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Agent-Based Energy Market Modeling with Machine Learning and Econometric Forecasting for the Net-Zero Emissions Transition

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Abstract

The transition of Türkiye's energy market toward net-zero emissions by 2053 requires modeling approaches capable of capturing complex interactions and long-term uncertainties. In this study, a long-term agent-based modeling (ABM) framework was developed, integrating econometric demand forecasting with a seasonal autoregressive integrated moving average (SARIMA) model and machine learning (ML)-based day-ahead market (DAM) price prediction. Of the ML models tested, CatBoost achieved the highest accuracy, outperforming XGBoost and Random Forest, and supported investment analysis through net present value (NPV) calculations. The framework represents major market actors—including generation units, investors, and the market operator—while also incorporating the impact of Türkiye's first nuclear power plant (NPP) under construction and the potential introduction of a carbon emissions trading scheme (ETS). All model components were validated against historical data, confirming robust forecasting and market replication performance. Hourly simulations were conducted until 2053 under alternative policy and demand scenarios. The results show that renewable generation expands steadily, led by onshore wind and solar photovoltaic (PV), while nuclear capacity, ETS implementation, and demand assumptions significantly reshape prices, generation mix, and carbon emissions. The nuclear plant lowers market prices, whereas an ETS substantially raises them, with both policies contributing to emission reductions. These scenario results were connected to actionable policy recommendations, outlining how renewable expansion, ETS design, nuclear development, and energy efficiency measures can jointly support Türkiye's 2053 net-zero target. The proposed framework provides an ex-ante decision-support framework for policymakers, investors, and market participants, with future extensions that can include other energy markets, storage integration, and enriched scenario design.

Keywords: agent-based modeling; machine learning; econometric forecasting; energy markets; electricity markets; carbon emissions trading

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1. Introduction

The transition toward carbon neutrality in energy markets involves numerous heterogeneous actors and complex interactions, making it difficult for traditional modeling approaches to capture long-term dynamics. Agent-based modeling (ABM) provides an effective framework for analyzing such complex systems. In electricity markets, ABM

enables the representation of producers, consumers, storage units, market operators, and regulators, while also capturing their individual decision-making behaviors and interactions. This approach allows researchers to investigate how the collective behavior of agents influences the overall system, thereby facilitating a better understanding of real-world dynamics [1]. In this way, newly introduced market participants, policies, regulations, and technologies can be examined in detail to support the development of effective decision-making frameworks.

In ABM studies, the accuracy of simulations can be improved by incorporating machine learning (ML) methods. Reinforcement learning (RL) techniques enable agents to learn and adapt their strategies in ways that more closely reflect real-world decision-making [2]. A typical application is the adjustment of bidding strategies for producers or consumers through learning during the simulation process [3]. Moreover, ML can be applied to predict exogenous variables such as demand or market prices, further enhancing model accuracy. Supervised ML methods are often used for such forecasting tasks [4]. In the literature, studies focusing on agent learning significantly outnumber those relying on external data prediction [5].

Among the general-purpose ABM software tools, the Recursive Porous Agent Simulation Toolkit (Repast) was one of the earliest platforms to integrate ML algorithms, including genetic algorithms, artificial neural networks (ANNs), and other methods [6]. Another widely used tool is AnyLogic, a commercially developed software that enables agent modeling and simulation with reduced coding requirements and advanced visualization features [7,8]. These general-purpose ABM platforms paved the way for energy market-specific simulation frameworks. For instance, the Simulator for Electric Power Industry Agents (SEPIA) models stakeholders such as power plants, consumers, suppliers, and transmission operators [9]. Similarly, the Electricity Market Complex Adaptive Systems (EMCAS) tool incorporates independent system operators (ISOs) and regulators, allowing users to define market rules and observe their effects [10]. The Multi-Agent System that Simulates Competitive Electricity Markets (MASCEM) further extends this approach by introducing virtual producers that represent groups of agents and make strategic group decisions on their behalf [11].

Several ABM frameworks have also been developed to represent specific national electricity markets. For instance, the National Electricity Market Simulation System (NEMSIM) models the Australian market, incorporating contracts, investments, and carbon emissions [12]. ElectTrans simulates the Dutch system by capturing long-term capacity additions and plant retirements, while ElecSim provides a framework for analyzing investment decisions in the UK market [13,14]. The electricity markets investment suite–agent-based simulation (EMIS-AS) broadens this perspective by integrating financing options, technology preferences, and risk tolerance into investment decision-making [15]. Nexus-e simulates the Swiss electricity market, including cross-border trading [16,17]. As a last example, Guven et al. [18] developed a long-term ABM model with yearly resolution that integrates climate projections and policy scenarios, demonstrating how renewable incentives and nuclear development influence emissions and energy costs.

Despite these advances, the number of studies remains limited, with a review of ABM–ML integration in local energy markets between 2000 and 2019 indicating that only a small number of works existed, particularly those employing ML for external data prediction [5]. Long-term studies are particularly challenging, as they require reliable projections of market behavior and policy developments. Consequently, most research has concentrated on short-term analyses [19]. Nevertheless, incorporating ML-based forecasting of external variables can significantly enhance the accuracy of ABM simulations. For example, Fraunholz et al. [20] employed the power agent-based computational economics

(PowerACE) platform to predict European day-ahead prices from 2020 to 2050, with ANN models achieving the highest accuracy. Similarly, Kell et al. [21] assessed forecasting models within the ElecSim tool for UK hourly demand data (2011–2017), finding that the extra trees regressor outperformed offline methods, whereas online retraining with a multilayer perceptron produced superior results.

Studies conducted between 2016 and 2021 show that ABM–ML research in energy markets has primarily focused on specific applications such as bidding and price forecasting [22]. Most studies have been limited to electricity markets, with relatively little attention paid to broader system perspectives. Although some research has incorporated carbon emissions trading mechanisms, the number of such studies is still limited [23]. Another notable shortcoming is that only a few studies explicitly discuss verification and validation procedures [24]. In ABM, verification ensures that the model has been correctly implemented, whereas validation examines whether the model structure and behavior accurately reflect real-world dynamics [25]. Notably, 58% of the studies published between 2014 and 2024 relied on artificial data, limiting their ability to validate models under actual market conditions and often resulting in less realistic simulations compared with those based on real-world data [19]. This study addresses those gaps by presenting an ABM application that integrates machine learning and econometric forecasting, specifically designed for the Turkish energy market.

Türkiye's electricity market is liberalized and is rapidly increasing its renewable electricity production share. By the end of September 2025, total installed capacity reached 121 GW, of which 61% was derived from renewable energy resources (hydropower, wind, solar, geothermal, and biofuel). Solar photovoltaics (PVs) have shown the strongest growth momentum, with capacity more than doubling within two years to reach 24.1 GW [26]. Market operations are administered by the Energy Exchange Istanbul (EXIST), which oversees the hourly day-ahead and intraday electricity markets, while the Turkish Electricity Transmission Corporation (TEIAS)—a state-owned enterprise—manages transmission system reliability through balancing power and ancillary services. Electricity prices are strongly influenced by hydrology and fuel costs, since hydropower (reservoir and run-of-river) still has the largest installed capacity, and natural gas and coal-fired generation continue to play a critical role in meeting rising demand [26]. The Turkish natural gas market is organized around BOTAS, the state-owned pipeline operator and principal importer, alongside the EXIST-operated natural gas spot market. In practice, gas prices for power plants are largely governed by BOTAS's wholesale tariff-setting mechanisms, meaning that the marginal costs of the electricity market are heavily influenced by BOTAS's pricing decisions [27].

Türkiye ratified the Paris Agreement on 7 October 2021 and committed to achieving net-zero greenhouse gas emissions by 2053 [28]. The National Energy Plan foresees a large additional capacity for renewables consistent with this target, while the Akkuyu Nuclear Power Plant (NPP), whose first unit is scheduled to start test production in 2025, is expected to significantly alter the emissions' trajectory [29]. Complementary climate policy instruments are also evolving. A draft regulation for a national emissions trading scheme (ETS)—aligned in structure with the European Union (EU) ETS—was published in 2023 to establish allowance allocation and auctioning mechanisms [30]. In parallel, Türkiye supports low-carbon investment through feed-in tariffs (FITs) and renewable energy resource area (YEKA) schemes, which provide long-term power purchase guarantees and auctions for increased wind and solar PV capacities, respectively [31,32]. Moreover, the EXIST guarantee of origin system certifies renewable electricity and enables voluntary green-energy trading [33]. TEIAS continues to expand high-voltage infrastructure and interconnection projects to facilitate renewable integration, although a comprehensive

long-term grid expansion master plan is not publicly disclosed. Together, these market, policy, and infrastructure initiatives frame Türkiye's transition toward a more flexible, low-carbon electricity system.

This study examines how renewable energy integration, nuclear deployment, a potential carbon trading scheme, and various demand scenarios may shape electricity market dynamics, investment decisions, generation mix, prices, and emissions. Through scenario-based simulations, the model projects possible future developments of the Turkish market, thereby providing valuable insights for policymakers and investors seeking to align with the 2053 net-zero target.

