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A decision support framework for fuel-specific carbon capture and utilization under carbon tax uncertainty in the energy industry

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Abstract

This study develops a decision support framework for the system-level optimization of Carbon Capture and Utilization (CCU) investments under carbon tax uncertainty management. Covering seven fuel types and power networks, missing annual emission data were resolved via PCHIP interpolation, while future emission trajectories were forecasted using a DWT-LSBoost hybrid machine learning model. The economic reliability of these investments was evaluated at a 90% capture efficiency based on payback periods and Net Present Value. Results indicate breakeven carbon prices of 6.4 $/tCO$_2$ for fuel oil and 37.4 $/tCO$_2$ for natural gas units. Corresponding NPVs were calculated at $145.74 million and $47.01 million, respectively. Sensitivity analysis identifies CAPEX and operating costs as the primary risk drivers in the system's financial performance. This framework serves as a robust strategic tool for stakeholders to manage economic risks and assess the viability of fuel-specific CCU pathways in evolving policy landscapes.

Keywords: *carbon capture and utilization, machine learning forecasting, carbon tax uncertainty, uncertainty management, decision support systems*

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Highlights

- Develops a fuel-specific decision support framework for CCU under carbon tax uncertainty.
- Quantifies emission intensity impacts on CCU investment feasibility across various fuels.
- Aligns short-term CCU investments with long-term policy via dynamic emission projections.
- Combines technoeconomic analysis with scenario-based carbon pricing for breakeven insights.
- Evaluates CO2-to-ethanol conversion pathways under diverse energy and cost assumptions.

1. Introduction

The increase in atmospheric carbon concentrations resulting from fossil fuel consumption and industrial activities necessitates the implementation of urgent and strategic measures to mitigate global warming and environmental degradation [1–3]. CO_2 plays a central role in climate change processes, with fossil fuel consumption in the transportation sector, industrial emissions, and power plants constituting the primary sources of these emissions [4]. Beyond end-of-pipe carbon management strategies, the environmental burden associated with energy use can also be mitigated through the increasing adoption of alternative and environmentally preferable fuels, which may reduce the life-cycle impacts of transport and industrial energy systems [5,6]. In addition, improvements in tribological performance through advanced lubricant formulations, friction-reduction strategies, self-organization mechanisms, and superlubricity may contribute to lower energy losses and, indirectly, to reduced emissions in mechanical and industrial systems [7–11]. In this context, the implementation of Carbon Capture and Utilization (CCU) strategies is of critical importance for environmental sustainability and the energy security of future generations [12]. The goal of carbon neutrality has become a priority on

international agendas, encouraging countries to accelerate climate action. In achieving the targets set by the Paris Agreement, CCU technologies are considered promising low carbon solutions due to their high scalability and emission reduction potential [2,3,13–15]. Closing the carbon cycle depends on converting captured CO_2 into value added products [16]. Among the main products obtained in this process, ethanol, acetaldehyde, and methane stand out. Ethanol, in particular, positioned as an alternative biofuel, has significant strategic potential in reducing dependence on hydrocarbon fuels and mitigating greenhouse gas emissions [1,13,17,18]. Ethanol produced from CO_2 not only contributes to the diversification of energy resources but also enables higher compression ratios in engines due to its higher octane number compared to fossil fuels, thereby improving thermal efficiency. However, the success of such circular approaches depends not only on scientific advancements but also on the support of carbon pricing mechanisms, Renewable Energy Sources (RES) integration, and effective policy instruments [1,19]. The literature indicates that a coal fired power plant with a 90% carbon capture rate experiences a 20-30% loss in thermal efficiency, and that each 10% increase in decarbonization capacity reduces energy production efficiency by approximately 1.24% [14,18]. In terms of process parameters, the synthesis of one kilogram of ethanol requires 4.383 MJ of thermal energy and 36.8 MJ of electrical energy.

Within the scope of this study, it is assumed that the electrical input is primarily supplied from RES in order to maintain the green ethanol status of the produced ethanol. While the conversion of CO_2 to methanol is commercially viable at Technology Readiness Level (TRL) 9, ethanol production via electrochemical approaches is generally assessed at TRL 5-6 due to cost and scalability constraints. However, recent technological advancements suggest that this level has progressed to approximately TRL 7 [18,20]. At the global level, many countries have adopted policies promoting the use of biofuels such as ethanol in order to minimize the environmental impacts of the transportation sector and to achieve renewable energy targets [21–24].

In the literature, various incentive mechanisms such as the 45Q tax credit in the United States have been proposed to enhance the economic feasibility of Carbon Capture, Utilization and Storage (CCUS) technologies, and such subsidies have been shown to shorten investment payback periods [25,26]. In addition, the economic impacts of allocating carbon tax revenues between RES and Carbon Capture and Storage (CCS) technologies have been analyzed, emphasizing that RES support provides significant economic benefits within the framework of Green Tax Reform [27]. Similarly, a substantial body of research has examined the impacts of carbon capture technologies on energy economy environment systems. These studies have primarily focused on technical aspects such as the prediction of CO_2 solubility in amino acid salt solutions using machine learning, the development of next generation amine solvents with low regeneration heat, and the comparison of different capture configurations [28–32]. At the regional level, emission projections have been conducted using ARIMA and LMDI models, heat recovery networks have been optimized through pinch analysis, and high Net Present Value (NPV) outcomes have been reported based on strategic source sink matching in regions such as the United Kingdom [33–36]. Furthermore, short term implementation strategies have been developed by analyzing the market potential and technological maturity of products such as methanol, methane, and calcium carbonate [37,38]. In parallel, numerous studies have investigated carbon related uncertainties across different regions [39–41], while others have focused on pathways to achieve future carbon neutrality targets [42–44]. Notably, although significant progress has been made in North America and Europe in recent years, several studies have also addressed the multifaceted challenges of CCUS deployment, encompassing technical, economic, regulatory, and social dimensions [45–47]. Furthermore, recent studies have addressed sustainability and decarbonization from different perspectives, including alternative fuel utilization, life cycle environmental assessment, and real-world CO_2 emission analysis. In parallel, other studies have focused on renewable energy forecasting, condition-based maintenance, and reliability-oriented system management, all of which support the broader transition toward more efficient and sustainable energy systems [48-51]. In hydrogen-based energy systems, data-driven and machine-learning approaches have also been applied to predict PEM fuel-cell performance and to identify critical operational faults, thereby supporting the reliable and

efficient operation of low-carbon energy conversion technologies [52–54].

