44	25.29	0	194.96
MENR	52.9	29.6	35.1	7.5	35.5	24.3	4.8	189.7

Subsequent studies may expand on this work by comparing other climate scenarios to the high-emission one employed in this work. Even though this work relies predominantly on projections from selected GCMs following a high-emission pathway, examination of several Representative Concentration Pathways or Shared Socioeconomic Pathways would provide a more complete sense of how alternative climate policies and emission paths might influence electricity production and carbon emissions. Sensitivity analyses with different climate projections can contribute to the robustness of the findings and include data on the range of likely future situations with alternative climate mitigation approaches.

Subsequent research should also involve a broader sensitivity analysis of the key parameters in the ABM. While this analysis provides a baseline projection of electricity generation, demand, and CO_2 emissions for different policy scenarios, further exploration of parameter uncertainties—such as varying social acceptance rates of renewable technologies, fuel price volatility, and technology learning curves—would improve model accuracy. Monte Carlo simulation or global sensitivity analysis techniques can be employed to put numbers to the impact of parameter change on the model outputs and hence increase policy recommendation confidence.

Lastly, widening the scope of research to a larger geographical extent or cross-country comparison would enhance its applicability. Although this research is done in Türkiye, the same can be applied for other regions of the world with varied energy infrastructure, climatic situations, and policy regimes. Lessons learned from the comparative performance of policy instruments in various nations with varying economic and technological realities would be highly effective in guiding global energy transition policy. Moreover, integration of global energy trade patterns and interconnections of electricity across borders would also highlight the role of regional cooperation in impacting carbon emissions as well as energy security.

5. CONCLUSION

The present study develops a comprehensive impact analysis related to climate-energy policies on the Turkish electricity market for a set of key variables: electricity demand, renewable electricity generation, capacity expansions, electricity prices, and CO_2 emissions. The research is based on sound methodological framework, including the selection of four GCMs that better simulate the Turkish climate and, subsequently, using them in order to produce future projections for the SSP5-8.5 scenario. This is a sensible approach, where the projections can be done based on dependable climate data, giving much credibility to the findings.

This identification is done using three skills, skills comprising normalized Root Mean Square Error, Kling-Gupta Efficiency, and a modified index of agreement. Among the evaluated GCMs, the most promising ones are ACCESS-CM2, INM-CM5-0, INM-CM4-8, and ACCESS-ESM-1-5. Further, these models are used to project future climate over Türkiye under the SSP5-8.5 scenario, which is a pessimistic one and generally known as a Business-as-Usual scenario. Utilizing these models, the study provides a comprehensive analysis of how projected climate changes could affect the electricity sector in Türkiye. This information helps in formulating effective climate-energy policies to mitigate adverse impacts and promote sustainable energy practices.

Indeed, the analysis here shows that this rise in temperature due to climate change will raise electricity demand for cooling hugely in the country's Mediterranean and southeastern parts. As a matter of fact, all these call for proactive strategies by the government on how to manage increased demand by promoting energy-efficient building practices, providing incentives toward sustainable cooling technologies, and increasing public awareness. Besides, PTMSs such as TSW and DPRCs are highly promising systems to reduce cooling energy consumption.

It estimates some key energy indicators regarding electricity demand, cooling-degree-days, and electricity generation from wind and solar power systems after the climate data processing, which are essential in evaluating the future energy landscape in

Türkiye. Furthermore, it identifies utility function weights for the investment decisions of technological alternatives through AHP and MAUT methods. These methodologies provide a systematic approach to investment priority setting across different energy technologies, based on multiple criteria and the various preferences of the stakeholders.

A further step involves the development of an ABM that will simulate various policy scenarios. This model allows studying interactions at detailed levels among different agents interacting in the energy system, like Independent Power Producers and government agencies. After the performance of a number of simulation scenarios, the ABM draws useful inferences from the potential consequences of various policy decisions on energy demand, production, and CO_2 emissions.

The study evaluates a number of policy scenarios, with a strong role for renewable energy sources in the future electricity mix. The increase in solar and wind capacities is a common outcome across the scenarios and creates a structural break in CO_2 emissions from electricity generation starting in 2032. This study shows that the combination of nuclear power deployment with carbon taxation and RES subsidies gives the highest possible reduction in cumulative CO_2 emissions, showcasing the strength of their interaction within this combined policy approach.

It also identifies the impact of these policies concerning electricity prices, which will further decline until 2029 and thereafter stabilize. It also shows that the most relevant driver of a reduction in electricity price is provided by the introduction of subsidies to RES due to the low marginal cost of the RES power generation. Indeed, coupling nuclear power plants with RES subsidies is found as the pathway able to optimally reduce CO_2 emissions and electricity prices while providing economic and environmental goals.

The alignment of the study's projections with the National Energy Plans issued by the MENR further validates the reliability of the established GCM-ABM framework. This close correlation underscores the robustness of the model in capturing potential future scenarios and its utility as a tool for policymakers to evaluate the effectiveness of different energy-climate policies.

The findings of this study can be summarized as follows:

- Climate Models: ACCESS-CM2, INM-CM5-0, INM-CM4-8, and ACCESS-ESM-1-5 are detected as the most successful models for reflecting unique climate conditions of Türkiye.
- Solar Power Production: Projections indicate a decrease in electricity production from solar power plants in Türkiye due to reduced efficiency caused by rising temperatures.
- Cooling Degree Days: There is a significant increase projected in CDDs across nearly all cities, especially in the Mediterranean region and southeastern Türkiye, due to the impacts of global warming.
- Electricity Demand: Future electricity demand is estimated to increase to 456.2 TWh in 2030, 521.4 TWh in 2035, and 571 TWh in 2040, considering variations in CDDs, electricity prices, income, and population.
- Renewable Energy Capacity: Despite various policy implications, Renewable Energy Source capacity shares are not expected to exceed 71% in any scenario, with fossil fuel-based power plants remaining as baseload and load-following sources.
- Fossil fuel based-Power Plants: Coal power plants continue to serve as primary base-load sources, while natural gas power plants are expected to play a more significant role in load-following and peak demand due to the intermittent nature of electricity generation from wind and solar power plants.
- CO_2 Emissions: Following RES capacity expansions, electricity generation-based CO_2 emissions are projected to peak in 2032 and then decline across all scenarios.
- Policy Impact on Emissions: Proper policy implementation has the potential to reduce cumulative CO_2 emissions by over 11% from 2022 to 2040 compared to the baseline scenario.
- Electricity Prices: Electricity prices are forecasted to decrease significantly until 2029 due to capacity expansions, stabilizing thereafter. Optimal rates are achieved with the concurrent implementation of carbon tax and RES subsidy policies.
- Optimal Policy Combination: The most effective combination for minimizing both CO_2 emissions and electricity prices involves deploying nuclear power plants and implementing RES subsidies adjusted for inflation.