The Turkish energy market is modeled as a holistic system that encompasses the central electricity market, carbon emission trading scheme, generation units, investors, and the market operator. While the primary emphasis is on long-term projections, the model also incorporates short-term simulations for verification, thereby enhancing the reliability of long-term outcomes. Real market data are employed, and multiple supervised ML techniques, together with an econometric approach based on the seasonal autoregressive integrated moving average (SARIMA) method, are applied to forecast exogenous demand and price variables. The integration of econometric and ML methods represents a methodological innovation, strengthening the robustness of the long-term ABM framework. The main contributions of this study can be summarized as follows:

- Developing a long-term ABM framework for Türkiye's energy market that integrates econometric (SARIMA) demand forecasting with ML-based (CatBoost) day-ahead price (DAP) prediction;
- Integrating ML for exogenous data prediction to enhance ABM accuracy and benchmarking multiple ML models to identify the best-performing approach;
- Demonstrating the value of combining ABM, econometric forecasting, and ML methods for long-term policy and investment assessment;
- Quantifying the effects of nuclear commissioning, carbon pricing, and demand variations on electricity prices, generation mix, and emissions;
- Introducing a short-term ABM component for model verification and validation, thereby increasing confidence in long-term outcomes;
- Conducting hourly simulations through 2053 to capture market granularity and realistic operational dynamics;
- Employing real-world, publicly available data to ensure transparency, reproducibility, and policy relevance.

The remainder of this paper is structured as follows. Section 2 introduces the overall modeling framework, including materials and data, as well as the econometric and ML methods employed for electricity demand and price forecasting. Section 3 presents the agent representation and the design of the day-ahead market (DAM), ETS, and investment modules. Section 4 reports the results of long-term simulations, highlighting how alternative policy and demand scenarios shape electricity market prices, generation mix, and carbon emissions trajectories. It also provides a practical policy translation, connecting the simulation results to actionable recommendations for Türkiye's energy transition. Finally, Section 5 summarizes the conclusions and outlines directions for future research.

2. Methods Used in ABM of Energy Markets

2.1. Materials and Scope

The subject of this research is Türkiye's national energy market and its transition toward the 2053 net-zero emissions target. This study addresses the problem of how policy, investment, and demand developments influence long-term generation mix, market prices, and carbon emissions under uncertain future conditions. The main research objective is to

develop a comprehensive long-term ABM framework that integrates econometric demand forecasting and ML-based price prediction to evaluate energy policy and investment pathways. The following hypotheses were formulated to guide this analysis:

- Investors will prioritize renewable technologies with higher net present value (NPV) returns, leading to the steady expansion of onshore wind and solar PV capacity;
- The inclusion of nuclear capacity in Türkiye's generation portfolio will lower wholesale electricity prices and reduce emissions relative to a system without nuclear power;
- The introduction of a national ETS will increase market prices but accelerate emission reductions;
- Higher electricity demand trajectories will raise prices and slow the decarbonization rate, whereas lower demand will have the opposite effect.

This study employs publicly available datasets from EXIST, TEIAS, and other national institutions, complemented by international data and forecasts covering fossil fuel prices, carbon prices, investment and operation costs, and plant lifetime parameters (Table 1).

The software framework for the proposed ABM was implemented using AnyLogic 8.9.6 Personal Learning Edition, chosen for its flexibility in defining agents and customizable interactions. AnyLogic was complemented by an in-house Python 3.10 application, which was used for data preprocessing, econometric analysis, ML model training, and the post-processing of simulation outputs. The Python environment included widely used scientific libraries—Pandas, NumPy, Scikit-learn, CatBoost, and Matplotlib—to ensure robustness and reproducibility. Data transfer between Python and AnyLogic was managed via structured Microsoft Excel (.xlsx) interfaces. Simulation results were analyzed in Python for model validation, visualization, and scenario-based policy interpretation.

The analyses and simulations in this study were performed on an HP Z4 G4 Workstation equipped with an Intel(R) Xeon(R) W-2123 CPU (3.60 GHz, 4 cores/8 threads), 64 GB DDR4-2933 MHz RAM (CL 21, two Kingston KSM29RD4/32HDR modules), and a 512 GB Samsung MZVL2512HCJQ SSD. The system is built on an HP 81C5 motherboard (BIOS version P61 v02.95, 21 November 2024) and operates on Microsoft Windows 11 Pro 64-bit (Build 26100.1).

The proposed framework connects external data prediction with agent-based modeling to capture both the short- and long-term dynamics of the Turkish energy market. As shown in Figure 1, the external econometric model (SARIMA) provides long-term electricity demand projections, while the CatBoost ML model supplies DAP forecasts that feed into the investor agent's decision-making process. Within the ABM environment, the market operator agent clears the DAM and, under the relevant scenarios, a prospective carbon ETS. Thermal power plant agents (natural gas, imported coal, and domestic coal), renewable agents (solar PV, wind, hydropower, geothermal, and biofuel), and the NPP agent submit bids based on their cost structures, technical constraints, and policy environment. The Akkuyu NPP is modeled as a baseload generation unit, following Türkiye's official commissioning plan. Its installed capacity is treated as an exogenous parameter in the scenario design, reflecting a fixed policy commitment rather than an endogenous investment decision.

Table 1. Data sources and descriptions used in the simulation model.

Data	Description	Start	Resolution	Source
Net electricity demand	Electricity demand excluding internal consumption of unlicensed generation	2016	Hourly	[34]
DAM price	DAM electricity price	2009	Hourly	[34]
Natural gas plant fuel price	Natural gas sales price tariff	2014	Monthly	[27]
Licensed power plant list	Licensed power plant list	2020	-	[34]
Licensed power plant unit list	List of generation units of the power plants	2020	-	[34]
FIT installed capacity	Installed capacity of power plants supported under the feed-in tariff (FIT) scheme	2016	Monthly	[34]
FIT licensed generation	Generation of licensed power plants under the FIT scheme, by energy source	2016	Hourly	[34]
Total day-ahead plan	Day-ahead generation schedule by energy source	2014	Hourly	[34]
Total generation	Realized generation by energy source	2015	Hourly	[34]
Net international generation	Net electricity imports (imports minus exports)	2015	Hourly	[34]
Plant generation	Realized generation by the power plant	2019	Hourly	[34]
DAM bid cap	Bid limit cap in DAM	2021	Monthly	[35]
Total installed capacity	Installed capacity by energy source	2019	Monthly	[36]
Total unlicensed generation	Unlicensed generation by energy source	2018	Hourly	[34]
System usage and operating fee	Electricity transmission system usage and operating fee	2021	Yearly	[37]
Total gas transmission fee	Total natural gas entry, exit, and transmission charges	2019	Yearly	[34]
Gross electricity demand	Total electricity demand	1975	Monthly	[38]
Fossil fuel and CO_2 price	Forecast of natural gas, coal, and carbon dioxide (CO_2) emission prices	2022	Yearly	[39]
Plant investment and O&M cost	Investment and operation and maintenance (O&M) costs by plant type	2021	Yearly	[39–41]
Hydropower plant cost	Investment and O&M costs of hydropower plants	2010	Yearly	[42]
Plant lifetime and commissioning	Lifetimes and commissioning periods by plant type	2021	-	[40,41,43]
Thermal plant efficiency	Thermal efficiency values for natural gas and imported coal power plants	2021	-	*
New thermal plant efficiency	Thermal efficiency rate of thermal power plants to be constructed	2021	Yearly	[41]
Realized plant investment	Licensing and commissioning dates of power plants and commissioned capacity	2003	Daily	[44]
Generation license	Electricity generation licenses by company and power plant	2016	Daily	[45]

* Authors' own data (not publicly available).

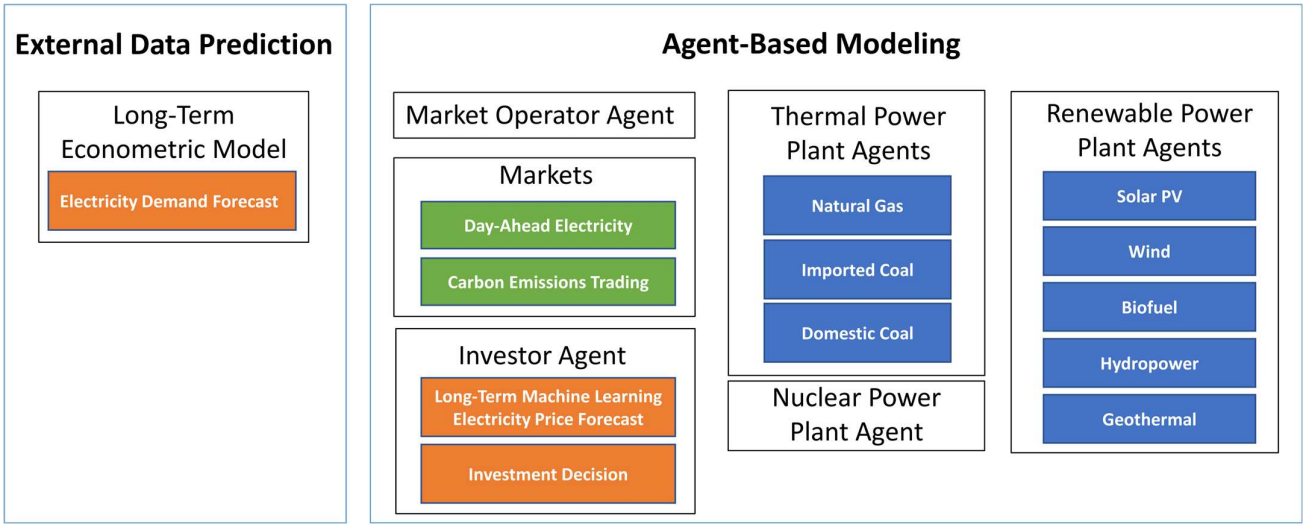


Figure 1. Scope of the study.