More recently, carbon pricing instruments, including carbon taxes and emission trading systems, have become proactive cost and management factors for companies aiming to reduce emissions [55]. However, previous CCU/CCUS techno-economic studies have generally considered selected economic indicators or fixed policy conditions, while the combined evaluation of forecasting accuracy, fuel-specific feasibility, carbon-tax uncertainty, and breakeven carbon prices remains limited. In this study, these criteria are integrated within a unified decision-support framework for seven fuel types. Accordingly, the specific contribution of this work is the joint assessment of emission forecasting, techno-economic performance, and policy-dependent investment thresholds rather than the consideration of these factors separately. In this context, the present study proposes a comprehensive decision support framework to evaluate the economic feasibility of CCU and ethanol production for seven different fossil fuel types used in the Türkiye electricity sector under carbon price uncertainty. Within the scope of the study, missing emission data for the 1990-2022 period were completed using Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation, and 10 year emission projections were generated using a hybrid machine learning model. A detailed techno economic analysis was conducted, incorporating fuel-specific NPV, Internal Rate of Return (IRR), and breakeven carbon prices.

1.1. Motivaiton for our study

This study aims to model the economic feasibility of a hybrid system that integrates commercially mature carbon capture technologies with emerging electrochemical ethanol production processes, specifically under the market conditions of the Türkiye energy sector. Moving beyond a theoretical proof of concept, the conducted analyses provide concrete empirical evidence regarding the operational boundaries, economic breakeven points, and potential contributions of the system to the technological commercialization roadmap. In recent years, CCUS technologies have gained significant global momentum, with an 80% increase in carbon storage capacity and a 30% increase in carbon capture capacity recorded [2]. These data indicate that the technology is rapidly evolving from laboratory scale to large scale industrial applications. However, since a major portion of global primary energy demand remains dependent on fossil fuels, combating climate change requires a dual strategy that encompasses the radical reduction of existing greenhouse gas emissions along with the proactive prevention of future emissions [56]. Beyond these environmental imperatives, the geopolitical risks and pressures on energy security arising from a chronic dependence on fossil resources have made the decarbonization of energy systems a strategic priority. In this context, the gradual reduction of fossil fuel dependency and the conversion of captured emissions into value added fuels are of critical importance for both ecological sustainability and the establishment of national energy security. These strategic necessities constitute the primary motivation for this study.

1.2. Innovations and contributions

The original contributions of this study are structured around four primary dimensions. In contrast to previous studies that generally examine selected CCU/CCUS technologies, fuel types, or policy conditions separately, this study integrates emission-data completion, hybrid forecasting, and fuel-specific techno-economic analysis under carbon-tax uncertainty. The proposed framework therefore provides a unified comparison of breakeven carbon prices and investment performance across seven fuel types. First, the missing values in the historical emission dataset of Türkiye for the 1990-2022 period were completed using the PCHIP method to preserve physical monotonicity. The smooth and consistent dataset obtained through this method established a robust foundation not only for analyzing past emission trends but also for developing high accuracy projection models that reflect the decarbonization momentum for 2030 and beyond. Second, unlike many studies in the literature, this research does not limit the CCU investment analysis to a single plant type. Instead, it calculates fuel-specific heterogeneous breakeven carbon prices individually for seven different fuel types, including lignite, hard coal, asphaltite, imported coal, natural gas, fuel oil, and diesel, as well as for transmission and distribution losses. This approach stands as one of the rare studies that quantitatively demonstrates the asymmetric impacts of carbon pricing mechanisms on facilities with varying emission intensities.

Furthermore, dynamic sensitivity simulations were conducted within the scope of the study under the condition of carbon tax uncertainty. Investment decisions were evaluated not only through static NPV values but also based on the response of the financial system to carbon tax volatility. These analyses, which reveal how Simple and Discounted Payback Periods (SPP and DPP) evolve across different carbon price scenarios, provide a dynamic financial decision framework that defines risk thresholds for investors. Finally, a Türkiye specific CCU Deployment Decision Support Map was created by synthesizing technical emission data with financial risk parameters. This map identifies which fuel types and carbon price levels constitute an economic safe zone for investment, thereby serving as a concrete strategic guide for policymakers and investors. Consequently, this study establishes a scientific basis for positioning CCU technologies not only as an environmental solution but also as a fuel based economic optimization instrument in line with the 2053 net zero emission targets of Türkiye.

2. Materials and methods

The methodological framework proposed in this study encompasses the modeling of the historical emission data of Türkiye through hybrid machine learning methods and the integration of these models into fuel based techno economic analysis scenarios. To operationalize this framework the study consists of three primary stages. The first stage involves the decomposition and preprocessing of historical emission data for the period between 1990 and 2022. This is followed by the second stage where projections for 2030 and 2050 are generated by utilizing Discrete Wavelet Transform (DWT) and the LSBoost algorithm. In the final stage, the economic feasibility of green ethanol production for seven different fuel types is analyzed based on carbon price sensitivity. This integrated structure provides a decision support mechanism that not only forecasts emissions but also determines critical breakeven carbon prices for investors. The technical details of this methodological flow along with the characteristics of the dataset and the mathematical infrastructure of the algorithms used are discussed respectively in the following subsections.

2.1. Data source and preprocessing

The historical energy and emission data utilized in this study were compiled at an annual resolution [57]. During the data integration phase, PCHIP interpolation was used to complete the missing years while preserving the local trend and monotonicity of the emission series. Although interpolation may introduce uncertainty into subsequent forecasts and economic estimates, its shape-preserving structure minimizes artificial fluctuations and provides a consistent dataset for the analyses. The pseudocode of this method is presented in Algorithm 1 [58].