- Policy Impact Estimation: The model demonstrates promise in estimating the impact of various energy-climate policies beyond those studied, on electricity prices, capacity additions, and CO_2 emissions.

In conclusion, this study highlights some key lessons to be learned from the interaction of climate change and energy policy, with feasible recommendations on how to manage the consequences of climate change for the electricity sector in Türkiye. With an integrated and diversified energy policy promoting renewable energy, energy efficiency, and nuclear power, Türkiye would be well equipped to respond to the challenges brought about by climate change and head toward a sustainable and resilient energy future. This study provides a foundation for future analyses of alternate policy scenarios, their implications, and is intended to inform the ongoing sustainable energy development debate.

Although the proposed GCM-ABM framework demonstrates high performance, there are several limitations to this study that present opportunities for future research:

- Expansion of GCMs: Currently, the study is based on 13 GCMs. A larger number of GCMs included in the analysis may give more robust and possibly more precise climate projections, allowing a fuller understanding of potential climate impacts on the energy system of Türkiye.
- Inclusion of Electric Vehicles (eVs): Electricity demand from the growing share of eVs is excluded from the analysis because this percentage is close to negligible in Türkiye. While eV percentages go up, a more feasible prediction of these could be derived for eV demand addition into future updates of the model. Its inclusion shall become imperative when this kind of transport becomes generally in use in order to arrive at valid previsions and improve management strategies concerning such demand on grids.
- Integration of Additional Renewable Technologies: Future research could concentrate on the integration of other renewable technologies, such as advanced bioenergy and new storage solutions, to complete the vision of how renewables could be integrated into and impact the electricity system.

REFERENCES

Acharya, N., Shrivastava, N. A., Panigrahi, B. K., & Mohanty, U. C. (2014). Development of an artificial neural network based multi-model ensemble to estimate the northeast monsoon rainfall over south peninsular India: an application of extreme learning machine. *Climate dynamics*, *43*, 1303-1310. https://doi.org/10.1007/s00382-013-1942-2

Adenaw, L., & Lienkamp, M. (2021). Multi-Criteria, Co-Evolutionary Charging Behavior: An Agent-Based Simulation of Urban Electromobility. *World Electric Vehicle Journal*, *12*(1), 18.

Ahmed, K., Sachindra, D. A., Shahid, S., Demirel, M. C., & Chung, E. S. (2019). Selection of multi-model ensemble of general circulation models for the simulation of precipitation and maximum and minimum temperature based on spatial assessment metrics. *Hydrology and Earth System Sciences*, *23*(11), 4803-4824. https://doi.org/10.5194/hess-23-4803-2019

Ahmed, K., Sachindra, D. A., Shahid, S., Iqbal, Z., Nawaz, N., & Khan, N. (2020). Multi-model ensemble predictions of precipitation and temperature using machine learning algorithms. *Atmospheric Research*, *236*, 104806. https://doi.org/10.1016/j.atmosres.2019.104806

Al Irsyad, M. I., Halog, A., & Nepal, R. (2019). Estimating the impacts of financing support policies towards photovoltaic market in Indonesia: A social-energy-economy-environment model simulation. *Journal of environmental management*, *230*, 464-473.

Allen, P., Robinson, M., Butans, E., & Varga, L. (2019). Innovations for sustainable lifestyles: an agent-based model approach. *Sustainability Science*, *14*(2), 341-354.

Asadollah, S. B. H. S., Sharafati, A., & Shahid, S. (2022). Application of ensemble machine learning model in downscaling and projecting climate variables over different climate regions in Iran. *Environmental Science and Pollution Research*, 1-20. https://doi.org/10.1007/s11356-021-16964-y

Azar, E., & Menassa, C. C. (2011, December). A decision framework for energy use reduction initiatives in commercial buildings. In Proceedings of the 2011 Winter Simulation Conference (WSC) (pp. 816-827). IEEE.

Babatunde, K. A., Mahmoud, M. A., Ibrahim, N., & Said, F. F. (2023). Malaysia's electricity decarbonisation pathways: Exploring the role of renewable energy policies using agent-based modelling. *Energies*, *16*(4), 1720.

Bağçaci, S. Ç., Yucel, I., Duzenli, E., & Yilmaz, M. T. (2021). Intercomparison of the expected change in the temperature and the precipitation retrieved from CMIP6 and CMIP5 climate projections: A Mediterranean hot spot case, Turkey. *Atmospheric Research*, *256*, 105576.

Balint, T., Lamperti, F., Mandel, A., Napoletano, M., Roventini, A., & Sapio, A. (2017). Complexity and the economics of climate change: a survey and a look forward. *Ecological Economics, 138*, 252-265.

Batibeniz, F., Hauser, M., & Seneviratne, S. I. (2023). Countries most exposed to individual and concurrent extremes and near-permanent extreme conditions at different global warming levels. *Earth System Dynamics*, *14*(2), 485-505. https://doi.org/10.5194/esd-14-485-2023, 2023.

Baur, D., Emmerich, P., Baumann, M. J., & Weil, M. (2022). Assessing the social acceptance of key technologies for the German energy transition. *Energy, Sustainability and Society*, *12*(1), 1-16. https://doi.org/10.1186/s13705-021-00329-x

Beckenbach, F., Daskalakis, M., & Hofmann, D. (2018). Agent-based analysis of industrial dynamics and paths of environmental policy: The case of non-renewable energy production in Germany. *Computational Economics*, *52*(3), 953-994.

Bleda, M., & Valente, M. (2009). Graded eco-labels: a demand-oriented approach to reduce pollution. *Technological forecasting and social change*, *76*(4), 512-524.

Buchmann, T., Wolf, P., & Fidaschek, S. (2021). Stimulating E-Mobility Diffusion in Germany (EMOSIM): An Agent-Based Simulation Approach. *Energies*, *14*(3), 656.

Caprioli, C., Bottero, M., & De Angelis, E. (2020). Supporting policy design for the diffusion of cleaner technologies: a spatial empirical agent-based model. *ISPRS International Journal of Geo-Information*, *9*(10), 581.

