Optimizing the U.S. Transformation Path to a Low-Carbon EV Ecosystem: Balancing Renewable Energy Integration and EV Adoption

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Muhammed Abdullah Aljohani

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Abstract

The study aimed to develop a temporal-optimization framework for the United States' transition to a low-carbon electric transportation system over the period 2025–2050. Unlike conventional assessments that emphasize achieving an end-of-year target, the study evaluates progress by minimizing cumulative life-cycle carbon dioxide equivalent emissions from vehicle production, operation, and end-of-life. Methodologically, it employs a random search optimization approach that explores thousands of feasible annual trajectories for the electricity mix (solar, wind, Other Green, and fossil fuel) and for electric-vehicle (EV) adoption rates, subject to realistic growth bounds and accounting for fleet-turnover dynamics, sales substitution, and annual vehicle retirement. The objective function is defined as the sum of annual emissions across the transition horizon, thereby capturing the cumulative nature of carbon impacts. Results indicate that the optimized pathway achieves the lowest cumulative emissions, at approximately 21.66 billion tCO_2e, compared with about 32.57 billion tCO_2e under the baseline scenario, representing a reduction of roughly 33.50%. This improvement follows mainly from a scale effect between fleet size and annual sales: the existing vehicle fleet is far larger than the number of vehicles sold in any given year, so the one-time manufacturing penalty associated with building an electric vehicle is outweighed many times over by the operating-emission savings that accumulate across the much larger stock of vehicles already on the road. The results further suggest that pairing the pace of grid decarbonization with the pace of vehicle electrification produces the lowest cumulative outcome. Accordingly, the study recommends adopting cumulative life-cycle emissions as a core monitoring metric and linking EV incentives to measured progress in grid decarbonization and in expanding public charging.

Keywords: temporal optimization; cumulative emissions; life-cycle assessment; electric vehicles; power-sector decarbonization.

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List of Abbreviations

AI – Artificial Intelligence

BEV – Battery Electric Vehicle

CH_4 – Methane

CO_2 - Carbon Dioxide

DOE - Department of Energy

EPA - Environmental Protection Agency

EV - Electric Vehicle

GHG - Greenhouse Gases

HDD – Heavy-Duty Diesel

HDV – Heavy-Duty Vehicle

HEV - Hybrid Electric Vehicle

HFCs - Hydrofluorocarbons

ICCT - International Council on Clean Transportation

ICEV - Internal Combustion Engine Vehicle

IEA - International Energy Agency

LCA - Life Cycle Assessment

LCOE - Levelized Cost of Electricity

LDD - Light-Duty Diesel

LDG - Light-Duty Gasoline

LDT - Light-Duty Truck

LDV - Light-Duty Vehicles

LPG - Liquefied Petroleum Gas

N_2O - Nitrous Oxide

NEDC - New European Driving Cycle

NEVI - National Electric Vehicle Infrastructure

NGV - Natural Gas Vehicle

NO_2 – Nitrogen Dioxide

NREL – National Renewable Energy Laboratory

PEV – Plug-in Electric Vehicle

PHEV – Plug-in Hybrid Electric Vehicle

PKT – Passenger Kilometers Traveled

PM2.5 – Particulate Matter (diameter ≤ 2.5 micrometers)