Uncertainties may arise in long term emission datasets due to factors such as reporting approaches and data revisions [48]. To address the discontinuities caused by missing years, a wavelet based denoising step was applied for signal correction and noise reduction following the annual continuity achieved with PCHIP, utilizing the wdenoise function with sym4 and a leveling of 3. A damped Exponential Smoothing approach was implemented to model the main trend and curvature, where the model parameters were specified as alpha=0.75, beta=0.25, and phi=0.80. In the final stage, a residual learning step consistent with the data was performed for the remaining components of the trend, during which a regression model was trained using LSBoost with 400 learning cycles, a learning rate of 0.02, and a base decision tree featuring a maximum of 8 splits and a minimum leaf size of 1. Additionally, a feature base of historical errors was established by using a lag of p=5 for time delays.

Algorithm 1. Pseudocode for the PCHIP algorithm.

Input:

$S = \{(yk, \varphi(yk), \varphi'(yk))\}_{k=1}^{s}$, *with* $y1 < y2 < \ldots < ys$, *relevance values* $\varphi(yk)$ *and preliminary derivative* $\varphi'(yk)$

Output:

$\varphi(y)$: *a Piecewise Cubic Hermite Interpolating Polynomial*

Algorithm Steps:

for $k \leftarrow 1$ *to* $s - 1$ *do*

$hk \leftarrow yk + 1 - yk$

$\delta k \leftarrow (\varphi(yk + 1) - \varphi(yk)) / hk$

$ak \leftarrow \varphi(yk)$

end for

$\{bk\}_{k=1}^{s-1} \leftarrow check_slopes\ (\{\varphi'(yk)\}_{k=1}^{s-1}, \{\delta k\}_{k=1}^{s-1})$ ▷*Monotone Cubic Spline*

for $k \leftarrow 1$ *to* $s - 1$ *do*

$ck \leftarrow (3\delta k - 2bk - bk + 1) / hk$

$dk \leftarrow (bk + bk + 1 - 2\delta k) / hk^2$

10: $end\ for$

11: $return\ \varphi(y) = ak + bk(y - yk) + ck(y - yk)^2 + dk(y - yk)^3, y \in [yk, yk + 1]$

Beyond emission forecasting, reliable techno-economic assessment requires cost models that account for relevant technical and site-specific characteristics, as demonstrated in geographically differentiated hydropower investment cost estimation [59]. The selected hybrid structure was preferred because the available annual emission series contains both a smooth long-term trend and short-term deviations that may not be adequately represented by a single forecasting method. Accordingly, PCHIP was used to preserve the continuity of the historical series, DWT denoising to reduce irregular fluctuations, damped Exponential Smoothing to represent the underlying trend, and LSBoost to learn the remaining nonlinear residual behavior. This combination integrates the strengths of conventional time-series modeling and machine-learning-based residual learning without relying on a single forecasting component. Ten year forecasts were generated as the prediction horizon throughout the study and uncertainty bands were calculated, providing these projections as inputs for the scenario calculations in the subsequent sections. The emission projections and techno economic analyses carried out in this work rely on the precise definition of physicochemical parameters specific to fuel types. The carbon content, oxidation factors, Lower Heating Values (LHV), and calculated emission factors for the solid, liquid, and gaseous fuel groups evaluated within the scope of the analysis are presented in Table 1.

Table 1. Emission factors and fundamental combustion parameters of the analyzed fuels [60].

Category	Fuel Type	Carbon Content	Oxidation Factor	Emission Factor	Lower Heating Value
Solid Fuels	Lignite	28.0	96	101.20	11,900
	Bituminous Coal	26.10	93	90.02	25,800
	Anthracite	27.40	94	87.98	26,700
	Petroleum Coke	26.07	98	95.58	31,000
Liquid Fuels	Fuel Oil	21.10	98	75.82	41,816
	LPG	16.87	98	61.81	50,179
Gaseous Fuels	Natural Gas	15.30	99	54.98	38,931

Based on these parameters, significant differences in emission factors are observed among the various fuel types. The emission factors for lignite and other coal derivatives are approximately twice as high as those for natural gas. This discrepancy suggests that the economic viability of carbon capture technologies may be reached at lower carbon price thresholds for facilities utilizing high carbon intensity fuels. When considering lower heating values, natural gas exhibits a higher energy density compared to coal types, which translates into a lower carbon intensity per unit of energy produced. Consequently, the choice of fuel type emerges as a decisive variable in both technical emission calculations and carbon price threshold analyses. Within the scope of this study, these parameters were utilized to develop scenarios for different fuel based operations, allowing for a comparative analysis of how carbon prices influence CCU investment decisions.

2.2. Emission forecasting and fuel intensity matrix

Future emission forecasting in this study was conducted using a two stage approach based on fuel types. In the first stage, the total emission intensity at the national scale was forecasted on an annual basis, while the second stage involved calculating the amount of capturable CO_2 using a fuel-specific emission intensity matrix. For the macro level forecasts, a hybrid method integrating DWT denoising, damped Exponential Smoothing, and LSBoost residual learning was applied to generate ten year projections for the 2023-2032 period. The annual energy production values (MWh) obtained from these projections were multiplied by fuel distribution scenarios to provide inputs for the capturable CO_2 calculations. The fuel types and their corresponding emission factors utilized in the study are presented in Table 2 [61].

Table 2. Evaluated fuel types and their corresponding emission factors.

Fuel Type	Emission Factor (tCO_2/MWh)	Fuel Type	Emission Factor (tCO_2/MWh)
Lignite	1.122	Fuel Oil	1.2140
Hard Coal	1.045	Diesel	0.862
Asphaltite	1.078	Transmission Line	0474
Imported Coal	0.800	Distribution Line	0.510
Natural Gas	0.400		

Based on these values, the amount of carbon captured and utilized for each fuel type was calculated using Equation 1.

$$Captured_{CO2} = Generation\ x\ \frac{EF_{kgCO2/MWh}}{1000} x\ \eta_{capture} \quad (1)$$

In this calculation, the carbon capture and utilization efficiency of the system was assumed to be 0.90. This approach allowed for comprehensive calculations across different scenario conditions under the influence of fuel uncertainty.