Carvalho, D., Rocha, A., Costoya, X., DeCastro, M., & Gómez-Gesteira, M. (2021). Wind energy resource over Europe under CMIP6 future climate projections: What changes from CMIP5 to CMIP6. *Renewable and Sustainable Energy Reviews*, *151*, 111594. https://doi.org/10.1016/j.rser.2021.111594

Castaneda-Gonzalez, M., Poulin, A., Romero-Lopez, R., & Turcotte, R. (2023). Weighting climate models for hydrological projections: effects on contrasting hydroclimatic regions. *Climatic Change*, *176*(12), 170. https://doi.org/10.1007/s10584-023-03643-9

Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T., ... & van den Bergh, J. (2020). A review of agent-based modeling of climate-energy policy. *Wiley Interdisciplinary Reviews: Climate Change*, *11*(4), e647.

Çetin, İ. I. (2023). *Potential impacts of climate change on wind energy resources in Türkiye* (Doctoral dissertation). Middle East Technical University, Graduate School of Natural and Applied Sciences, ANKARA.

Chappin, E. J. L., & Dijkema, G. P. J. (2009). On the impact of CO2 emission-trading on power generation emissions. *Technological Forecasting and Social Change*, *76*(3), 358-370.

Chappin, E. J., de Vries, L. J., Richstein, J. C., Bhagwat, P., Iychettira, K., & Khan, S. (2017). Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab). *Environmental modelling & software*, *96*, 421-431.

Chatzimouratidis, A. I., & Pilavachi, P. A. (2008). Multicriteria evaluation of power plants impact on the living standard using the analytic hierarchy process. *Energy policy*, *36*(3), 1074-1089. https://doi.org/10.1016/j.enpol.2007.11.028

Chen, F. W., & Liu, C. W. (2012). Estimation of the spatial rainfall distribution using inverse distance weighting (IDW) in the middle of Taiwan. *Paddy and Water Environment*, *10*, 209-222. https://doi.org/10.1007/s10333-012-0319-1

Chen, H., Wang, C., Cai, W., & Wang, J. (2018). Simulating the impact of investment preference on low-carbon transition in power sector. *Applied Energy*, *217*, 440-455.

Chen, L. J., Zhu, L., Fan, Y., & Cai, S. H. (2013). Long-term impacts of carbon tax and feed-in tariff policies on China's generating portfolio and carbon emissions: a multi-agent-based analysis. *Energy & environment*, *24*(7-8), 1271-1293. https://doi.org/10.1260/0958-305X.24.7-8.1271

Cong, R. G., & Wei, Y. M. (2010). Potential impact of (CET) carbon emissions trading on China’s power sector: A perspective from different allowance allocation options. *Energy*, *35*(9), 3921-3931.

Czupryna, M., Franzke, C., Hokamp, S., & Scheffran, J. (2020). An agent-based approach to integrated assessment modelling of climate change. *Journal of Artificial Societies and Social Simulation*, *23*(3), 7.

Damiani, E., & Sissa, G. (2013, October). An agent based model of environmental awareness and limited resource consumption. In Proceedings of the Fifth International Conference on Management of Emergent Digital EcoSystems (pp. 54-59).

Desmarchelier, B., Djellal, F., & Gallouj, F. (2013). Environmental policies and eco-innovations by service firms: An agent-based model. *Technological Forecasting and Social Change*, *80*(7), 1395-1408.

Dey, A., Sahoo, D. P., Kumar, R., & Remesan, R. (2022). A multimodel ensemble machine learning approach for CMIP6 climate model projections in an Indian River basin. *International Journal of Climatology*, *42*(16), 9215-9236. https://doi.org/10.1002/joc.7813

Dineva, K., & Atanasova, T. (2020). Systematic look at machine learning algorithms–advantages, disadvantages and practical applications. *20th International Multidisciplinary Scientific GeoConference SGEM 2020*, Sofia, Bulgaria. https://doi.org/10.5593/sgem2020/2.1/s07.041

Doczy, R., & AbdelRazig, Y. (2017). Green buildings case study analysis using AHP and MAUT in sustainability and costs. *Journal of Architectural Engineering*, *23*(3), 05017002. https://doi.org/10.1061/(ASCE)AE.1943-5568.000025

D'Orazio, P., & Valente, M. (2018). Do Financial constraints hamper environmental innovation diffusion? An agent-based approach. An Agent-Based Approach (April 16, 2018). SWPS, 10.

Dubey, S., Sarvaiya, J. N., & Seshadri, B. (2013). Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world–a review. *Energy procedia*, *33*, 311-321. https://doi.org/10.1016/j.egypro.2013.05.072

Dutta, R., Chanda, K., & Maity, R. (2022). Future of solar energy potential in a changing climate across the world: A CMIP6 multi-model ensemble analysis. *Renewable Energy*, *188*, 819-829. https://doi.org/10.1016/j.renene.2022.02.023

Eppstein, M. J., Grover, D. K., Marshall, J. S., & Rizzo, D. M. (2011). An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy*, *39*(6), 3789-3802.

Ernst, A., & Briegel, R. (2017). A dynamic and spatially explicit psychological model of the diffusion of green electricity across Germany. *Journal of Environmental Psychology*, *52*, 183-193.

***EU Carbon Permits.** (2024). Retrieved March 27, 2024, from https://tradingeconomics.com/commodity/carbon*

Fan, J., Wang, X., Wu, L., Zhou, H., Zhang, F., Yu, X., ... & Xiang, Y. (2018). Comparison of Support Vector Machine and Extreme Gradient Boosting for predicting daily global solar radiation using temperature and precipitation in humid subtropical climates: A case study in China. *Energy conversion and management*, *164*, 102-111. https://doi.org/10.1016/j.enconman.2018.02.087

Fu, Y., Zhuang, H., Shen, X., & Li, W. (2023). Assessment and prediction of regional climate based on a multimodel ensemble machine learning method. *Climate Dynamics*, *61*(9), 4139-4158. https://doi.org/10.1007/s00382-023-06787-7

Gerst, M. D., Wang, P., & Borsuk, M. E. (2013). Discovering plausible energy and economic futures under global change using multidimensional scenario discovery. *Environmental Modelling & Software*, *44*, 76-86.