Investor agents decide on new capacity additions and retirements according to projected demand and prices, thereby updating the generation portfolio over time. As illustrated in Figure 2, these interactions create a feedback loop in which demand, market prices, emissions, and investment decisions co-evolve on an hourly basis until 2053, providing a comprehensive view of how policy, technology, and market forces can shape Türkiye's pathway to net-zero emissions.

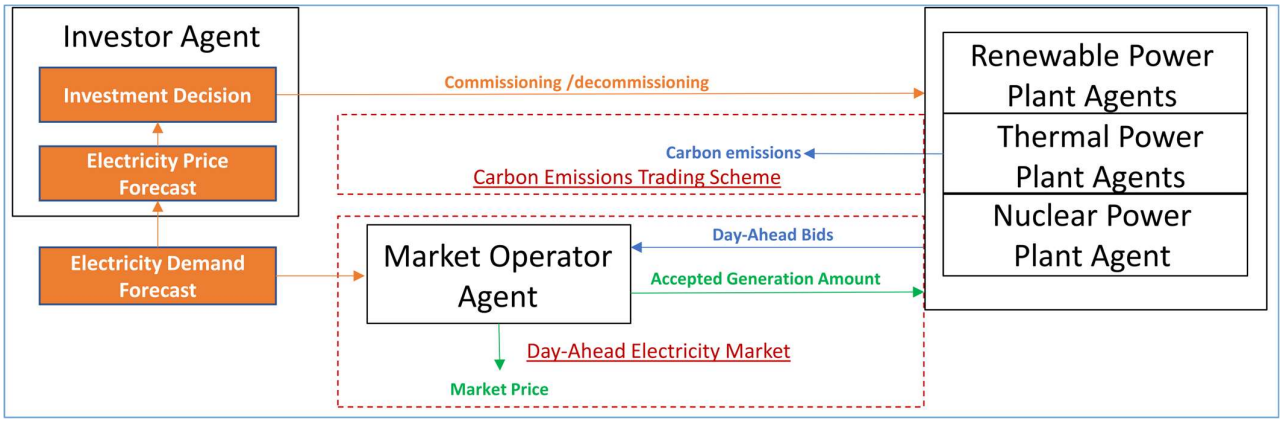


Figure 2. Long-term agent and market interactions.

The overall research procedure followed in this study is summarized in Figure 3, which presents the integrated workflow combining econometric, ML, and ABM components. The process begins with data collection from national and international sources, followed by preprocessing and variable computation in Python. A short-term ABM is first developed and validated in AnyLogic to ensure model accuracy before extending it into a long-term ABM that incorporates nuclear generation, an ETS module, and investor decision-making based on NPV analysis. Electricity demand is forecasted using an econometric SARIMA model, while multiple ML models are trained to predict DAP, with CatBoost achieving the best performance. Scenario-based simulations are then conducted for the period 2022–2053 under varying policy and demand assumptions. Finally, post-processing and sensitivity analyses are performed in Python to evaluate prices, generation mix, emissions, and investment outcomes, leading to policy interpretation and conclusions.



Figure 3. Research algorithm of the study.

2.2. Econometric Demand Forecasting Model

Long-term electricity demand was modeled econometrically, as time-series models generally outperform alternatives for electricity demand forecasting [46]. Accordingly, consistent with [47] and given the role of seasonality, this study adopted the seasonal [48]. After selecting an appropriate specification, the model forecasts future values as a linear function of past observations and a random error term. In SARIMA $(p, d, q) \times (P, D, Q)_S$, p is the autoregressive order, d the differencing order, q the moving-average order, and P, D, Q are their seasonal counterparts [49]. $S = 12$ denotes the annual seasonal cycle in the monthly electricity demand data. This value was selected because electricity consumption in Türkiye exhibits strong annual seasonality, with demand patterns repeating every 12 months due to climatic and economic cycles. The complete list of symbols and parameters used in all mathematical formulas is summarized in Table A1 (Appendix A).

Monthly gross electricity consumption data for 1975–2021 were used to build the time series. Because stationarity (i.e., constant mean and variance over time) is a prerequisite for reliable econometric forecasting, we tested it using unit-root tests, namely the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. The initial ADF p-value was 0.99, indicating non-stationarity, which was expected for inherently seasonal demand. We applied a natural log transformation, after which the ADF p-value became 0.13. We then differenced the logged series with a 12-month seasonal period; the ADF p-value fell to 0, and the ADF statistic was –4.67, confirming stationarity at the 1% level (Table 2). As a robustness check, we also applied the PP test, which indicated stationarity (PP statistic –11.7, p-value~0). To assess multicollinearity, we computed the Variance Inflation Factor; values were below 10, indicating no serious multicollinearity.

Table 2. Critical values for unit-root tests.

Significance Level	Confidence Level	Critical Value
%1	%99	−3.44
%5	%95	−2.87
%10	%90	−2.57

We further examined distributional properties. High kurtosis (7.843) suggested heavy tails. Taking the log of first differences improved normality:

- Skewness: –0.179;
- Kurtosis: 2.954;
- Jarque–Bera: 3.123; *p*-value = 0.209.

Given the monthly frequency and sample size, this proximity to normality was sufficient. The ADF statistic (–4.36) and PP statistic (–53.30), both with *p*-value~0 confirmed suitability for modeling. The 2022 forecast yielded a monthly mean absolute percentage error (MAPE) of 3.5% and the annual total differed by 1.9% compared to historical (actual) demand data from 2022. After validation, the model was run monthly for the 2022–2053 period (Figure 4). Hourly demand was then obtained by allocating monthly forecasts using the observed 2021 hourly shape.

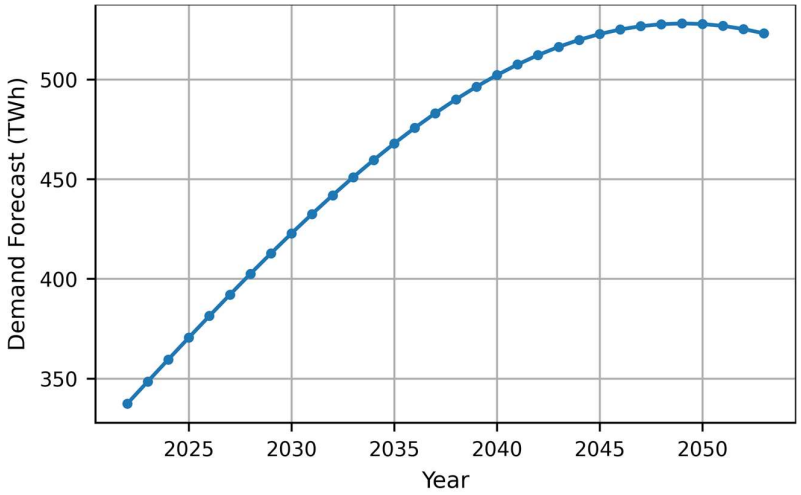


Figure 4. SARIMA demand forecast.

2.3. ML-Based Day-Ahead Price Forecasting Model

An ML-based approach is applied for DAM electricity price forecasting, as it can capture potential mark-ups or strategic bidding behavior that may arise under tight supply conditions. The input data used in the model consist of hourly natural gas fuel cost (*GasCost*), coal fuel cost (*CoalCost*), and residual demand (*ResDem*) for the 2017–2020 period. Residual demand is defined as total demand (*TotDem*), forecasted using the SARIMA model, minus demand met by price-independent resources (*IndDem*), such as renewable and NPPs (Equation (1)). The output variable is DAP.

$$ResDem = TotDem - IndDem, \quad (1)$$

Outliers were removed from the training set using the interquartile range (IQR × 1.5) method, which reduced the dataset from 35,064 to 34,987 observations. For validation, 20% of the training data were randomly selected, and the 2021 data were used for testing. Correlation analysis showed that some feature–target correlations exceeded 0.6, particularly between *GasCost* and DAP. To mitigate bias, a transformed dependent variable ($DAPFac$)

was defined (Equation (2)). The ML model was constructed using *CoalCost* and *ResDem* as inputs, with *DAPFac* as the output. All input variables were scaled to the [−1, 1] range using min–max scaling.

$$DAPFac = \frac{DAP}{GasCost}, \quad (2)$$

CatBoost, XGBoost, and Random Forest models were trained on historical data for the 2017–2020 period, with their hyperparameters optimized through grid-search cross-validation. Each trained model was then evaluated on the 2021 historical dataset, and the test results were compared. As summarized in Table 3, CatBoost achieved the best overall performance during the test period, recording the lowest monthly mean absolute percentage error (MAPE, 6.09%) and annual average error (−1.94%). In comparison, XGBoost yielded 6.60% MAPE and −4.32% average error, while Random Forest produced 6.49% MAPE and −5.58% average error. Thus, CatBoost outperformed XGBoost and Random Forest across both indicators. This superiority is consistent with CatBoost's ordered (unbiased) gradient-boosting design [50].