2.3. Techno economic assessment framework

This section models a calculation chain that extends from the amount of capturable CO_2 to the production of ethanol as a usable product, including income-expense flows and payback periods based on simple and discounted financial indicators. The fundamental equations for carbon capture and ethanol production along with the hydrogen and energy requirements are presented in Equations 2 and 3.

$$Ethanol_{yr} = Captured_{CO2}\ x\ \frac{46}{88}\ x\ \eta_{selec.} \quad (2)$$

$$H_{2yr} = Ethanol_{yr}\ x\ H_{2_per_ethanol} \quad (3)$$

The coefficient of 46/88 represents the stoichiometric factor for the conversion of CO_2 to ethanol while $\eta_{capture}$ denotes the efficiency of the system. In a similar manner, the equations governing electrolyzer energy consumption and cost structures are provided in Equations 4 -11.

$$E_{H2} = H_{2yr}\ x\ Electrolyzer_{per_kg_H2} \quad (4)$$

$$E_{cap.} = Captured_{CO2yr}\ x\ e_{cap.} \quad (5)$$

$$CAPEX = Captured_{CO2yr}\ x\ capex_{per_CO2} \quad (6)$$

$$CRF(r,n) = \frac{r(1+r)^n}{(1+r)^n - 1} \quad (7)$$

$$OPEX_{yr} = CAPEX\ x\ opex_{fraction} + H_{2_cost} + Electricity_{cost} \quad (8)$$

$$Revennue_{yr} = Ethanol_{yr}\ x\ \rho_{ethanol} + Captured_{CO2_yr}\ x\ \rho_{carbon} \quad (9)$$

$$Cashflow_{yr} = Revennue_{yr} - OPEX_{yr} \quad (10)$$

$$\rho_{carbon} = \frac{CAPEX_{yr} + OPEX_{yr} - Ethanol_Revennue_{yr}}{Captured_{CO2_yr}} \quad (11)$$

Equation 4 defines the annual electrical energy consumed during the electrolytic hydrogen production process required for green ethanol synthesis while Equation 5 denotes the specific energy consumption necessary for the operation of the carbon capture unit. The initial capital expenditure of the investment is estimated based on the annual CO_2 capture capacity through Equation 6 and this total cost is converted into an annualized equivalent using the Capital Recovery Factor established in Equation 7. Total annual operating costs are formulated in Equation 8 as the aggregate of fixed maintenance expenditures and variable costs associated with hydrogen and electricity consumption. Furthermore, the total annual revenue of the system is derived from the combination of ethanol market sales and the avoided costs resulting from carbon tax exemptions as specified in Equation 9. Finally, the annual net cash flow of the project is determined via Equation 10 and the critical carbon price threshold leading the investment to economic profitability is calculated through the breakeven formulation presented in Equation 11. All parameters pertaining to these equations are detailed in Table 4.

The values reported in Table 3 were used as baseline economic; therefore, the calculated breakeven carbon prices should be interpreted as scenario-specific results, since variations in hydrogen cost, Capital Expenditures (CAPEX), the Operational Expenses (OPEX), or the discount rate may shift the resulting economic thresholds.

Table 3. Technical and economic parameters utilized in the assessment framework [62–67].

Parameter Description	Value	Unit
Annual energy production	1e6	MWh/year
Carbon capture efficiency	0.90	-
Process selectivity (Etanol)	0.85	-
Hydrogen requirement per unit of ethanol	0.1304	tH_2/tEtanol
Specific energy consumption of electrolyzer	50	kWh/kgH_2
Specific energy requirement for capture	0.25	MWh/tCO_2
Unit investment cost (Base)	850	USD/tCO_2
Annual operating expense ratio	0.04	% CAPEX
Hydrogen supply price	2.5	USD/kg
Electricity unit price	0.06	USD/kWh
Ethanol sales price	950	USD/ton
Discount rate	0.08	-
Project economic life	20	year

3. Results and discussion

3.1. Emission trends and long term decarbonization

In this section, the trends in historical carbon emission data of Türkiye are analyzed in detail and the PCHIP method is utilized to complete missing data points with high accuracy. The historical dataset regarding the electricity generation of Türkiye and the corresponding CO_2 emissions was compiled to establish a robust baseline for future projections. As demonstrated in Table 4, while total energy production is consistently recorded, significant data gaps are present within the carbon emission intensities.

The cells marked in green in the table represent the data calculated using the PCHIP method which was selected to ensure data continuity without generating artificial oscillations.

Unlike standard cubic splines, PCHIP was specifically chosen for its monotonicity preserving properties. In energy emission datasets, sudden non-physical overshooting or undershooting which is common in spline interpolation can lead to misleading results. PCHIP ensures that the interpolated values remain consistent with the local trends of historical data providing a more shape preserving and physically meaningful transition between known data points.

Following this process, graphs showing the calculated values based on data from the last five years along with error and performance metrics and the predicted carbon emissions for the next ten years are provided in Fig. 1.

Table 4. Historical electricity generation and carbon intensity data with PCHIP completions.