Gholami, H., Lotfirad, M., Ashrafi, S. M., Biazar, S. M., & Singh, V. P. (2023). Multi-GCM ensemble model for reduction of uncertainty in runoff projections. *Stochastic Environmental Research and Risk Assessment*, *37*(3), 953-964. https://doi.org/10.1007/s00477-022-02311-1

Guven, D. (2023). Development of multi-model ensembles using tree-based machine learning methods to assess the future renewable energy potential: case of the East Thrace, Turkey. *Environmental Science and Pollution Research*, *30*(37), 87314-87329. https://doi.org/10.1007/s11356-023-28649-9

Guven, D., Kayalica, M. O., Kayakutlu, G., & Isikli, E. (2021). Impact of climate change on sectoral electricity demand in Turkey. *Energy Sources, Part B: Economics, Planning, and Policy*, *16*(3), 235-257. https://doi.org/10.1080/15567249.2021.1883772

Ha, S., Zhou, Z., Im, E. S., & Lee, Y. M. (2023). Comparative assessment of future solar power potential based on CMIP5 and CMIP6 multi-model ensembles. *Renewable Energy*, *206*, 324-335. https://doi.org/10.1016/j.renene.2023.02.039

Hansen, P., Liu, X., & Morrison, G. M. (2019). Agent-based modelling and socio-technical energy transitions: A systematic literature review. *Energy Research & Social Science*, *49*, 41-52.

Held, A. M. (2010). Modelling the future development of renewable energy technologies in the European electricity sector using agent-based simulation.

Herrmann, J. K., & Savin, I. (2017). Optimal policy identification: Insights from the German electricity market. *Technological forecasting and social change*, *122*, 71-90.

Hesselink, L. X., & Chappin, E. J. (2019). Adoption of energy efficient technologies by households–Barriers, policies and agent-based modelling studies. *Renewable and Sustainable Energy Reviews*, *99*, 29-41.

Hicks, A. L., & Theis, T. L. (2014). An agent based approach to the potential for rebound resulting from evolution of residential lighting technologies. *The International Journal of Life Cycle Assessment*, *19*(2), 370-376.

Hicks, A. L., Theis, T. L., & Zellner, M. L. (2015). Emergent effects of residential lighting choices: prospects for energy savings. *Journal of Industrial Ecology*, *19*(2), 285-295.

Hofer, C., Jäger, G., & Füllsack, M. (2018). Large scale simulation of CO2 emissions caused by urban car traffic: An agent-based network approach. *Journal of Cleaner Production*, *183*, 1-10.

Homsi, R., Shiru, M. S., Shahid, S., Ismail, T., Harun, S. B., Al-Ansari, N., ... & Yaseen, Z. M. (2020). Precipitation projection using a CMIP5 GCM ensemble model: a regional investigation of Syria. *Engineering Applications of Computational Fluid Mechanics*, *14*(1), 90-106. https://doi.org/10.1080/19942060.2019.1683076

Isley, S. C., Lempert, R. J., Popper, S. W., & Vardavas, R. (2015). The effect of near-term policy choices on long-term greenhouse gas transformation pathways. *Global Environmental Change*, *34*, 147-158.

Jensen, T., & Chappin, É. J. (2017). Reducing domestic heating demand: Managing the impact of behavior-changing feedback devices via marketing. *Journal of environmental management*, *197*, 642-655.

Jerez, S., Tobin, I., Vautard, R., Montávez, J. P., López-Romero, J. M., Thais, F., ... & Wild, M. (2015). The impact of climate change on photovoltaic power generation in Europe. *Nature communications*, *6*(1), 10014. https://doi.org/10.1038/ncomms10014

Jia, M., Srinivasan, R. S., Ries, R., Weyer, N., & Bharathy, G. (2019). A systematic development and validation approach to a novel agent-based modeling of occupant behaviors in commercial buildings. *Energy and Buildings*, *199*, 352-367.

Jose, D. M., Vincent, A. M., & Dwarakish, G. S. (2022). Improving multiple model ensemble predictions of daily precipitation and temperature through machine learning techniques. *Scientific Reports*, *12*(1), 4678. https://doi.org/10.1038/s41598-022-08786-w

Kangur, A., Jager, W., Verbrugge, R., & Bockarjova, M. (2017). An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology*, *52*, 166-182.

Karimi, M. J., & Vaez-Zadeh, S. (2021). An agent-based model for electric energy policy assessment. *Electric Power Systems Research*, *192*, 106903.

Khodabandelu, A., & Park, J. (2021). Agent-based modeling and simulation in construction. *Automation in Construction*, *131*, 103882. https://doi.org/10.1016/j.autcon.2021.103882

Kilickaplan, A., Bogdanov, D., Peker, O., Caldera, U., Aghahosseini, A., & Breyer, C. (2017). An energy transition pathway for Turkey to achieve 100% renewable energy powered electricity, desalination and non-energetic industrial gas demand sectors by 2050. *Solar Energy*, *158*, 218-235.

Kim, G., Ahn, J. B., Kryjov, V. N., Lee, W. S., Kim, D. J., & Kumar, A. (2021). Assessment of MME methods for seasonal prediction using WMO LC-LRFMME hindcast dataset. *International Journal of Climatology*, *41*, E2462-E2481. https://doi.org/10.1002/joc.6858

Klein, M., Lüpke, L., & Günther, M. (2020). Home charging and electric vehicle diffusion: agent-based simulation using choice-based conjoint data. *Transportation Research Part D: Transport and Environment*, *88*, 102475.

Köhler, J., Whitmarsh, L., Nykvist, B., Schilperoord, M., Bergman, N., & Haxeltine, A. (2009). A transitions model for sustainable mobility. *Ecological economics*, *68*(12), 2985-2995.

Kowalska-Pyzalska, A. (2016, June). An analysis of factors enhancing adoption of smart metering platforms: An agent-based modeling approach. In 2016 13th International Conference on the European Energy Market (EEM) (pp. 1-6). IEEE.

Kraan, O., Kramer, G. J., & Nikolic, I. (2018). Investment in the future electricity system-An agent-based modelling approach. *Energy*, *151*, 569-580.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A., & Sapio, A. (2018). Faraway, so close: coupled climate and economic dynamics in an agent-based integrated assessment model. *Ecological Economics*, *150*, 315-339.

Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., ... & Park, Y. (2023). IPCC, 2023: Climate Change 2023: Synthesis Report, Summary for Policymakers. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.

Lee, K., & Han, T. W. (2016). How vulnerable is the emissions market to transaction costs?: An ABMS Approach. *Energy Policy*, *90*, 273-286.