PPP – Public-Private Partnership

tCO_2e – Metric tons of carbon dioxide equivalent

V2G – Vehicle-to-Grid

VKT – Vehicle Kilometers Traveled

ZTC – Zero-Carbon Technology Cost

ZEV – Zero-Emission Vehicle

NOx – Nitrogen Oxides

CHAPTER ONE INTRODUCTION AND GENERAL INFORMATION

1.1 Background and Motivation

1.1.1 The Urgency of Reducing Lifecycle CO_2 Emissions

When petroleum-based fuels combust in vehicle engines, they release CO_2 alongside other greenhouse gases, including methane (CH_4), nitrous oxide (N_2O), and hydrofluorocarbons (HFCs) into the atmosphere. The progressive buildup of these gases traps heat and drives the long-term warming associated with contemporary climate change (Congressional Budget Office, 2022). The transportation sector is one of the main causes of anthropogenic greenhouse gas (GHG) emissions in the United States. Transportation remained the largest single source of U.S. greenhouse gas emissions in both 2021 and 2022, generating 29% and 28% of total national GHG output in those years respectively (EPA, 2024a). Within that sector, carbon dioxide is responsible for approximately 97% of total warming potential (Congressional Budget Office, 2022). This study treats hydropower and nuclear energy, grouped with other minor clean sources as "Other Green," as technologies whose absolute electricity output changes only slowly, while solar and wind are modeled as the primary renewable sources subject to optimization and expected to capture most new generation growth.

Transportation's final consumer sector emissions come from various sources, including automobiles, trucks, commercial airplanes, and railroads. Burning fossil fuels for energy was responsible for more than 92% of U.S. carbon dioxide output during the study period, totaling roughly 4.6 billion metric tons (Congressional Budget Office, 2022). As a result, the United States has recently decarbonized the transport industry as a top priority (Muratori et al., 2023), considering it was responsible for 29% of the country's total GHG emissions in 2021 (EPA, 2024a).

Addressing the emissions linked to the transport sector is now essential to meeting ambitious climate objectives (Muratori et al., 2023). Meanwhile, the second largest family expenditure for Americans is transportation. Thus, a deliberate shift to a green transportation future will lead to a more equitable and cost-effective transportation system with improved air quality and better public health outcomes, increased energy security, optimized accessibility and quality of life. Therefore, this study adopts a lifecycle modeling approach to evaluate carbon emissions across vehicle production, energy use, and end-of-life disposal. In addition, it applies optimization

techniques to examine whether slower, more gradual deployment pathways for electric vehicles and renewable energy may, in some cases, result in lower cumulative CO_2 emissions than faster, front-loaded transition strategies.

Along with low public transport usage, the United States currently boasts the most passenger kilometers traveled (PKT) per capita globally. The nation relies heavily on petroleum-based energy and has a sizable fleet of outdated, inefficient cars (Horesh & Quinn, 2024). The three main goals of national initiatives to reduce GHG emissions from transport in the US have been to increase convenience, boost efficiency, and switch to cleaner options (Muratori et al., 2023). These initiatives aim to lower the total vehicle kilometers traveled (VKT), boost ridership, improve fuel efficiency, and implement low-emission technologies now and in the future. As a result, tackling the emissions from the transportation sector requires both the identification of technological and societal solutions and a thorough understanding of the emissions spectra of average, present, and future vehicle types.

For three primary reasons, reducing emissions from mobility has been more difficult than from the electric power industry. First, the price of transport services has little effect on their demand. The locations where people live, work, and socialize, as well as where businesses manufacture and sell their goods, all contribute to the demand for mobility (Congressional Budget Office, 2022). Although their sites are subject to change, they usually occur gradually. Second, the transportation industry relies heavily on petroleum, a single fossil fuel. There are currently few affordable alternatives to petroleum despite its price per unit of energy being substantially more significant than other fossil fuels. According to the Congressional Budget Office (2022), the cost of embedded CO_2 in the transportation industry is more than twice that of the other sectors. Lastly, individuals often keep their cars for a long time, which delays the impact of new car models with higher fuel economy. Open innovation strategies in the transport sector may accelerate low-carbon transitions through partnerships and collaborative technology development (Muratori et al., 2023).

1.1.2 Role of Renewable Energy and EVs

Numerous studies have evaluated the greenhouse gas emissions linked to different inland transportation options. A systematic comparison of GHG emission factors across passenger transport modes by Noussan et al. (2022) found that light-duty vehicles generate the highest per-

passenger emissions, while non-motorized modes and rail produce the lowest. In Germany and Israel, Creutzig (2021) examined the greenhouse gas emissions of shared and public transportation options, including cars, buses, and rail. They found that shared electric scooters had lower emissions than single-occupant cars but more significant emissions than buses and rail. Due to low ridership, the power consumption of buses per PKT in the US is significantly higher than in other countries, according to Horesh and Quinn (2024), which highlights the importance of assessing GHG emissions within US-specific constraints. Zhao et al. (2023) find that ICEVs' market share may decline as EVs become the primary alternative, and that this shift in market share can drastically lower CO_2 emissions.