Year	Energy (MWh)	Carbon (kton)	Emission Factor ($kgCO_2/MWh$)	Year	Energy (MWh)	Carbon (kton)	Emission Factor ($kgCO_2/MWh$)
1990	57543000	39701	0.6899360	2007	191558129.4		0.5587480
1991	60246300		0.6667250	2008	198418000		0.5523700
1992	67342200		0.6466410	2009	194812926		0.5479640
1993	73807500		0.6308510	2010	211207700	115387	0.5463200
1994	78321700		0.6205210	2011	229395100	127040	0.5538043
1995	86247400	53199	0.6168190	2012	239496800	128300	0.5357065
1996	94861700		0.6193680	2013	240153953	123322	0.5135123
1997	103295800		0.6254470	2014	251962817	133897	0.5314157
1998	111022400		0.6327020	2015	261783303.5	136984	0.5232725
1999	116439900		0.6387810	2016	274407749	144592	0.5269239
2000	124921600	80116	0.6413300	2017	297277522.9	155663	0.5236286
2001	122724700		0.6356180	2018	304801885	158626	0.5204233
2002	129399500		0.6215110	2019	303897559.6	149585	0.4922218
2003	140580500		0.6035540	2020	306703092.4	141859	0.4625288
2004	150698300		0.5862910	2021	334723000.1	159351	0.4760683
2005	161956200	93006	0.5742660	2022	328379000.3	155937	0.4748690
2006	176299800		0.5663100				

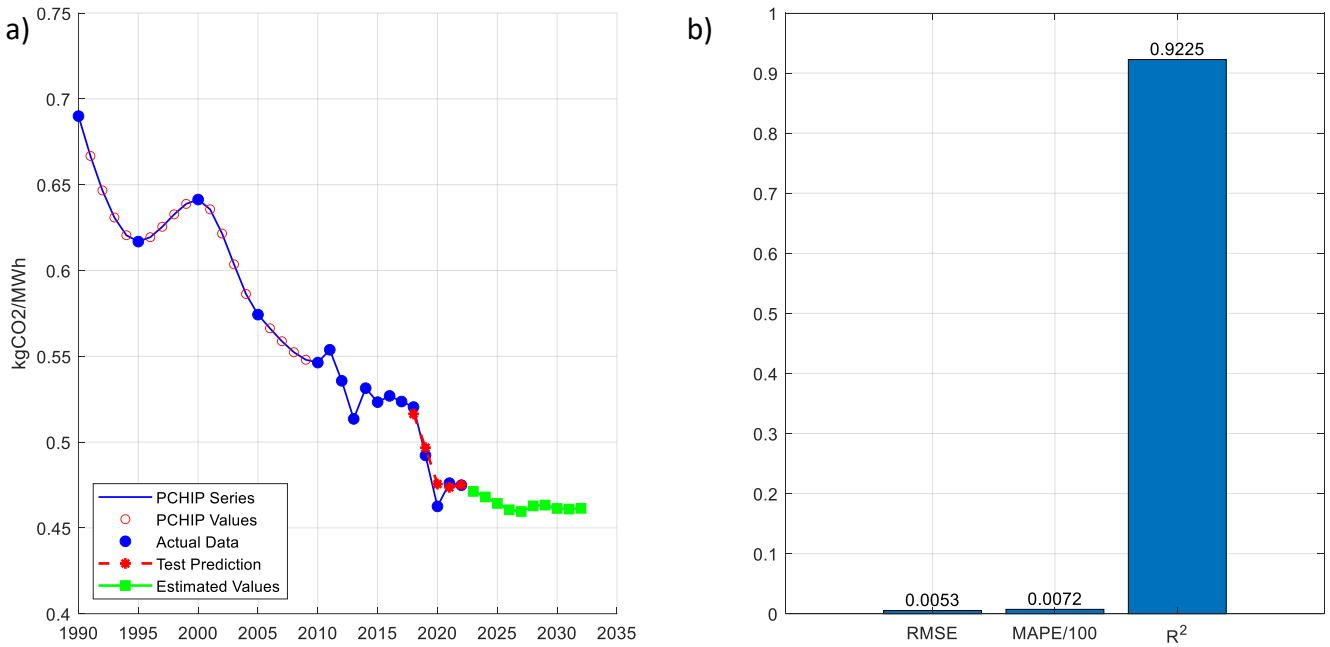

Figure 1. (a) PCHIP and future forecast data, (b) Error and performance metrics.

Consequently, the performance metrics of the model were calculated with an R^2 value of 0.92, an RMSE value of 0.0053, and a MAPE value of 0.0072. The predicted CO_2 values for the upcoming years generated by this model are presented in Table 5.

The resulting 10 years projection establishes a strategic time horizon for analyzing the scope of decarbonization and the technological transformation within the energy sector of Türkiye.

Table 5. Future CO_2 emission projections generated by the hybrid model.

Year	Predicted	Year	Predicted
2023	0.471269	2028	0.462849
2024	0.468044	2029	0.463270
2025	0.464268	2030	0.461319
2026	0.460559	2031	0.460976
2027	0.459553	2032	0.461393

3.2. Breakeven carbon prices by fuel type

The carbon intensities and specific emission factors of different

fuel types utilized in electricity generation are the fundamental variables that determine the financial feasibility of CCU investments. In this context, determining the breakeven carbon prices at which the investment becomes economically profitable for each fuel type is of critical importance for managing the risk perception of investors and defining effective carbon pricing thresholds for policymakers. Within this study, current emission data and technology costs related to dominant fuel types in the Türkiye electricity grid such as lignite, hard coal, asphaltite, imported coal, natural gas, fuel oil, and diesel were synthesized. The technical capacities, unit emission intensities, and investment cost structures forming the basis of the analyses are presented in Table 6 from a comparative perspective.

The parametric data presented in the table serve as inputs for a dynamic financial model that simulates the lifelong balance of costs and revenues for the investment. Specifically, the correlation between fuel-specific tCO_2/MWh values and annual capture capacities determines the extent to which the investment can benefit from economies of scale. Based on these quantitative findings, the critical thresholds where the carbon tax transforms from a cost burden into an income stream incentivizing the investment were identified, and the resulting economic performance metrics are visualized in Fig. 2.

Table 6. Fuel-specific feasibility analysis of CCU integration.