Lee, T., Yao, R., & Coker, P. (2014). An analysis of UK policies for domestic energy reduction using an agent-based tool. *Energy Policy*, *66*, 267-279.

Li, F. G. (2017). Actors behaving badly: Exploring the modelling of non-optimal behaviour in energy transitions. *Energy Strategy Reviews*, *15*, 57-71.

Li, F. G., & Strachan, N. (2017). Modelling energy transitions for climate targets under landscape and actor inertia. *Environmental Innovation and Societal Transitions*, *24*, 106-129.

Liang, X., Yu, T., Hong, J., & Shen, G. Q. (2019). Making incentive policies more effective: An agent-based model for energy-efficiency retrofit in China. *Energy Policy*, *126*, 177-189.

Lin, H., Wang, Q., Wang, Y., Wennerstern, R., & Sun, Q. (2016). Agent-based modeling of electricity consumption in an office building under a tiered pricing mechanism. *Energy Procedia*, *104*, 329-335.

Lin, K., Chao, L., Lee, H. H., Xin, R., Liu, S., Ho, T. C., ... & Tso, C. Y. (2021). Potential building energy savings by passive strategies combining daytime radiative coolers and thermochromic smart windows. *Case Studies in Thermal Engineering*, *28*, 101517. https://doi.org/10.1016/j.csite.2021.101517

Lionello, P., & Scarascia, L. (2018). The relation between climate change in the Mediterranean region and global warming. *Regional Environmental Change*, *18*, 1481-1493. https://doi.org/10.1007/s10113-018-1290-1

Liu, D. (2020). A rational performance criterion for hydrological model. *Journal of Hydrology*, *590*, 125488. https://doi.org/10.1016/j.jhydrol.2020.125488

Lu, M., Cheung, C. M., Li, H., & Hsu, S. C. (2016). Understanding the relationship between safety investment and safety performance of construction projects through agent-based modeling. *Accident Analysis & Prevention*, *94*, 8-17. https://doi.org/10.1016/j.aap.2016.05.014

Macal, C. M., & North, M. J. (2005). Tutorial on agent-based modeling and simulation. In *Proceedings of the Winter Simulation Conference*, Orlando, FL, United States of America, 4 December.

Marashli, A., Gasaymeh, A., & Shalby, M. (2022). Comparing the Global Warming Impact from Wind, Solar Energy and Other Electricity Generating Systems through Life Cycle Assessment Methods (A Survey). *International Journal of Renewable Energy Research (IJRER)*, *12*(2), 899-920.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., ... & Zhou, B. (2021). Climate change 2021: the physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change, 2(1), 2391.

Matsumoto, K. I. (2008). Evaluation of an artificial market approach for GHG emissions trading analysis. *Simulation Modelling Practice and Theory*, *16*(9), 1312-1322.

McCoy, D., & Lyons, S. (2014). Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. *Energy Research & Social Science*, *3*, 89-101.

MENR- Ministry of Energy and Natural Resources. (2023). Renewable energy. Retrieved March 7, 2024, from https://enerji.gov.tr/eigm-resources-en

Moglia, M., Podkalicka, A., & McGregor, J. (2018). An agent-based model of residential energy efficiency adoption. *Journal of Artificial Societies and Social Simulation, 21*(3).

Monasterolo, I., & Raberto, M. (2016). A hybrid system dynamics–agent based model to assess the role of green fiscal and monetary policies. Available at SSRN 2748266.

Monasterolo, I., & Raberto, M. (2018). The EIRIN flow-of-funds behavioural model of green fiscal policies and green sovereign bonds. *Ecological Economics*, *144*, 228-243.

Mueller, M. G., & De Haan, P. (2009). How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new cars—Part I: Model structure, simulation of bounded rationality, and model validation. *Energy Policy*, *37*(3), 1072-1082.

Nannen, V., & van den Bergh, J. C. (2010). Policy instruments for evolution of bounded rationality: Application to climate–energy problems. *Technological Forecasting and Social Change*, *77*(1), 76-93.

Natarajan, S., Padget, J., & Elliott, L. (2011). Modelling UK domestic energy and carbon emissions: an agent-based approach. *Energy and Buildings*, *43*(10), 2602-2612.

Niamir, L., Filatova, T., Voinov, A., & Bressers, H. (2018). Transition to low-carbon economy: Assessing cumulative impacts of individual behavioral changes. *Energy policy*, *118*, 325-345.

Niamir, L., Ivanova, O., & Filatova, T. (2020). Economy-wide impacts of behavioral climate change mitigation: Linking agent-based and computable general equilibrium models. *Environmental Modelling & Software*, *134*, 104839.

Niu, W., Li, T., Zhang, X., Hu, T., Jiang, T., & Wu, H. (2019). Using XGBoost to discover infected hosts based on HTTP traffic. *Security and Communication Networks*, *2019*(1), 2182615. https://doi.org/10.1155/2019/2182615

Oğulata, R. T. (2003). Energy sector and wind energy potential in Turkey. *Renewable and Sustainable Energy Reviews*, *7*(6), 469-484.

Ozcan, M., Öztürk, S., & Oguz, Y. (2015). Potential evaluation of biomass-based energy sources for Turkey. *Engineering Science and Technology, an International Journal*, *18*(2), 178-184.

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., ... & van Ypserle, J. P. (2014). *Climate change 2014: synthesis report*. (Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change). Geneva: Intergovernmental Panel on Climate Change.

Palmer, J., Sorda, G., & Madlener, R. (2015). Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation. *Technological Forecasting and Social Change*, *99*, 106-131.

Ponta, L., Raberto, M., Teglio, A., & Cincotti, S. (2018). An agent-based stock-flow consistent model of the sustainable transition in the energy sector. *Ecological economics*, *145,* 274-300.

Prodhan, F. A., Zhang, J., Sharma, T. P. P., Nanzad, L., Zhang, D., Seka, A. M., ... & Mohana, H. P. (2022). Projection of future drought and its impact on simulated crop yield over South Asia using ensemble machine learning approach. *Science of The Total Environment*, *807*, 151029. https://doi.org/10.1016/j.scitotenv.2021.151029

Quintero, F., Krajewski, W. F., Seo, B. C., & Mantilla, R. (2020). Improvement and evaluation of the Iowa Flood Center Hillslope Link Model (HLM) by calibration-free approach. *Journal of Hydrology*, *584*, 124686. https://doi.org/10.1016/j.jhydrol.2020.124686

Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. *Environmental Modelling & Software*, *70*, 163-177.