Table 3. Comparison of ML models on historical data from 2021.

Metric	CatBoost	XGBoost	Random Forest
Average Error (%)	−1.94%	−4.32%	−5.58%
MAPE (%)	6.09%	6.60%	6.49%

Using long-term capacity mix and fuel prices, the investor projects hourly DAP with the CatBoost model for 2022–2053, which serves as a reference for investment decisions (Table 4). Figure 5 illustrates the yearly average of the predicted prices. All monetary values are expressed in constant 2022 United States dollars (USD_2022) to eliminate the effect of inflation. For brevity, USD_2022 is hereafter denoted simply as USD throughout the paper.

Table 4. Fossil fuel and carbon price inputs.

Price Type	2022	2030	2050
Natural Gas (USD/MWh)	110.2	23.5	24.2
Coal (USD/MWh)	35.6	8.2	8.5
CO_2 (USD/ton)	120	129	135

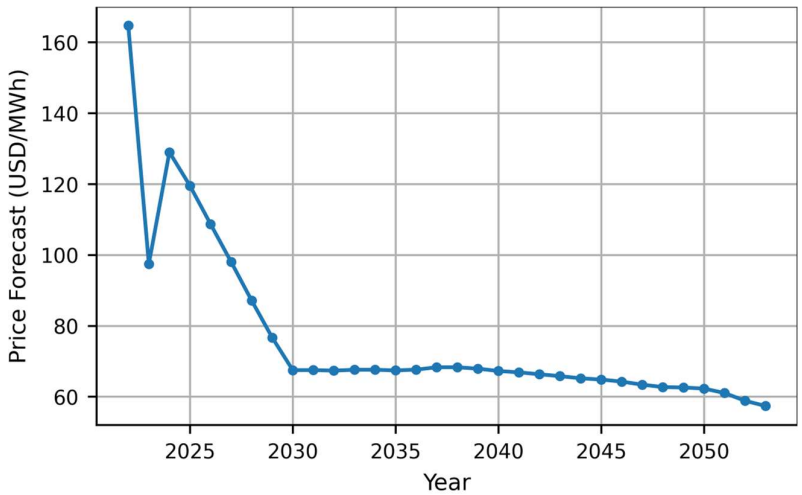


Figure 5. CatBoost DAP forecast.

3. Models and the Framework

3.1. Agent Modeling

The key agents and their modeling assumptions are summarized below.

Market Operator Agent: The operator manages the DAM by clearing 24-h bids and calculating hourly market prices. Prices are determined according to DAM rules and the merit-order principle, with the results of accepted bids reported to each generator.

Nuclear Power Plant Agent: Nuclear plants are modeled as baseload units operating at full capacity every hour, regardless of market prices. Their installed capacity is provided as input according to commissioning schedules.

Renewable and Domestic Coal Agents: For renewable technologies, capacity factors (*CapacityFactor*s) are computed for each hour of the day and month using historical data on installed capacity (*InstalledCapacity*) and actual generation (*ActualGeneration*) (Equation (3)). Domestic coal plants are modeled analogously, as they benefit from state incentives and sell power via power purchasing agreements rather than marginal cost bidding. The calculated capacity factors, together with projected future installed capacities, are then used to estimate future hourly generation.

$$CapacityFactor = \frac{Actual\ Generation}{InstalledCapacity \times OperatingHours}, \tag{3}$$

Natural Gas and Imported Coal Agents: Every day, the plant agents submit their bids for 24 h of the next day to the market operator. These bids are expressed as price–quantity pairs, with the bid quantities equal to the full installed capacity of each plant. The bid prices correspond to the marginal fuel cost (MFC) of the plants, which are primarily driven by fuel costs:

$$MFC = \frac{Unit\ Fuel\ Cost}{Thermal\ Efficiency}, \tag{4}$$

The installed capacity of each plant is defined as its maximum historically observed hourly electricity output. For natural gas plants, thermal efficiencies are taken directly as input parameters, with cogeneration plants being the exception. In the case of cogeneration, efficiency is presented by the maximum monthly economic efficiency ratio observed in the past (Equation (5)). This formulation captures the dependence of cogeneration output on steam demand at associated facilities rather than purely technological performance. Consequently, cogeneration plants are assumed to operate with lower marginal costs than other natural gas-fueled power plants.

$$Monthly\ Economic\ Efficiency = \frac{Avg\ GasCost}{Avg\ DAP}, \tag{5}$$

Investor Agent: Investors decide on new capacity additions and plant retirements. Decisions are based on long-term price forecasts, investment returns, and plant lifetimes.

3.2. Day-Ahead Market Modeling

The price of Turkish DAM is determined daily via a merit-order mechanism, with marginal plants—primarily natural gas and imported coal—setting the price. In the merit-order process, bids with the lowest prices are accepted first. Hourly bids from N power plants are sorted in ascending order of price (p_i) and their corresponding production capacities (q_i):

$$p_{(1)} \leq p_{(2)} \leq \cdots \leq p_{(N)},\ q_{(1)}, q_{(2)}, \ldots, q_{(N)}, \tag{6}$$

The bids are accepted sequentially until the hourly demand is met, with the corresponding generation capacities accumulated. Cumulative generation (G_j) is calculated iteratively until hourly demand (Dem) is met:

$$G_j = \sum_{i=1}^{j} q_i,\ j = 1, 2, \ldots, N, \tag{7}$$

The marginal plant (j^*) is defined as the smallest j for which,

$$G_{j^*} \geq Dem, \tag{8}$$

and the DAP is set as:

$$DAP = p_{(j^*)}\ , \tag{9}$$

Plants bidding below the DAM price perform production at the offered capacity, while those bidding above produce zero. The marginal plant adjusts to meet residual demand. Moreover, a price cap (P_{cap}) is also applied and given the model as input:

$$DAP = min\left(DAP, P_{cap}\right), \tag{10}$$

The short-term ABM, including the DAM module, was calibrated and validated using a combination of historical (actual) data from 2019–2020 and 2021. Technical parameters of generation agents—such as available capacities and technology-specific thermal efficiencies—were derived from power plant-level records from 2019 to 2020 to reflect representative operating conditions prior to major market and fuel-price shifts. Using these fixed parameters, the model was then behaviorally calibrated on 2021 hourly data so that the simulated dispatch reproduced observed merit-order behavior and day-ahead price formation. The resulting configuration was verified and validated against 2021 historical (actual) DAP and generation volumes to assess model accuracy. The ABM reproduced monthly DAP with an average error of 0.49% and a MAPE of 4.01%, closely matching observed market outcomes. Calibrated components include (i) plant available capacity, (ii) technology-specific thermal efficiencies, (iii) the merit-order clearing algorithm of the DAM, and (iv) generator bidding at the marginal fuel cost (MFC) as defined in Equation (4), reflecting observed price setting by marginal gas and coal units. Verification confirmed that each plant agent produced consistent outputs and that simulated generation by technology aligned with historical data from 2021 (Table 5). It should be noted that short-term modeling was not applied for solar power due to the limited deployment of licensed solar capacity; instead, actual generation figures were used directly.

Table 5. Comparison of monthly generation by energy source in 2021.

Energy Source	Actual Generation (TWh)	Simulated Generation (TWh)	Error (%)
Biofuel	6.7	6.6	−2.1
Lignite	49.2	48.9	−0.7
Geothermal	10.1	10.0	−0.9
Imported Coal	54.9	55.1	0.4
Natural Gas	107.7	108.0	0.3
Solar PV	1.5	1.5	0.0
Hydropower	55.5	56.3	1.4
Wind	30.9	29.9	−3.4
Total	316.5	316.3	−0.1

Price elasticity of electricity demand is not modeled explicitly in the short-term ABM. Demand is treated as exogenous and fixed to 2021 actual hourly values. In the long-term ABM, the SARIMA forecast provides the exogenous demand input, capturing historical macroeconomic and seasonal drivers. The SARIMA model was validated on actual data from 2022 before its application. This design choice avoids double-counting price feedback between SARIMA and the ABM and is consistent with the study's primary focus on supply-side dispatch, policy scenarios, and investment responses.

3.3. Emissions Trading Modeling

A draft regulation for the establishment of a Turkish ETS was published on 13 November 2023, but has not come into force. Its provisions are closely aligned with those of the EU ETS, particularly regarding the allocation of emission allowances through both free allocation and auctions [30]. The draft envisions a primary market, where allowances are auctioned annually, and a secondary market, where continuous trading occurs through spot transactions or bilateral contracts. Since allocation amounts, demand levels, and reference prices remain undefined, allowance prices in this study are assumed to follow EU ETS prices. The start of the Turkish ETS is assumed to coincide with the launch of the EU's Carbon Border Adjustment Mechanism (CBAM) in 2026.