Fuel Type	Emission (tCO_2/MWh)	Captured CO_2 (t/year)	Ethanol (t/year)	CAPEX (M$)	OPEX (M$/year)	Revenue (M$/year)	Breakeven ($/$tCO_2$)	NPV (M$)
Lignite	1.12	751897.1	334081.5	639	276	355	8.8	131.87
Hard Coal	1.04	700296.3	311154.4	595	257	331	10.5	122.82
Asphaltite	1.08	722410.9	320980.3	614	266	341	9.7	126.7
Imported Coal	0.8	536112	238204.3	456	197	253	17.3	94.02
Natural Gas	0.4	268056	119102.2	228	98.55	127	37.4	47.01
Fuel Oil	1.24	830973.6	369216.7	706	306	392	6.4	145.74
Diesel	0.86	577660.7	256665.1	491	212	273	15.4	101.31

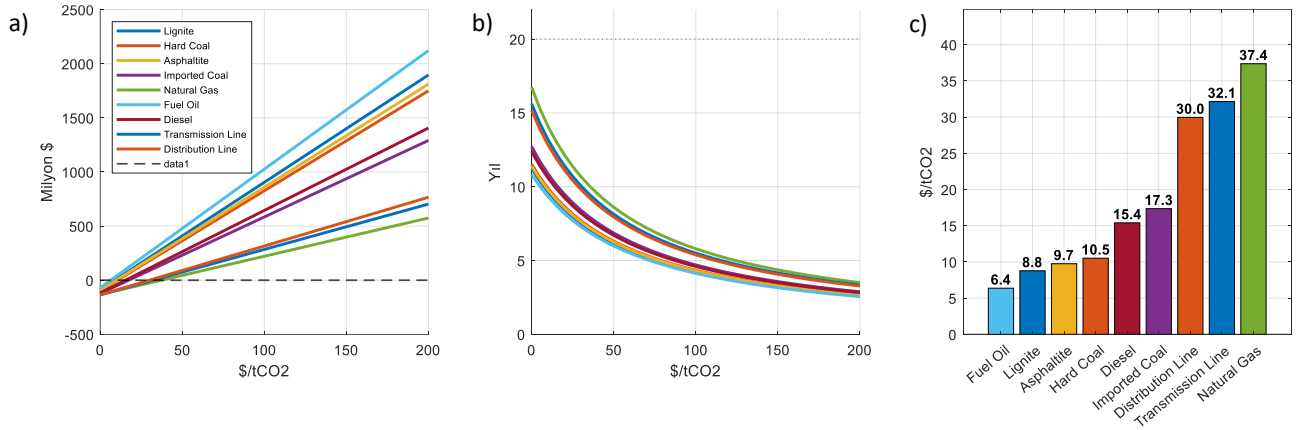

Figure 2. Techno economic analysis of carbon capture and ethanol production investments: (a) Variation of NPV across fuel types, (b) Dynamic investment payback periods relative to carbon tax levels, (c) Breakeven carbon price thresholds for specific fuel types.

The graphical analyses presented in Figure 3 confirm the direct relationship between the carbon intensity of fuel types and their economic viability. While fuels with high carbon intensity such as lignite and fuel oil offer a greater CO_2 capture potential per unit of energy, the high operational costs and initial capital burdens of these plants indicate a requirement for higher breakeven carbon prices to reach profitability. Conversely, fuels with lower carbon intensity such as natural gas exhibit a positive economic trend even at lower carbon price thresholds. This situation demonstrates the heterogeneous fuel based impacts of carbon pricing and emphasizes that investment decisions must be shaped not only by emission quantities but also by the specific cost benefit balance of the fuel.

3.3. Investment payback sensitivity under carbon tax uncertainty

CCU investments are projects requiring high fixed capital and investor decisions exhibit high sensitivity toward carbon price expectations. Consequently, quantitatively evaluating how the investment payback period changes under different carbon tax levels is of critical importance for understanding both the risk perception of investors and the effectiveness of carbon price mechanisms for policymakers. This section delineates the

trajectory of payback periods relative to carbon tax fluctuations for different fuel types while determining the dominant parameters and evaluating how uncertainty influences practical investment strategies. The results of this analysis are presented in Fig. 3.

These sensitivity analyses demonstrate that carbon tax mechanisms directly shape investor behavior and the financial ratios of the project. The findings prove that carbon prices must rise above critical threshold values for CCU projects to become economically sustainable under current technology costs and market conditions. In particular, the widening gap between the Discounted Payback Period (DPP) and the Simple Payback Period (SPP) at low carbon prices highlights the impact of the time value of money and risk premiums during the initial years of the project. This situation indicates that a carbon tax alone is insufficient and further emphasizes the strategic importance of complementary incentive mechanisms such as capital support to mitigate CAPEX uncertainties as well as guaranteed purchase prices for green ethanol and low interest green financing. Finally, the faster investment recovery observed in high emission intensity scenarios involving lignite and coal based operations confirms the economic rationality of focusing decarbonization policies primarily on these carbon intensive assets.