Ramsey, D. M., Kowalska-Pyzalska, A., & Bienias, K. (2018). Diffusion of Electric Vehicles: An Agent-Based Modelling Approach. In Transactions on Computational Collective Intelligence XXXI (pp. 118-135). Springer, Berlin, Heidelberg.

Rehman, S., Alhems, L. M., Alam, M. M., Wang, L., & Toor, Z. (2023). A review of energy extraction from wind and ocean: Technologies, merits, efficiencies, and cost. *Ocean Engineering*, *267*, 113192. https://doi.org/10.1016/j.oceaneng.2022.113192

Rengs, B., Scholz-Wäckerle, M., & van den Bergh, J. (2020). Evolutionary macroeconomic assessment of employment and innovation impacts of climate policy packages. *Journal of Economic Behavior & Organization*, *169*, 332-368.

Richstein, J. C., Chappin, E. J., & de Vries, L. J. (2014). Cross-border electricity market effects due to price caps in an emission trading system: An agent-based approach. *Energy Policy*, *71*, 139-158.

Richstein, J. C., Chappin, E. J., & de Vries, L. J. (2015). Adjusting the CO2 cap to subsidised RES generation: Can CO2 prices be decoupled from renewable policy?. *Applied Energy*, *156*, 693-702.

Ritchie, H., Rosado, P., & Roser, M. (2020). Breakdown of carbon dioxide, methane and nitrous oxide emissions by sector. *Our World in Data*. Retrieved June 5, 2023, from https://ourworldindata.org/emissions-by-sector

Ritchie, H., Rosado, P., & Roser, M. (2023). CO_2 and Greenhouse Gas Emissions. *Our World in Data*. Retrieved June 5, 2023, from https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions.

Ritchie, H., Rosado, P., & Roser, M. (2024). Electricity mix. *Our World in Data*. Retrieved May 2, 2024, from https://ourworldindata.org/electricity-mix

Rubin, E. S., Azevedo, I. M., Jaramillo, P., & Yeh, S. (2015). A review of learning rates for electricity supply technologies. *Energy Policy*, *86*, 198-218. https://doi.org/10.1016/j.enpol.2015.06.011

Saaty, T. L. (2001). Fundamentals of the analytic hierarchy process. The analytic hierarchy process in natural resource and environmental decision making, 15-35.

Safarzyńska, K., & van den Bergh, J. C. (2017). Integrated crisis-energy policy: Macro-evolutionary modelling of technology, finance and energy interactions. *Technological Forecasting and Social Change*, *114*, 119-137.

Safarzyńska, K., & van den Bergh, J. C. (2018). A higher rebound effect under bounded rationality: Interactions between car mobility and electricity generation. *Energy Economics*, *74*, 179-196.

Saglam, M., Spataru, C., & Karaman, O. A. (2023). Forecasting Electricity Demand in Turkey Using Optimization and Machine Learning Algorithms. *Energies*, *16*(11), 4499. https://doi.org/10.3390/en16114499

Salman, S. A., Shahid, S., Ismail, T., Al-Abadi, A. M., Wang, X. J., & Chung, E. S. (2019). Selection of gridded precipitation data for Iraq using compromise programming. *Measurement*, *132*, 87-98. https://doi.org/10.1016/j.measurement.2018.09.047

Sawadogo, W., Abiodun, B. J., & Okogbue, E. C. (2019). Projected changes in wind energy potential over West Africa under the global warming of 1.5 C and above. *Theoretical and Applied Climatology*, *138*, 321-333. https://doi.org/10.1007/s00704-019-02826-8

Schröder, T., & Wolf, I. (2017). Modeling multi-level mechanisms of environmental attitudes and behaviours: The example of carsharing in Berlin. *Journal of Environmental Psychology*, *52*, 136-148.

Silvia, C., & Krause, R. M. (2016). Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. *Energy Policy*, *96*, 105-118.

SIO- Scripps Institution of Oceanography. (2023). Carbon dioxide concentration at Manua Loa Observatory. *Scripps CO2 Program*. Retrieved July 7, 2023, from https://scripps.ucsd.edu/programs/keelingcurve/.

Sopha, B. M., Klöckner, C. A., & Hertwich, E. G. (2011). Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation. *Energy Policy*, *39*(5), 2722-2729.

Sopha, B. M., Klöckner, C. A., & Hertwich, E. G. (2013). Adoption and diffusion of heating systems in Norway: Coupling agent-based modeling with empirical research. *Environmental Innovation and Societal Transitions, 8*, 42-61.

Stavrakas, V., Papadelis, S., & Flamos, A. (2019). An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers. *Applied Energy, 255*, 113795.

Sun, L., Lan, Y., & Jiang, R. (2023). Using CNN framework to improve multi-GCM ensemble predictions of monthly precipitation at local areas: An application over China and comparison with other methods. *Journal of Hydrology*, *623*, 129866. https://doi.org/10.1016/j.jhydrol.2023.129866

Tah, J. H. (2005). Towards an agent-based construction supply network modelling and simulation platform. *Automation in Construction*, *14*(3), 353-359. https://doi.org/10.1016/j.autcon.2004.08.003

Tang, L., Wu, J., Yu, L., & Bao, Q. (2015). Carbon emissions trading scheme exploration in China: A multi-agent-based model. *Energy Policy*, *81*, 152-169.

Tang, L., Wu, J., Yu, L., & Bao, Q. (2017). Carbon allowance auction design of China's emissions trading scheme: A multi-agent-based approach. *Energy Policy*, *102*, 30-40.

TEDC. (2023). *Turkey Electricity Distribution and Consumption Statistics 2022*. Ankara: Türkiye Elektrik Dağıtım A.Ş. Headquarters

TurkStat- Turkish Statistical Institute. (2017a). Population and annual average population growth rate by provinces, 2017- 2023.

TurkStat- Turkish Statistical Institute. (2017b). Population Projections, 2018-2080.

Url-1 <https://www.milliyet.com.tr/vitrin/jeotermal-enerjide-yatirimlar-ancak-tesvikle-yapilabilir-6709870>, date retrieved 22.04.2024.

Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of operational research*, *169*(1), 1-29. https://doi.org/10.1016/j.ejor.2004.04.028

van der Vooren, A., & Brouillat, E. (2015). Evaluating CO2 reduction policy mixes in the automotive sector. *Environmental Innovation and Societal Transitions*, *14*, 60-83.