For modeling purposes, the implications of the proposed Turkish ETS are translated into carbon cost additions to plant-level marginal costs (MC), based on forecasted EU ETS prices:

$$MC = MFC + P_{CO_2} \times EF, \tag{11}$$

where EF denotes the emission factor, P_{CO_2} represents the unit carbon price, and the MFC corresponds to the marginal fuel cost calculated in Equation (4). For Türkiye, emission factors are 0.374 (gas), 0.806 (imported coal), and 1.152 (lignite) tCO_2/MWh, taken from the Ministry of Energy and Natural Resources [51]. These values are also closely aligned with EU-average emission intensities reported by Eurostat [52]. Using emission factor (EF) values, total CO_2 *Emissions* are calculated as follows:

$$CO_2\ Emissions = Generation\ \times EF \tag{12}$$

Emissions costs enter the long-term ABM solely through the marginal cost (MC) calculation, as defined in Equation (11). The emission factors (EFs) are fixed by fuel type (natural gas, imported coal, and lignite), and no endogenous abatement within power plants is modeled. Consequently, emissions reductions in the ETS scenario result from re-dispatch away from carbon-intensive units, rather than from within-plant efficiency improvements. To evaluate the robustness of these assumptions, a sensitivity analysis on emission factors is introduced in Section 4.1 (Stated Policies Scenario), where lower emission factor cases are tested to represent potential efficiency or technology upgrades.

3.4. Proposed Investment Framework

Investor decisions follow the process shown in Figure 6. First, announced licensed projects are commissioned according to their construction periods in Table 6, and plants reaching the end of their lifetimes are retired [53]. For each energy source, future capacity mixes are projected by deriving the average annual new installed capacity during 2020–2023 and adding it to the end-of-2023 installed capacity (Table 7).

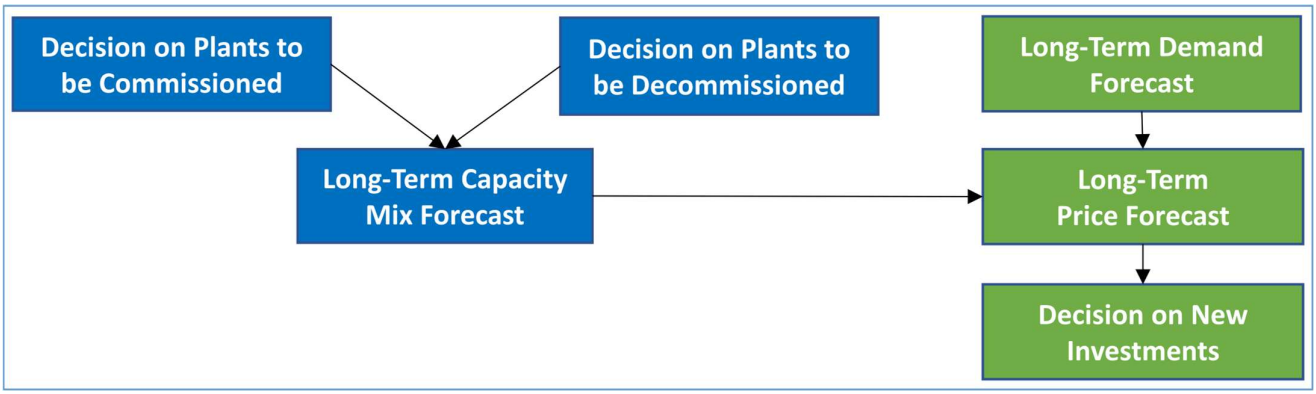


Figure 6. Decision-making process of the investor agent.

Table 6. Technical parameters of power plants by energy source.

Energy Source	Construction Period (Years)	Lifetime (Years)
Natural Gas	2	30
Coal	5	40
Biofuel	2	25
Geothermal	3	25
Solar PV	1	30
Onshore Wind	1	25
Reservoir Hydropower	4	60
Run-of-River Hydropower	2	60

Table 7. End-of-year installed capacity by energy source, 2019–2023 (GW).

Energy Source	2019	2020	2021	2022	2023
Wind	7.6	8.8	10.6	11.4	11.7
Reservoir Hydropower	20.6	22.9	23.3	23.3	23.5
Run-of-River Hydropower	7.9	8.1	8.2	8.3	8.3
Solar PV	6	6.7	7.8	9.5	11.3
Geothermal	1.5	1.6	1.7	1.7	1.7
Biofuel	1.2	1.5	2.0	2.3	2.4
Lignite	11.3	11.3	11.4	11.4	11.4
Natural Gas	25.9	25.7	25.6	25.3	25.4
Imported Coal	9.0	9.0	9.0	10.4	10.4

Investors may consider technical, economic, environmental, and social factors when making investment decisions [54]. In this study, the primary criterion is economic return, with environmental consideration used as a secondary factor. Accordingly, beyond pre-announced projects, investors are assumed to further invest only in renewable energy resources.

For each year, electricity sales revenues (R_{sales}) are calculated as the product of electricity generation and market prices. Unit running costs—including fuel, emission, and O&M costs listed in Table 8—are multiplied by annual production to obtain generation costs (C_{gen}). Net Revenue (R_{net}) is then calculated as follows:

$$R_{net} = R_{sales} - C_{gen}, \quad (13)$$

Table 8. Costs by energy source and year.

Energy Source	Investment Cost (MUSD/MW)			Fuel, Emission, O&M Costs (USD/MWh)		
	2022	**2030**	**2050**	**2022**	**2030**	**2050**
Natural Gas	1	1	1	170	125	130
Coal	2	2	2	125	150	160
Biofuel	4	4	4	71	71	71
Geothermal	5.4	5.4	5.4	19	19	19
Solar PV	0.99	0.62	0.45	10	10	10
Onshore Wind	1.75	1.67	1.61	20	15	15
Reservoir Hydropower	1.17	1.17	1.17	10	10	10
Run-of-River Hydropower	2.15	2.15	2.15	27	27	27

Investment viability is evaluated using the NPV method:

$$NPV = \sum_{t=0}^{n} \frac{R_{net,t}}{(1+i)^t}, \quad (14)$$

where $R_{net,t}$ denotes the net revenue in year t, i is the inflation-adjusted real discount rate, and n is the plant project lifetime. A central real discount rate of 6% was adopted, with 4% and 8% used for sensitivity analysis. These values are consistent with the real cost of capital for renewable power generation reported by the International Energy Agency [39]. The results indicate that solar PV and onshore wind investments offer the highest returns among renewables, even under higher discount rate assumptions (Table 9). Note that biofuel is excluded from the investment analysis, as high costs generally restrict it to mandated waste-to-energy (WtE) projects.

Table 9. NPV (MUSD/MW) sensitivities by real discount rate (i).

Energy Source	i = 0.04	i = 0.06	i = 0.08
Onshore Wind	1.31	0.83	0.47
Unlicensed Solar PV	1.63	1.37	1.18
Licensed Solar PV	2.26	1.9	1.63
Geothermal	−0.84	−1.76	−2.43
Reservoir Hydropower	0.87	0.41	0.09
Run-of-River Hydropower	−0.48	−0.79	−1.02

Two types of investors are considered: large and small.

- Large investors: Their budget is defined as the average annual investment costs of all licensed projects commissioned during 2021–2023, representing the recovery period following the COVID-19 downturn. The annual budget is therefore set at USD 1.88 billion. Their commissioning assumptions are summarized in Table 10.

Table 10. Assumptions for future capacity additions by energy source.

Energy Source	Assumptions
Biofuel	Investment continues only in mandatory WtE projects. From 2025 onward, annual additions are fixed at the planned 2025 commissioning capacity of 25 MW.
Geothermal	Investment remains very limited, with much potential unused. Projected biofuel and geothermal combined capacity is 5100 MW by 2035 [29]. After subtracting the biofuel share, average geothermal additions are assumed to be 22.8 MW/year from 2025 onward.
Hydropower	Total capacity is projected to reach 35.1 GW by 2035, using all remaining potential [29]. This implies average annual additions of 250.3 MW until 2035.
Lignite	A total of 1700 MW of new capacity is foreseen between 2024 and 2030, considering the remaining domestic coal reserves [29]. This is modeled as a 145 MW addition in 2028, followed by 777.5 MW/year in 2029–2030.
Imported coal	No new capacity, due to high fuel costs and environmental concerns.
Natural gas	By 2030, 2.4 GW of natural gas capacity and 0.6 GW of cogeneration capacity are foreseen [29]. This is modeled as three 800 MW combined-cycle units commissioned between 2027 and 2029, and twelve 50 MW cogeneration units distributed between 2028 and 2030.
Onshore wind	Onshore wind is considered the most attractive investment. Large investors allocate all residual budgets, after licensed projects, to onshore wind.