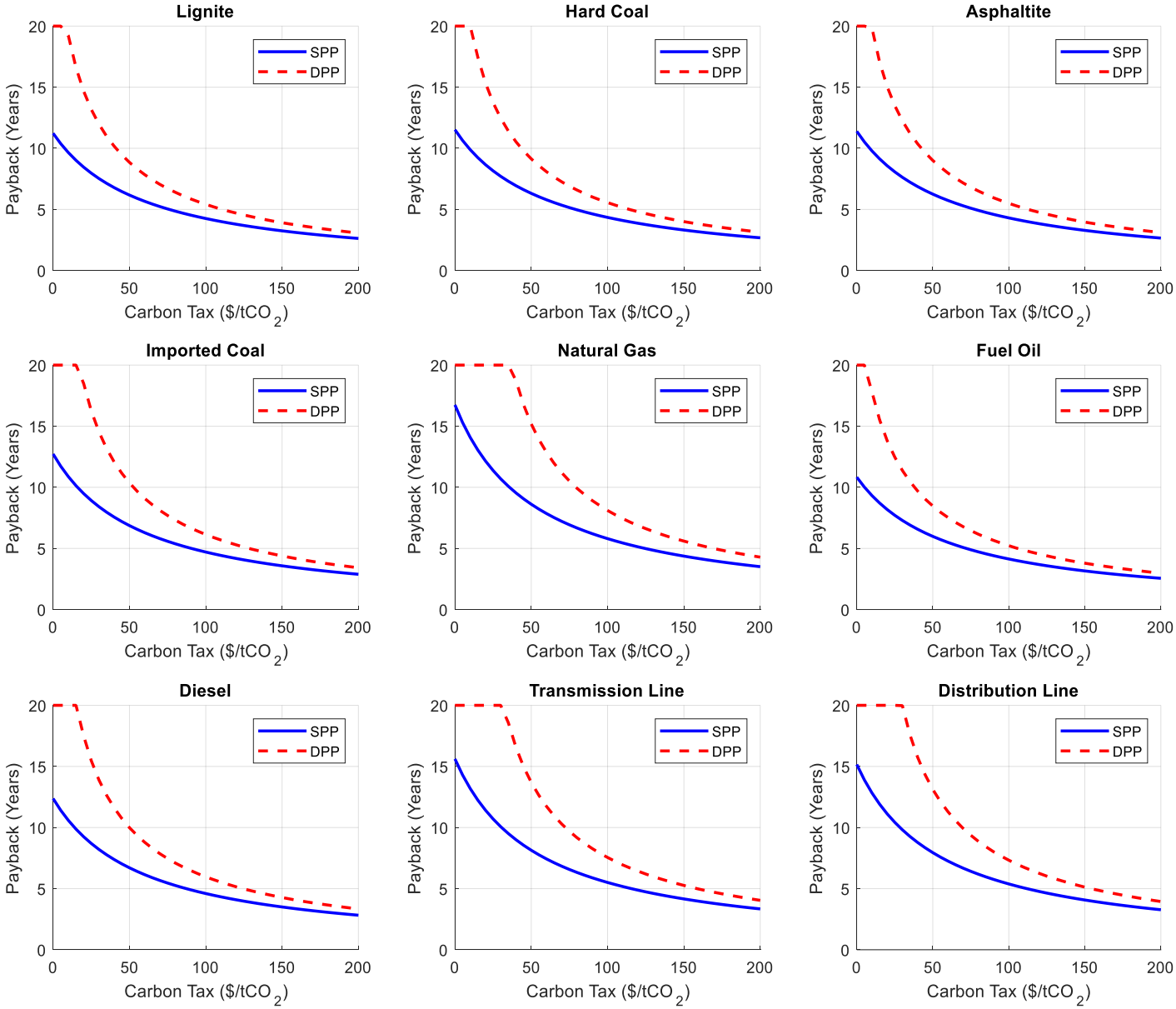

Figure 3. Simple and discounted payback periods relative to carbon tax levels for: (a) lignite, (b) hard coal, (c) asphaltite, (d) ımported coal, (e) natural gas, (f) fuel oil, (g) diesel, (h) transmission line, (i) distribution line.

3.4. Sensitivity analysis

The commercial scale deployment of CCU technologies depends not only on technical efficiency but also on a holistic simulation of country specific economic parameters and policy instruments. In line with Türkiye's 2053 net zero emission targets, determining which fuel types and which carbon pricing thresholds constitute a safe zone for investment in energy intensive sectors is a strategic necessity. In this section, emission projections, breakeven prices, and sensitivity analyses obtained in the previous sections are synthesized to present a comprehensive decision support framework for investors and policymakers. The analysis aims to reveal the combined effects of uncertainties in carbon pricing and operational variables on the NPV of the investment. Accordingly, the sensitivity results obtained under different carbon tax scenarios are presented in Fig. 4.

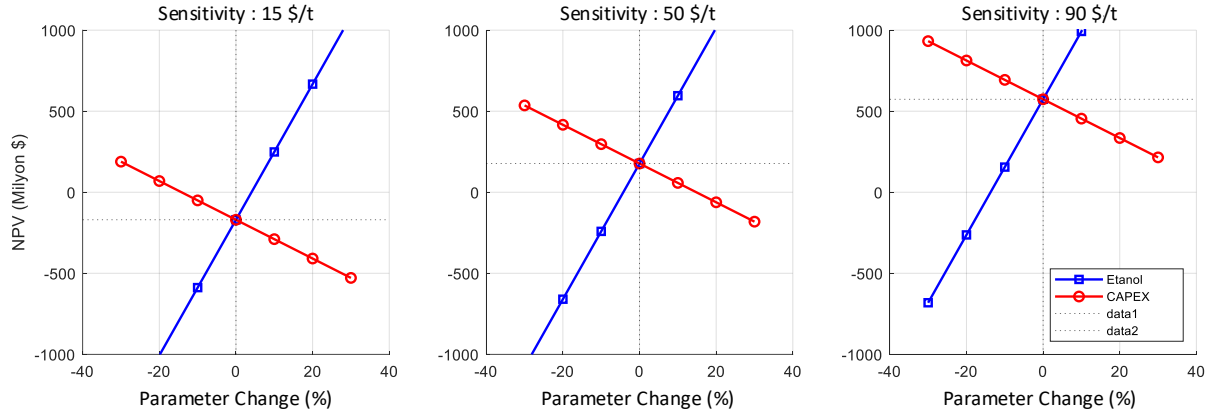

Figure 4. Sensitivity analysis of NPV under different carbon tax scenarios.

The parametric sensitivity analyses presented in Figure 5 reveal the key drivers and risk areas that determine the financial sustainability of CCU investments in Türkiye. The results demonstrate that the economic performance of the project shows significantly higher sensitivity to changes in ethanol sales prices compared to changes in CAPEX. This finding indicates that the profitability of the project is directly dependent on the market value of the produced green fuel and its support through carbon certification mechanisms rather than solely on cost control.

In low carbon tax scenarios, the concentration of NPV curves in the negative region indicates that the project cannot be sustained solely by market revenues. As the carbon tax threshold increases, even small improvements in technological efficiency significantly reduce the investment payback period. In particular, the steepness of the blue curve provides scientific evidence that a guaranteed purchase price mechanism may be a more effective incentive tool than direct capital support for policymakers. As a result, this analysis emphasizes that in Türkiye's decarbonization pathway, the integration of CCU technologies requires not only technological development but also the establishment of an ecosystem that ensures price stability.