EVs are also valuable instruments for reducing carbon emissions on their own: their extensive use drives innovation in transportation technology, and rising EV sales boost manufacturers' bottom lines (Zhao et al., 2023). Manufacturers can increase R&D expenditure to raise the bar for transportation technology by using the money from EV sales (IEA, 2023b). Transportation technology will reduce urban traffic congestion and consequently reduce vehicle exhaust emissions. Guo et al. (2020) found that higher air pollution levels were positively associated with electric vehicle sales across twenty major Chinese cities, suggesting that consumers respond to local air-quality conditions by shifting toward electric vehicles. The findings suggest that public concern about air pollution can itself be a driver of accelerated EV adoption. When comparing conventional automobiles to electric cars (EVs), Fuinhas et al. (2021) found that EVs could lower CO_2 emissions.

Several options, including electric and hybrid vehicles (EHVs), can aid in lowering the use of fossil fuels and the accompanying greenhouse gas emissions worldwide. Plug-in electric vehicles (PEVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs) make up EHVs in general.

Using a lifecycle assessment, Arshad et al. (2022) found that internal combustion engine vehicles generally produce higher lifecycle emissions than electric vehicles. Using a lifecycle methodology, Gao et al. (2023) confirmed that ICE vehicles have higher lifecycle total energy and GHG emissions than EVs. According to Li et al. (2025), encouraging the use of electric vehicles helps reduce greenhouse gas and PM2.5 emissions and nitrogen oxide releases at the national level in most Chinese provinces. According to Shaukat & Khan (2025), electrifying heavy-duty vehicles (HDVs) helps to decrease NO_2 and fine particulate matter (PM2.5)

pollution, which in turn leads to long-lasting improvements in air quality. Unlike HEVs and PHEVs, PEVs produce no tailpipe emissions during operation, giving them a stronger potential environmental advantage (Squalli, 2024). Additionally, PEVs powered by renewable energy sources are likely more ecologically benign since clean, sustainable energy sources like wind, solar, hydro, and nuclear can produce the electricity needed to charge PEVs.

The need for clean technologies, like EVs, has arisen from the costs of carbon emissions to the environment and human health. Since EVs may help lower health risks and carbon emissions that affect the environment and ecosystems, they are a more effective and ecologically friendly alternative (Chen & Ma, 2024). To reduce GHG emissions and air pollution, transport must be electrified. In 2019, global EV sales hit a record 2.1 million units, up 40% from the prior year, pushing the total worldwide fleet to 7.2 million vehicles (IEA, 2020). China held the largest share of that market at roughly 47%, followed by Europe at around 25%, while the United States and Canada together accounted for less than 10%. Hence, electric mobility will be key in reducing future emissions of greenhouse gases and improving air quality, besides helping governments achieve their energy diversification objectives.

As global concerns about climate change intensify, the potential of electric vehicles (EVs) to reduce carbon emissions in the transportation sector has come under increasing scrutiny. EVs start their life with a higher carbon footprint than conventional vehicles because manufacturing the lithium-ion battery pack requires significant energy during the mining and processing of materials like lithium, cobalt, and nickel (Arshad et al., 2022). During the use phase, however, the carbon performance of EVs is strongly influenced by the cleanliness of the electricity supply (Gao et al., 2023). When powered by low-carbon energy sources such as solar and wind, EVs can achieve substantially lower lifecycle emissions than ICEVs; conversely, reliance on coal-based electricity may result in higher overall emissions (Arshad et al., 2022). In addition, effective recycling and secondary use of end-of-life batteries can further reduce lifecycle carbon emissions by lowering the demand for raw material extraction and energy-intensive production processes.