- Small investors: These investors are assumed to invest exclusively in unlicensed small-scale solar PV projects, mainly due to their lower upfront costs. Historically, almost all solar investments in Türkiye have taken this form, and the trend is expected to continue. The budget of small investors is defined as the average annual investment costs of unlicensed solar projects commissioned during 2021–2023, yielding 1.12 billion USD.

Finally, the Akkuyu NPP, developed by the state, is included exogenously in the model rather than by the investor agents. The plant consists of four units of 1200 MW each, assumed to enter operation sequentially between 2026 and 2029.

4. Results and Discussion

The installed capacities after 2023 are determined after final investment decisions, commissioning, and retirement years of all existing plants and incorporated into the agent-based framework. The framework is run on an hourly basis with multiple scenarios until 2053. Following the preference of investors, most of the installed capacity addition is expected to be 60.4 GW and 24.3 GW for solar PV and wind, respectively (Table 11). The results are presented in the following subsections.

4.1. Stated Policies Scenario

The Stated Policies scenario reflects the current trajectory and legislation adopted by the Turkish state. In this scenario, the Akkuyu NPP, which is currently in the commissioning phase, is included. As nuclear power constitutes a major addition in Türkiye's generation mix, its commissioning capacity serves as a key parameter in the long-term projections, strongly influencing price formation and emissions outcomes within the Stated Policies scenario. The Stated Policies scenario excludes ETS because it is still pending legislation.

Table 11. Results of the investment decision module.

Energy Source	Capacity Additions (GW)	Capacity Retired (GW)	2053-End Capacity (GW)
Wind	24.3	9	27
Reservoir Hydropower	2.3	0	25.7
Run-of-River Hydropower	1.1	0	9.4
Solar PV	60.4	9.5	62.2
Geothermal	0.7	1.4	1
Biofuel	1.2	1.8	1.8
Lignite	1.7	2.6	10.5
Natural Gas	3.8	7.8	21.3
Imported Coal	0	3.6	6.8
Nuclear	4.8	0	4.8

The generation mix that meets the demand forecast in this scenario (Figure 4) is shown in Figure 7a, and the resulting CO_2 emissions are reported in Figure 8. Total emissions increase from 2029 onward, driven by the commissioning of new natural gas and lignite power plants up to 2030. Although additional fossil capacity enters the system, the sharp decline in fossil fuel prices (Table 4) causes DAP to fall to 45.33 USD/MWh in 2030. After 2030, all new investments shift toward renewables, with steadily declining installation costs enabling annual onshore wind additions by large investors and solar PV additions by small investors. A turning point is reached in 2038, when renewable expansion reverses the upward emissions trend, peaking at 147.2 million tons (Mt) CO_2 before beginning to decline. By 2053, the renewable share of generation rises from 44.0% in 2022 to 63.1%, with wind and solar PV jointly reaching 35.8%. Gross annual emissions fall to 101.4 Mt CO_2, a 25.9% reduction from the initial 2022 level, driven primarily by a 45.0% decrease in imported coal plant generation. Natural gas plants, however, remain the largest non-renewable source at 14.8% of generation share in 2053, reflecting their flexibility in balancing intermittent renewable output.

Stated Policies—Without Nuclear represents a counterfactual future in which nuclear power is not included in the generation mix. It examines the impact of a situation where the planned nuclear plant is assumed not to be commissioned. In this case, the lost nuclear generation is partly replaced by higher-cost thermal plants, raising the average price after 2025 by 6.28 USD/MWh (Figure 9). The most significant impact occurs during hours that would otherwise be set by low-cost renewables in the Stated Policies scenario; here, marginal price-setting shifts to thermal plants (Figure 7b), which increases carbon emissions by 20.2 Mt CO_2 (+19.9%) in 2053 (Figure 8).

4.2. Emissions Trading Scenario

The Emissions Trading scenario assumes that a national ETS will be implemented during the first month of 2026. In the Emissions Trading scenario, high carbon costs lead to sharp price spikes during peak-demand hours when thermal units set the price. On average, prices rise by 57.91 USD/MWh from 2026 onward (Figure 9). In 2053, emissions trading reduces CO_2 output by 8.54 Mt (−8.4%) compared to the baseline, confirming it to be an effective mitigation tool—though less impactful than nuclear deployment.

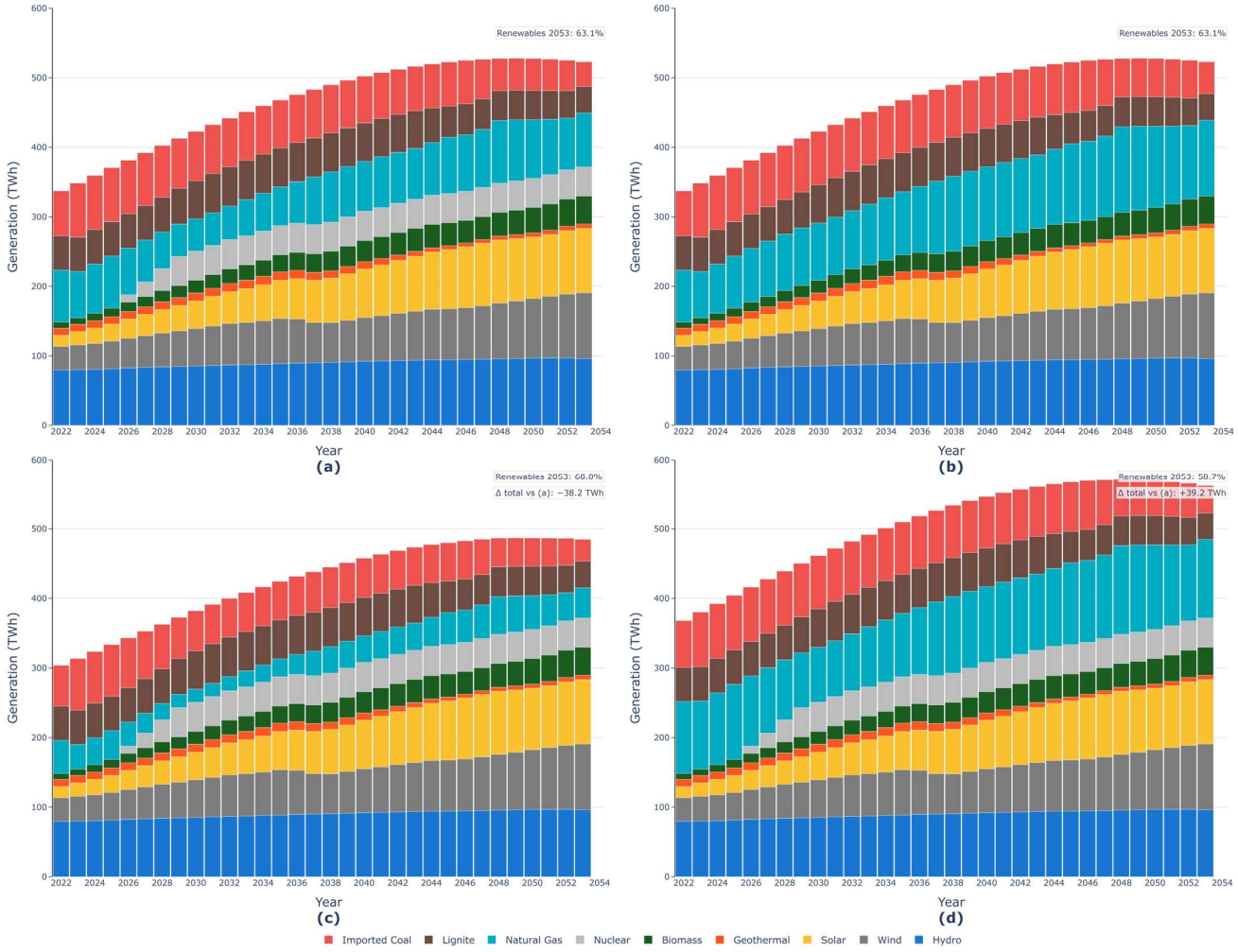


Figure 7. Generation mix under alternative scenarios: (**a**) stated policies; (**b**) stated policies—without nuclear; (**c**) low demand; (**d**) high demand.

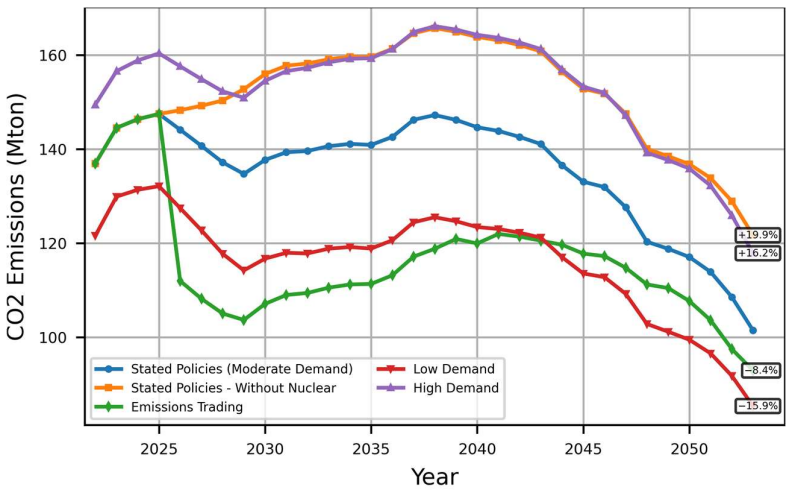


Figure 8. CO_2 emissions under alternative scenarios.