4. Policy implications and recommendations

The Carbon Border Adjustment Mechanism (CBAM) of the European Green Deal and the 2053 net zero emission vision of Türkiye mandate a fundamental restructuring of the energy industry. The techno economic analyses and sensitivity simulations conducted within the scope of this study reveal that CCU technologies are not only an environmental necessity but also an economic risk management tool in the decarbonization roadmap of Türkiye. Based on the findings, the primary policy implications and strategic recommendations for the national scale deployment of CCU technologies are presented below.

- The analysis results prove that the economic feasibility of CCU investments is directly dependent on carbon tax thresholds. It is critically important that the National Emission Trading System (ETS) planned for Türkiye be designed to consider the breakeven prices calculated especially for high carbon intensity fuels such as lignite and imported coal. Gradually increasing carbon prices can pull the payback periods of CCU projects to reasonable levels by providing a long term price signal to investors.

- The decision support map presented in the study shows that not all facilities have the same economic potential for CCU integration. It is recommended that policymakers identify critical facilities with the highest emission reduction potential and develop specific investment incentives, tax exemptions, low interest green loans, or direct capital supports for these projects. Public private partnership models should be evaluated as a strategic solution to overcome the financial barriers created especially by high CAPEX costs.
- Converting captured CO_2 into value added products such as ethanol transforms carbon from a waste into an economic input. In this context, a synergy should be established between Türkiye's biofuel blending mandates and the raw material needs of the chemical industry with CCU outputs. Carbon-utilization certification mechanisms may be considered as potential complementary instruments for diversifying project revenues; however, their effectiveness would require further assessment under specific regulatory and market conditions.
- Sensitivity analyses reveal the dominant effect of OPEX on investment decisions. To reduce these costs, the development of carbon capture equipment and catalyst systems with domestic resources should be encouraged. Additionally, the regional planning of infrastructure networks (CO2 hub/cluster) required for the transportation and processing of captured CO2 will allow for the utilization of economies of scale by reducing unit costs.

Consequently, Türkiye's ability to reach its climate targets while maintaining energy supply security depends on the alignment of technological innovation with a strong policy framework. This study emphasizes that positioning CCU technologies as a transition technology in the green transformation process of Türkiye may contribute to aligning economic and environmental objectives during the energy transition.

5. Conclusion

The decarbonization of energy systems within the scope of combating global climate change requires a delicate balance between technological innovation and economic sustainability. This study examined the integration potential of CCU technologies for different fuel types in the electricity generation portfolio of Türkiye through a holistic framework ranging from historical emission trends to future projections and comprehensive techno economic sensitivity analyses. The findings demonstrate the strategic role of CCU investments in the process of reaching the 2053 net zero emission targets of Türkiye while revealing the economic thresholds facing these investments with concrete data.

The primary results of the study are summarized through the following points:

- The 1990-2022 dataset enriched with the PCHIP interpolation method confirms that the grid emission intensity of Türkiye is in a gradual downward trend. The ten year projections predict that if the current decarbonization momentum continues, the emission intensity will decrease to levels of approximately \$0,46 $kgCO_2/MWh$ by 2030.
- The breakeven carbon prices calculated for different fuel types define the critical thresholds required for CCU investments to reach profitability. The analyses prove that while facilities based on high carbon intensity lignite and fuel oil show the highest sensitivity to carbon price increases, these plants require stronger financial incentive mechanisms due to high CAPEX.
- Sensitivity simulations conducted under carbon tax uncertainty reveal that investment payback periods exhibit high sensitivity not only to carbon prices but also to fluctuations in operational efficiency and capital costs. DPP analyses provided a more cautious and realistic risk profile for investors by considering the time value of capital costs.
- The developed decision support map identified which facilities are priority candidates for CCU integration in the decarbonization roadmap of Türkiye. It was demonstrated that if the carbon tax exceeds certain threshold values, CCU projects can transform from an environmental obligation into an economic opportunity through value added outputs such as ethanol production.

In conclusion, this study emphasizes that CCU technologies must occupy a central position in transition period strategies so

that Türkiye can reduce carbon emissions without endangering its energy supply security. Future studies focusing on the integration of carbon capture processes with renewable energy sources and the optimization of regional carbon transport infrastructures known as CO_2 hubs will accelerate the green transformation process of Türkiye.

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Nomenclature

$EF_{\frac{kgCO2}{MWh}}$	Emission factor
$\eta_{capture}$	CO_2 capture efficiency
$Ethanol_{yr}$	Annual ethanol production
$\eta_{selec.}$	Selectivity factor for ethanol production
H_{2yr}	Annual hydrogen amount
$H_{2_{per_{ethanol}}}$	Hydrogen requirement per unit ethanol
E_{H2}	Annual hydrogen-related energy requirement
$E_{cap.}$	Annual CO_2 capture cost
$Captured_{CO2yr}$	Annual amount of captured CO_2
$capex_{per_{CO2}}$	Capital cost per unit CO_2 captured
$CRF(r,n)$	Capital Recovery Factor
r	Discount rate
n	Project lifetime
$OPEX_{yr}$	Annual operational expenditure
$CAPEX$	Capital expenditure
$opex_{fraction}$	Fraction of CAPEX used for OPEX
H_{2_cost}	Hydrogen cost
$Electricity_{cost}$	Electricity cost
$Revennue_{yr}$	Annual revenue
$\rho_{ethanol}$	Ethanol price
ρ_{carbon}	Carbon price
$Cashflow_{yr}$	Annual cash flow
$CAPEX_{yr}$	Annualized capital expenditure
$Ethanol_Revennue_{yr}$	Annual revenue generated from ethanol sales
$Electrolyzer_{per_kg_H2}$	Electricity consumption of electrolyser per unit hydrogen