1.2 Problem Statement

The shift to electric vehicles is a major move in the global effort to fight climate change. However, such environmental benefits can only be achieved if the energy used to power the EV

charging infrastructure is sourced from renewable sources. Today, the main sources of electrical energy in the United States include fossil fuels. This poses a major challenge to realizing a low-carbon economy for electric vehicles because the energy used to generate electricity negates much of the benefits of green vehicles. It is aggravated by the increase in EV demand occasioned by the federal and state policy's thrust towards net-zero carbon emissions by 2050. The EIA (2023a) projected that EVs could make up as much as half of all new vehicle sales by 2030, which would add considerable new load to the national grid from charging demand. This is set to add pressure on the currently embedded fossil fuel-based power systems, contribute to higher carbon emissions, and thus prove counterproductive for national climate change policies. Recent studies focusing on the emissions of EVs over the product lifecycle are scarce, especially regarding the case of EVs fueled by renewable energy in the United States. Meeting these challenges will, therefore, require consideration of a strategic approach for the renewable energy mix for the charging infrastructure of EVs. Several factors stand in the way of integrating renewables into the EV charging network:

1. Intermittency and Reliability: Solar and wind power are fluctuating resources by the effect of the weather and the day/night cycle and thus not as constant a supply of power as fossil fuels. However, applications using more powerful storage technologies, such as lithium-ion and flow batteries, are still costly and present in only a few cases.
2. Limitations of Grid Infrastructure: Currently, the US grid system was developed with a focus on baseload resources and lacks the flexibility to integrate distributed generation, such as renewables and the peak load requirements of EV charging stations. Integrating high renewables into the grid will require significant capital expenditure across the transmission and distribution infrastructure and smart grid systems.
3. Policy and Economic: While federal policies work towards encouraging the use of clean energy, a lack of coherent and consistent policies across states and a weak regulatory environment deter innovation. However, the initial costs for renewable energy systems investments and storage are still high and thus can hinder investments, especially in the poorest districts of the world.
4. Lifecycle Emissions of EVs: Much of the existing literature focuses narrowly on operational (tailpipe and charging) emissions, but a complete account of EVs'

environmental impact requires examining the entire lifecycle, including manufacturing, in-use operation, and end-of-life disposal.

This study examines a transition pathway toward predominantly clean electricity for EV charging in the U.S. by following a projected electricity mix in which solar and wind account for approximately 45% and 42% of total generation, respectively, while other green sources, including hydropower and nuclear, contribute around 13%, with natural gas phased out entirely by the end of the study horizon. Rather than optimizing the composition of the energy mix, the analysis optimizes the deployment timeline of solar and wind generation, examining whether alternative growth trajectories can yield lower cumulative lifecycle CO_2 emissions. This approach challenges the conventional assumption that faster deployment necessarily produces superior environmental outcomes. For modeling purposes, the United States is treated as a single, unified electricity system, abstracting from regional variation in renewable resource availability.

1.3 Study Gap

This study draws on current electricity generation contributions, source-specific CO_2 emissions per mile, and projected growth trajectories to inform policymakers, energy providers, and stakeholders in the transportation sector. While electric vehicles are widely recognized as a key pathway for reducing greenhouse gas emissions, literature indicates that their environmental performance is highly sensitive to the carbon intensity of the electricity used for charging (Gao et al., 2023; ICCT, 2021). Despite this recognition, detailed assessments of lifecycle emissions from renewable-powered EV systems, particularly within the United States, remain limited and fragmented (Squalli, 2024).

On the other hand, most existing modeling studies rely on fixed or exogenously defined growth assumptions for both electric vehicle adoption and renewable energy deployment, which constrains their ability to capture the dynamic interactions between these systems over time (Barman et al., 2023; Muratori et al., 2023). In contrast, this study introduces an optimization framework that allows EV market penetration and renewable energy deployment rates to vary within policy-aligned constraints, enabling the identification of transition pathways that minimize cumulative lifecycle carbon emissions rather than short-term operational emissions (Ali et al., 2024).