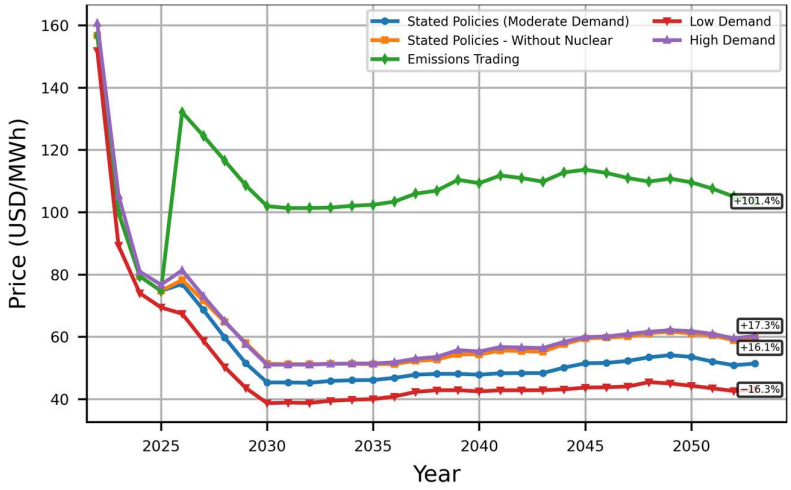


Figure 9. DAP under alternative scenarios.

To examine the robustness of results under potential technological improvements, a sensitivity analysis was conducted on the emission factors used in the Emissions Trading scenario. Two alternative cases were evaluated: a Low Emission Factor (EF) case (−10% from the base factors) representing moderate efficiency gains or partial abatement, and a Very Low EF case (−20%), reflecting substantial emission-intensity reductions (Table 12). The resulting ranges capture plausible near- to long-term efficiency improvements in Türkiye's generation fleet. Lower EFs reduce effective carbon-cost pass-through, thereby moderating DAP levels. Relative to the base Emissions Trading scenario case, average DAP decreased by 6.02 USD/MWh (5.5%) and 12.13 USD/MWh (11.1%) in the Low and Very Low cases, respectively. The nearly proportional decrease in average DAP across the two cases indicates a linear relationship between emission intensity and carbon-cost pass-through, confirming the consistency of the ETS cost mechanism within the ABM framework. Despite these quantitative differences, the qualitative conclusion remains unchanged: carbon pricing raises average electricity prices, although the magnitude of price impact depends on underlying emission-intensity assumptions.

Table 12. Emission factor (EF) price sensitivity scenarios.

Fuel	Base EF (Current)	Low EF (−10%)	Very Low EF (−20%)
Natural gas	0.374	0.337	0.299
Imported coal	0.806	0.725	0.645
Lignite	1.152	1.037	0.922

4.3. Demand Scenarios

Demand variations also have a significant effect on market outcomes. The SARIMA-based forecast used in the Stated Policies scenario is treated as Moderate Demand. Two additional cases are considered:

- High Demand scenario: Demand is increased by 9.1% relative to Moderate Demand to match the 2022 National Energy Plan forecast of 510.5 TWh by 2035 [29].
- Low Demand scenario: Demand is reduced by 10% relative to Moderate Demand.

In the High Demand scenario, more generation is supplied from higher-cost thermal plants, raising the average price by 6.46 USD/MWh over the simulation period (Figure 9). By 2053, demand reaches 562 TWh, and the reliance on gas plants suppresses the renewable share to 58.7% (Figure 7d). In contrast, the Low Demand scenario reduces average prices by 7.11 USD/MWh, while cutting gas generation substantially (Figure 7c). Renewables,

therefore, increase their share to 68.0% in 2053 when demand falls to 485 TWh. Even in the High Demand scenario, CO_2 emissions fall by 21.1% in 2053 compared to the initial simulation year, demonstrating the resilience of the emissions reduction pathway across different demand trajectories (Figure 8).

4.4. Practical Policy Translation

4.4.1. Renewable Integration and Investment

The baseline simulation indicates that, even with steady renewable expansion, existing measures alone will not deliver the 2053 net-zero target in the electricity sector. Residual power-sector emissions from thermal generation persist at 28.9% in 2053 under current commitments, despite large-scale renewable and nuclear deployment. Policymakers should therefore strengthen and extend existing mechanisms rather than relying solely on present measures. Key actions include:

- Expand renewable-support mechanisms. The duration and scope of existing FITs and YEKA auctions should be extended. Increasing support periods and guaranteed returns will sustain investor confidence, enhance expected returns, reduce policy discontinuity risk, and accelerate new renewable capacity additions.
- Facilitate affordable financing. Consistent with the assumptions of this study, the current level of renewable investment budgets should be maintained by improving access to affordable capital. Lowering the cost of capital will increase NPV returns and enable investments at the required scale.
- Modernize the electricity grid. To meet the assumptions of this study, Türkiye must modernize its transmission and distribution infrastructure to enable continuous renewable deployment. This requires expanding network capacity, upgrading digital infrastructure, deploying energy storage at scale, and improving transparency in grid-investment planning to attract private investors. These measures are essential for maintaining system security, affordability, and efficient renewable utilization. Grid-connection procedures for renewable plants should also be simplified and standardized to reduce bureaucratic barriers.
- Deepen regional energy-market integration. Türkiye's ties with EU energy markets and carbon policies should be strengthened by expanding cross-border interconnections, thereby enhancing flexibility, energy security, and cost efficiency.

The commissioning of the planned NPP shows a substantial decline in thermal generation and emissions—by 19.9% in 2053—because nuclear energy provides low-carbon baseload capacity. Policymakers should therefore commit to the existing plans and facilitate the safe expansion of nuclear energy. Specific measures include:

- Ensure timely completion and integration of Akkuyu NPP. Aligned with the study's stated policies, the on-schedule commissioning and grid integration of the Akkuyu NPP (2026–2029) should be facilitated while maintaining international safety and environmental standards.
- Plan the next phase of nuclear expansion. There is currently no detailed roadmap for subsequent nuclear projects. Türkiye should therefore prioritize the detailed planning of at least one additional nuclear power plant, ensuring coordination between nuclear and renewable expansion to minimize curtailment and maintain grid stability.

4.4.2. ETS and Emission Abatement

The ETS simulation shows that the introduction of an ETS significantly reduces CO_2 emissions—by 8.42% in 2053—by shifting generation toward cleaner energy sources. Policymakers should therefore accelerate ETS implementation and complementary emission reduction measures. Key recommendations include:

- Launch the ETS by 2026. The Turkish ETS should be implemented in 2026 with transparent and predictable allowance-allocation mechanisms to ensure market credibility and encourage renewable investment.
- Design a fair and stable carbon-price corridor. Carbon prices should be aligned with the EU ETS trajectory, but maintained within an affordable range to prevent excessive market-price impacts (+57.91 USD/MWh from 2026 onward, according to this study's results).
- Mandate emission-intensity improvements in thermal plants. Based on this study's emission-factor sensitivity analysis, regulatory measures should require thermal power plants to adopt abatement technologies. The main available methods include improving plant efficiency, applying post-combustion carbon capture, and blending fuels with low-carbon or carbon-neutral alternatives.

4.4.3. Demand Growth and Flexibility

The model's demand-side sensitivity analysis reveals that electricity-demand growth represents a major uncertainty for Türkiye's clean-energy transition. In the high-demand case (562 TWh by 2053), renewable-capacity expansion struggles to keep pace, reducing the renewable share of generation to 58.7% and increasing reliance on fossil backup, thereby raising emissions. Policymakers should therefore focus not only on renewable deployment but also on managing demand growth. Recommended actions include:

- Implement energy efficiency obligations effectively. Türkiye's Energy Efficiency 2030 Strategy and 2nd National Energy Efficiency Action Plan (NEEAP) (2024–2030) targets a 16% reduction in national energy consumption by 2030. The plan mandates energy efficiency obligations across industries, buildings, and equipment, and provides incentives for upgrading to more efficient appliances and processes [55]. Implementation of these targets should be closely monitored by responsible institutions.
- Promote flexibility and smart-grid infrastructure. Regulators should advance flexibility mechanisms—such as demand–response programs and distributed battery storage—to reduce peak loads and ensure that rising electrification (from electric vehicles and heat pumps) does not outpace renewable supply. This requires mandating the upgrading of distribution networks into smart-grid systems capable of managing flexible demand and integrating distributed resources, as recommended in SHURA's Transportation Sector Transformation Report (2024) [56].

5. Conclusions

In this study, a long-term ABM simulation of the Turkish energy market was performed to analyze how policy, investment, and demand trajectories will shape the pathway to net-zero emissions by 2053. The framework includes power plants across diverse technologies—wind, hydropower, solar PV, geothermal, biofuel, coal, natural gas, and nuclear—and represents investors, the market operator, the DAM, and a potential ETS. By running hourly simulations from 2022 to 2053 under alternative policy and demand scenarios, the model offers a forward-looking perspective on how Türkiye's energy sector can evolve during its low-carbon transition.