Veit, D. J., Weidlich, A., & Krafft, J. A. (2009). An agent-based analysis of the German electricity market with transmission capacity constraints. *Energy Policy*, *37*(10), 4132-4144.

Von Winterfeldt, D., & Fischer, G. W. (1975). Multi-attribute utility theory: models and assessment procedures. In Utility, Probability, and Human Decision Making ’73. *Selected Proceedings of an Interdisciplinary Research Conference*, Rome, Italy, 3–6 September.

Walzberg, J., Dandres, T., Samson, R., Merveille, N., & Cheriet, M. (2017, October). An agent-based model to evaluate smart homes sustainability potential. In 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC) (pp. 1-7). IEEE.

Wang, B., Zheng, L., Liu, D. L., Ji, F., Clark, A., & Yu, Q. (2018). Using multi-model ensembles of CMIP5 global climate models to reproduce observed monthly rainfall and temperature with machine learning methods in Australia. *International Journal of Climatology*, *38*(13), 4891-4902. https://doi.org/10.1002/joc.5705

Wang, G., Zhang, Q., Li, Y., & Li, H. (2018). Policy simulation for promoting residential PV considering anecdotal information exchanges based on social network modelling. *Applied energy*, *223*, 1-10.

Wang, H., Fang, H., Yu, X., & Liang, S. (2018). How real time pricing modifies Chinese households' electricity consumption. *Journal of Cleaner Production*, *178*, 776-790.

Wang, H., Wang, L., Yan, G., Bai, H., Zhao, Y., Ju, M., ... & Chen, L. (2022). Assessment and prediction of extreme temperature indices in the North China Plain by CMIP6 Climate model. *Applied Sciences*, *12*(14), 7201. https://doi.org/10.3390/app12147201

Wesseh Jr, P. K., & Lin, B. (2016). A real options valuation of Chinese wind energy technologies for power generation: do benefits from the feed-in tariffs outweigh costs?. *Journal of cleaner production*, *112*, 1591-1599. https://doi.org/10.1016/j.jclepro.2015.04.083

Willmott, C.J. (1981). On the validation of models. *Physical geography*, *2*(2), 184-194. https://doi.org/10.1080/02723646.1981.10642213

Wu, X., Xu, Y., Lou, Y., & Chen, Y. (2018). Low carbon transition in a distributed energy system regulated by localized energy markets. *Energy Policy*, *122*, 474-485.

Xu, L., Chen, N., Zhang, X., Chen, Z., Hu, C., & Wang, C. (2019). Improving the North American multi-model ensemble (NMME) precipitation forecasts at local areas using wavelet and machine learning. *Climate dynamics*, *53*, 601-615. https://doi.org/10.1007/s00382-018-04605-z

Xu, R., Chen, N., Chen, Y., & Chen, Z. (2020). Downscaling and projection of multi-cmip5 precipitation using machine learning methods in the upper han river Basin. *Advances in Meteorology*, *2020*, 1-17. https://doi.org/10.1155/2020/8680436

Yan, Y., Wang, H., Li, G., Xia, J., Ge, F., Zeng, Q., ... & Tan, L. (2022). Projection of future extreme precipitation in China based on the CMIP6 from a machine learning perspective. *Remote Sensing*, *14*(16), 4033. https://doi.org/10.3390/rs14164033

Yao, R., Hu, Y., & Varga, L. (2023). Applications of agent-based methods in multi-energy Systems—A systematic literature review. *Energies*, *16*(5), 2456.

Yilmaz, Y. (2019). *Investigating the hydroclimatic changes in the Euphrates-Tigris Basin under a changing climate* (Doctoral dissertation). Retrieved from https://acikbilim.yok.gov.tr/handle/20.500.12812/127287

Zhang, P., Li, N., Jiang, Z., Fang, D., & Anumba, C. J. (2019). An agent-based modeling approach for understanding the effect of worker-management interactions on construction workers' safety-related behaviors. *Automation in construction*, *97*, 29-43. https://doi.org/10.1016/j.autcon.2018.10.015

Zhang, P., Lu, J., & Chen, X. (2022). Machine-learning ensembled CMIP6 projection reveals socio-economic pathways will aggravate global warming and precipitation extreme. *Hydrology and Earth System Sciences Discussions*, *2022*, 1-40. https://doi.org/10.5194/hess-2022-235

Zhang, T., Siebers, P. O., & Aickelin, U. (2011). Modelling electricity consumption in office buildings: An agent based approach. *Energy and Buildings*, *43*(10), 2882-2892.

Zhao, F. (2012). Agent-based modeling of commercial building stocks for energy policy and demand response analysis. Georgia Institute of Technology.

Zhao, J., Mazhari, E., Celik, N., & Son, Y. J. (2011). Hybrid agent-based simulation for policy evaluation of solar power generation systems. *Simulation Modelling Practice and Theory*, *19*(10), 2189-2205.

Zhao, Z., Guo, Y., Dong, B., Zhu, J., Luo, N., & Gao, Z. (2023). A clustering-based multi-model ensemble projection of near-term precipitation changes over East China and its uncertainty. *Environmental Research Letters*, *18*(9), 094050.

Zhu, L., Chen, L., Yu, X., & Fan, Y. (2018). Buying green or producing green? Heterogeneous emitters’ strategic choices under a phased emission-trading scheme. *Resources, Conservation and Recycling*, *136*, 223-237.

Zhu, Q., Duan, K., Wu, J., & Wang, Z. (2016). Agent-based modeling of global carbon trading and its policy implications for China in the Post-Kyoto Era. *Emerging Markets Finance and Trade*, *52*(6), 1348-1360.

Zhuge, C., Dong, C., Wei, B., & Shao, C. (2021). Exploring the role of technology innovations in the diffusion of electric vehicle with an agent-based spatial integrated model. *Resources, Conservation and Recycling*, *174*, 105806

APPENDICES

APPENDIX A: Tables

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Table A.1 : Selected GCMs and their resolutions.