The relevance of this gap is amplified by the current structure of the U.S. electricity system, which remains predominantly fossil-fuel-based despite rapid growth in renewable capacity (U.S. Energy Information Administration, 2024a; EPA, 2024c). In the same context, Federal energy projections indicate that electric vehicles could represent close to half of all new vehicle sales by 2030, creating a significant increase in electricity demand tied to charging needs (EIA, 2023a; IEA, 2023b). Without a coordinated transition toward low-carbon electricity, rising EV adoption risks shifting emissions upstream rather than delivering net lifecycle reductions (Horesh & Quinn, 2024).

Addressing this challenge requires a strategic optimization of renewable energy deployment for EV charging infrastructure that explicitly accounts for lifecycle emissions from vehicle manufacturing, operation, and end-of-life processes (IPCC, 2014; IPCC, 2023). By quantifying current renewable contributions, evaluating emissions intensity per mile for individual energy sources, and projecting feasible growth trajectories, this study develops an evidence-based framework for transitioning the U.S. EV ecosystem toward a renewable electricity supply. In doing so, it provides actionable insights for policymakers and energy planners seeking to align transportation electrification with long-term climate objectives and energy security considerations (Chen & Ma, 2024; Rana et al., 2025).

1.4 Purpose of the Study

The purpose of the study is to identify and evaluate a time-optimized transition pathway for the United States that enables a shift toward a low-carbon transportation system while minimizing cumulative lifecycle carbon emissions over the period 2025‑2050. Specifically, the study aims to investigate how the temporal coordination between the deployment of renewable electricity and the use of electric vehicles (EV) affects emissions results across the vehicle's production, operation, and final phases.

To achieve this purpose, the study analyzes the role of sequencing and timing in integrating renewable energy sources into the electricity generation mix and assesses how these dynamics affect the operational carbon intensity of electric vehicles during the transition phase. Particular attention is given to the interaction between accelerated EV adoption and the corresponding decline in internal combustion engine vehicle sales, to understand how fleet turnover dynamics shape cumulative emissions trajectories under an optimal transformation scenario.

The study also aims to determine how an optimal transition scenario can balance the pace of transportation electrification with the objective of minimizing cumulative carbon emissions over time. By employing an optimization-based lifecycle assessment framework, the research evaluates alternative transition pathways to identify those that achieve emissions reductions most effectively throughout the entire transition horizon.

Taken together, this temporal and lifecycle perspective gives policymakers and energy planners a concrete basis for decisions about the design of a sustainable, low-carbon transportation system aligned with long-term U.S. climate objectives.

1.5 Research Questions

The transition toward electric vehicles (EVs) represents a critical inflection point in global efforts to mitigate climate change and reduce dependence on fossil fuels. However, the extent to which this transition delivers meaningful environmental benefits depends fundamentally on the carbon intensity of the electricity used to power EVs. Electrification alone does not guarantee emissions reduction; rather, the timing and pace of integrating low-carbon and renewable energy sources into the electricity generation mix play a decisive role in determining cumulative lifecycle carbon outcomes.

Governments and energy planners are increasingly confronted with a temporal coordination challenge: accelerating EV adoption while simultaneously decarbonizing the electricity system. An unbalanced transition characterized either by rapid electrification supported by a carbon-intensive grid or by delayed electrification despite cleaner electricity may lead to suboptimal emissions outcomes over the transition horizon. Therefore, electric mobility, particularly in urban areas, must be evaluated not only in terms of scale but also in terms of the sequencing and timing of supporting energy infrastructure deployment (Cui et al., 2022).

Despite significant progress, inadequate charging infrastructure remains a key constraint on the pace and structure of EV adoption. Limited availability of charging stations, especially fast-charging facilities, continues to shape adoption trajectories and slows the displacement of internal combustion engine vehicles (ICEVs) (Tejeida-Padilla et al., 2024). These infrastructure constraints interact with vehicle turnover dynamics, influencing both the rate at which EVs enter the fleet and the persistence of ICEVs within the existing stock. As a result, infrastructure

development is not merely a deployment issue but a factor that affects the temporal evolution of fleet composition and associated cumulative emissions.