The ABM simulation results highlight three main insights. First, under the Stated Policies scenario, renewable generation steadily expands to reach 63.1% of total production by 2053, with onshore wind and solar PV jointly accounting for 35.8%, supported by declining technology costs and continued investment. This expansion drives a 45.0% reduction in imported coal plant generation. Natural gas plants, however, retain a 14.8% share in 2053 due to their role in balancing intermittent renewable output. Emissions peak at 147.2 Mt CO_2 in 2038, before declining to 101.4 Mt CO_2 in 2053, representing a

25.9% reduction from the initial level. Excluding nuclear power increases average wholesale electricity prices by 6.28 USD/MWh over the simulation period and raises 2053 emissions by 20.2 Mt CO_2. Second, policy choices significantly influence both prices and emissions. Introducing an ETS results in much sharper price increases—averaging +57.91 USD/MWh—but reduces emissions by 8.54 Mt CO_2 in 2053 relative to the baseline. Third, demand scenarios alter the generation mix and fuel reliance. In the High Demand case (+9.1%), additional supply is primarily met by natural gas, raising average prices by 6.46 USD/MWh and limiting the renewable share to 58.7% in 2053. In the Low Demand case (–10%), prices fall by 7.11 USD/MWh, natural gas generation drops substantially, and the renewable share increases to 68.0%. Even under high demand, emissions are reduced by 21.1% by 2053 compared to 2022, confirming that the net-zero pathway is preserved, although the pace and composition of decarbonization differ across scenarios.

These findings provide actionable insights for both policymakers and market participants. For regulators, the results underscore the pivotal role of nuclear capacity and carbon pricing in shaping future prices and emissions, offering a framework to help design ETS rules and broader market policies that balance decarbonization with affordability. For private investors, the scenarios illustrate how renewable deployment, demand evolution, and policy choices influence the generation mix, investment risks, and long-term profitability, thereby supporting more informed investment strategies.

The scenario-based findings can be directly translated into policy pathways for accelerating Türkiye's transition toward its 2053 net-zero target. Under the Stated Policies framework, achieving deeper decarbonization requires expanding existing renewable support mechanisms (FITs and YEKA), maintaining affordable financing channels, modernizing the electricity grid with digitalized and storage-integrated infrastructure, and deepening regional energy-market integration with the EU. The nuclear policy track must ensure the timely completion of the Akkuyu NPP and initiate the planning of at least one additional plant to secure low-carbon baseload generation. In the Emissions Trading Scenario, early ETS implementation—ideally by 2026—should be combined with a predictable carbon-price corridor and technology mandates that improve thermal plant emissions efficiency. Finally, the Demand Scenarios highlight the need to couple renewable expansion with effective demand management. This entails enforcing the Energy Efficiency 2030 Strategy and 2nd NEEAP targets, promoting demand–response programs and distributed storage, and upgrading distribution networks into smart-grid systems. Collectively, these measures form an integrated policy package that aligns Türkiye's energy market development with its long-term climate commitments while safeguarding security of supply and investment stability.

Methodologically, this study demonstrates a novel integration of ABM, SARIMA econometric demand forecasting, and CatBoost ML-based price prediction, each validated against historical data. The SARIMA model achieved a monthly MAPE of 3.5% and an annual deviation of 1.9% on realized demand from 2022. The CatBoost model achieved a 6.09% MAPE and −1.94% average error on actual prices from 2021, outperforming the other benchmarked ML models. The ABM reproduced market behavior from 2021 with a 0.49% average price error and 4.01% MAPE. Furthermore, the investment evaluation was refined through NPV analysis using a central real discount rate sensitivity testing. These enhancements collectively improve the transparency, robustness, and empirical credibility of the proposed framework.

Several limitations should be acknowledged. First, the model does not explicitly capture policy uncertainty or the transmission mechanisms between electricity, carbon, and fuel markets, which may influence investment and pricing outcomes. Second, the transition of investor behavior over time is not dynamically represented, as investment decisions are

modeled through rational, economically driven assumptions. Third, the analysis assumes that Türkiye's electricity transmission infrastructure will receive adequate investment to integrate the projected renewable capacity additions. Relaxing these assumptions in future work would allow for a more comprehensive representation of long-term market dynamics. Fourth, demand-side behavioral responses are not endogenously represented, as price elasticity was excluded to prevent double-counting with the SARIMA forecast. Incorporating explicit demand–response behavior in future work could further enhance the realism of short-term market dynamics. Fifth, because high-resolution historical data remain limited, both the calibration and validation of the ABM were performed using observations from 2021. This represents an in-sample validation demonstrating that the model reproduces observed market behavior under current conditions. Future work will extend the calibration–validation process by incorporating additional historical years as they become available, enabling out-of-sample validation and broader robustness testing across different market states.

Future work may extend the framework in several other directions. First, model granularity can be improved by including ancillary markets and BESS dynamics. Second, the ABM framework could be enhanced by incorporating risk-awareness across all agents to better capture their heterogeneity. Third, incorporating local energy markets and their interactions with the national system would allow for a more integrated analysis. Fourth, wholesale and spot natural gas markets could be modeled in greater detail. Finally, generative artificial intelligence could be employed to enrich scenario generation and improve forecasting accuracy.

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Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-based modeling
ADF	Augmented Dickey–Fuller
BESS	Battery energy storage system
CO_2	Carbon dioxide
DAM	Day-ahead market
DAP	Day-ahead price
EF	Emission factor

ETS	Emissions trading scheme
EXIST	Energy Exchange Istanbul
EU	European Union
FIT	Feed-in tariff
GW	Gigawatt
IQR	Interquartile range
MAPE	Mean absolute percentage error
ML	Machine learning
Mt	Million tons
MW	Megawatt
MWh	Megawatt-hour
MUSD	Million United States dollars
NEEAP	National Energy Efficiency Action Plan
NPV	Net present value
NPP	Nuclear power plant
O&M	Operation and maintenance
PP	Phillips–Perron
PV	Photovoltaic
SARIMA	Seasonal autoregressive integrated moving average
TEIAS	Turkish Electricity Transmission Corporation
TWh	Terawatt-hour
USD	United States dollar
WtE	Waste-to-energy
YEKA	Renewable energy resource area

Appendix A

Table A1. Symbols and notations used in the equations.

Symbol	Description	Unit
p, d, q	Orders of autoregressive (p), differencing (d), and moving-average (q) terms	–
P, D, Q	Seasonal p, d, and q	–
S	Seasonal cycle length	months
$GasCost$	Natural gas unit price for plants	USD/MWh
$CoalCost$	Imported coal unit price for plants	USD/MWh
$ResDem$	Residual demand to be met by price-dependent plants	MWh
$TotDem$	Total hourly electricity demand	MWh
$IndDem$	Demand met by price-independent plants	MWh
DAP	Day-ahead price	USD/MWh
$DAPFac$	DAP to $GasCost$ ratio	–
$ActualGeneration$	Realized electricity generation in a given period	MWh
$InstalledCapacity$	Maximum power of the plant	MW
$OperatingHours$	Number of hours in a given period	–
$CapacityFactor$	Hourly utilization factor of the plant, between 0 and 1	–
$Unit\ Fuel\ Cost$	Fuel cost per unit of thermal input	USD/MWh
$Thermal\ Efficiency$	Electrical output per thermal input	–
MFC	Marginal fuel cost of a plant to produce one unit of electricity	USD/MWh
$Avg\ GasCost$	Monthly average natural gas unit price for plants	USD/MWh
$Avg\ DAP$	Monthly average DAP	USD/MWh
$Monthly\ Economic\ Efficiency$	Ratio of $Avg\ GasCost$ to $Avg\ DAP$	–
N	Number of plants participating in the DAM	–

Table A1. *Cont.*

Symbol	Description	Unit
p_i	i-th lowest bid price in merit order	USD/MWh
q_i	Offered quantity of i-th bid	MWh
G_j	Cumulative accepted quantity after j-th bid	MWh
j^*	Index of marginal plant or price-setting bid	–
Dem	Hourly electricity demand of the DAM	MWh
$p_{(j^*)}$	DAP setting bid price	USD/MWh
P_{cap}	Maximum price allowed to bid	USD/MWh
P_{CO_2}	Unit carbon price	USD/tCO_2
EF	Carbon emission amount per unit of electricity generation	tCO_2/MWh
MC	Marginal cost of a plant to produce one unit of electricity	USD/MWh
$Generation$	Electricity generation by the plant	MWh
CO_2 $Emissions$	Total carbon dioxide emissions	tCO_2
R_{sales}	Electricity sales revenue	USD
C_{gen}	Total electricity generation cost (fuel, emission, and O&M)	USD
R_{net}	Net revenue	USD
t	Time period	years
$R_{net,t}$	Net revenue in year t	USD
i	Real discount rate (inflation-adjusted)	-
n	Plant project lifetime	years

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