No	Model	Institute, Country	Horizontal Resolution
M1	ACCESS-CM2	Commonwealth Scientific and Industrial Research Organisation, Australia	1.9° x 1.3°
M2	ACCESS-ESM-1-5		1.9° x 1.2°
M3	BCC-CSM2-MR	Beijing Climate Center (BCC) and China Meteorological Administration (CMA), China	1.1° x 1.1°
M4	CMCC-ESM2	Euro-Mediterranean Centre on Climate Change coupled climate model, Italy	1.25° x 0.938°
M5	CMCC-CM2-SR5		
M6	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory, US	1.3° x 1°
M7	HadGEM3-GC31-LL	Met Office Hadley Centre, UK	1.25° x 1.875°
M8	IITM-ESM	Centre for Climate Change Research, Indian Institute of Tropical Meteorology, India	1.875° x 1.9°
M9	INM-CM4–8	Institute of Numerical Mathematics, Russia	2° x 1.5°
M10	INM-CM5–0		
M11	MIROC6	Japanese Modelling Community, Japan	1.4° x 1.4°
M12	MPI-ESM1–2-HR	Max Planck Institute for Meteorology, Germany	0.9° x 0.9°
M13	UKESM1–0-LL	Met Office Hadley Centre, UK	1.9° x 1.3°

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- **Guven, D.,** Kayalica, M. O., Sen, O. L. 2024: Integration of Climate Projections into Agent-Based Modelling for Electricity Sector Analysis in Türkiye. European Climate and Energy Modelling Platform, October 16-17, 2024 Brussels, Belgium.
- **Guven, D.,** Sen, O. L., Kayalica, M. O. 2024: Türkiye's Renewable Energy Outlook: GCM-Based Analysis and Future Projections Using the Extreme Gradient Boosting Algorithm. EGU General Assembly, April 14-19, 2024 Vienna, Austria.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Guven, D.** 2025. Assessing the environmental and economic viability of floating PV-powered green hydrogen: A case study on inland ferry operations in Türkiye. *Applied Energy*, *377*, 124768.
- **Guven, D.** 2024. Offshore wind-driven green hydrogen: Bridging environmental sustainability and economic viability. *International Journal of Hydrogen Energy*, *72*, 661-676.

- **Guven, D.**, and Kayalica, M.O. 2024. Environmental and economic assessment of hydrogen-powered ferries for inland transportation. *Ocean Engineering*, *301*, 117556.

- **Guven, D.** 2024. Analysing the Determinants of Surface Solar Radiation with Tree-Based Machine Learning Methods: Case of Istanbul. *Pure and Applied Geophysics*, 1-27.

- Dogan, A., **Guven, D.**, Kayalica, M.O., and Bayar, A.A. 2024. Scheduling Model for a Trigeneration System With Energy Storage Unit: A Hospital Application. *IEEE Transactions on Engineering Management*, *71*, 6146-6159.

- Qudaih, S., Bektas, Z., **Guven, D.**, Kayakutlu, G., and Kayalica, M.O. 2024. Technology Assessment of Hydrogen Storage: Cases Enabling the Clean Energy Transition. *IEEE Transactions on Engineering Management*, *71*, 5744-5756.

- **Guven, D.**, and Kayalica, M.O. 2023. Analysing the determinants of the Turkish household electricity consumption using gradient boosting regression tree. *Energy for Sustainable Development*, *77*, 101312.

- **Guven, D.**, Deliaslan, E., Yurtseven, M.B., and Kayakutlu, G. 2023. Prediction of Downward Surface Solar Radiation Using Particle Swarm Optimization and Neural Networks. In Decision Making Using AI in Energy and Sustainability: Methods and Models for Policy and Practice (pp. 105-117). Cham: Springer International Publishing.

- Kayakutlu, G., Kayalica, M. O., Düzdar Argun, İ., Acartürk, A., Deveci, K., Atmaca, Ş., **Guven, D.**, ... and Daim, T. 2023. Demand Response in Generation Capacity Planning Technology Roadmap: Turkey's Quest. In Next Generation Roadmapping: Establishing Technology and Innovation Pathways Towards Sustainable Value (pp. 233-250). Cham: Springer International Publishing.

- **Guven, D.** 2023. Development of multi-model ensembles using tree-based machine learning methods to assess the future renewable energy potential: case of the East Thrace, Turkey. *Environmental Science and Pollution Research*, *30*(37), 87314-87329.

- **Guven, D.**, and Kayalica, M.O. 2023. Life-cycle assessment and life-cycle cost assessment of lithium-ion batteries for passenger ferry. *Transportation Research Part D: Transport and Environment*, *115*, 103586.

- **Guven, D.**, Aydın, G.K., Kayalica, M.O. 2022. CO2 Emissions Analysis and Underlying Emission Trend in Selected Emerging Countries. In Environmental Sustainability, Growth Trajectory and Gender: Contemporary Issues of Developing Economies (pp. 89-103). Emerald Publishing Limited.

- Aydın, G.K., **Guven, D.**, and Kayalica, M.O. 2022. Gender Gap and CO2 Emissions in Emerging Markets Economies: A Panel Data Study. In Environmental Sustainability, Growth Trajectory and Gender: Contemporary Issues of Developing Economies (pp. 219-232). Emerald Publishing Limited.

- **Guven, D.**, Kayalica, M.O., and Kayakutlu, G. 2021. Critical power demand scheduling for hospitals using repurposed ev batteries. *Technology and economics of smart grids and sustainable energy*, *6*(1), 21.

- Deliaslan, E., **Guven, D.**, Kayalica, M.O., & Yurtseven, M.B. 2021. Grid Imbalance Prediction Using Particle Swarm Optimization and Neural Networks. In IFIP International Workshop on Artificial Intelligence for Knowledge Management (pp. 87-101). Cham: Springer International Publishing.
- **Guven, D.**, Kayalica, M.O., Kayakutlu, G., and Isikli, E. 2021. Impact of climate change on sectoral electricity demand in Turkey. *Energy Sources, Part B: Economics, Planning, and Policy*, *16*(3), 235-257.
- **Guven, D.**, Ozozen, A., Kayakutlu, G., and Kayalica, M.O. 2021. Predicting power deviation in the Turkish power market based on adaptive factor impacts. In IFIP International Workshop on Artificial Intelligence for Knowledge Management (pp. 213-234). Cham: Springer International Publishing.
- Kayalica, M.O., Ozozen, A., **Guven, D.**, Kayakutlu, G., and Bayar, A.A. 2020. Electricity consumption analysis based on Turkish household budget surveys. *Energy, Ecology and Environment*, *5*(6), 444-455.
- **Guven, D.,** Kayalica, M.O., and Kayakutlu, G. 2020. CO2 emissions analysis for East European countries: the role of underlying emission trend. *Environmental Economics*, *11*(1), 6.