Further, the rapid expansion of the global EV market highlights the urgency of addressing these timing effects. By 2023, the global EV stock surpassed 15 million vehicles, reflecting accelerating consumer acceptance driven by declining battery costs, expanded model availability, and policy support (IEA, 2023b). While this growth signals strong momentum, it also raises critical questions regarding the optimal pace of transition. Accelerated EV adoption, if misaligned with electricity decarbonization and vehicle stock turnover, may generate higher cumulative emissions in the short to medium term, despite long-term benefits (Muratori et al., 2023).

The central challenge is optimizing the temporal pathway of this transition. This requires evaluating the interaction between renewable energy deployment, EV adoption rates, and the decline of ICE vehicle sales in order to identify a transformation trajectory that minimizes cumulative lifecycle carbon emissions over time. To address these interrelated dynamics and align electrification speed with emissions reduction objectives, the present study formulates the following research questions:

Question 1: What time-optimized transition pathway enables the United States to move toward a low-carbon transportation system while achieving the minimum cumulative lifecycle carbon emissions associated with vehicle manufacturing, operation, and end-of-life processes over the period 2025–2050?

Question 2: To what extent does the sequencing and timing of renewable energy deployment within the electricity generation mix influence the effectiveness of reducing electric vehicle operational emissions during the transition period?

Question 3: How do the evolving temporal interactions between accelerated electric vehicle adoption and the contraction of internal combustion engine vehicle sales affect cumulative carbon emissions throughout the transition phase under the optimal transformation pathway?

Question 4: In what manner does the optimal transition scenario establish a temporally efficient balance between the rate of transportation electrification and the reduction of cumulative carbon emissions across the transition horizon?

The projected U.S. renewable electricity mix referenced in the study questions is derived from high-penetration pathways developed by the U.S. Department of Energy and the National

Renewable Energy Laboratory. These scenarios indicate that solar and wind energy are expected to account for approximately 45% and 42% of U.S. electricity generation by 2050. Hydropower, nuclear, and other minor clean sources, grouped as "Other Green," decline in percentage share from 25% in 2025 to 13% in 2050 as solar and wind capture most new generation growth, even as their own absolute output remains relatively stable. Even so, these assumptions are grounded in DOE's Solar Futures Study (2021) and NREL's 100% Clean Electricity by 2035 Study (2023). The corresponding 100% light-duty EV adoption target used for the optimized scenarios is grounded in the U.S. Department of State's Long-Term Strategy of the United States (2021), which describes light-duty vehicles as almost entirely electric by 2050 under its modeled net-zero pathways, and is consistent with the same administration's 2021 policy direction toward clean cars and trucks (White House, 2021).

On the other hand, Other Green generation is held relatively stable in absolute output, while the optimization focuses exclusively on the deployment trajectories and timing of solar and wind energy expansion. The research questions are designed to address critical gaps in understanding how the temporal coordination between renewable energy deployment and electric vehicle adoption influences cumulative lifecycle carbon emissions in the transportation sector.

The findings of this study are expected to offer policy-relevant insights for the U.S. energy and transportation sectors by clarifying how alternative transition pathways affect emissions outcomes under fixed renewable mix targets. By emphasizing lifecycle assessment across vehicle manufacturing, operation, and end-of-life stages, the study contributes to a more complete evaluation of the environmental performance of electric vehicles relative to internal combustion engine vehicles. In addition to emissions mitigation, the results have broader implications for energy security and system resilience, as a renewable-powered EV charging infrastructure can reduce dependence on imported fossil fuels and exposure to energy price volatility.

1.6 Research Variables

Every electricity source generates some level of greenhouse gas emissions across its full lifecycle, but renewables produce far less than fossil fuel plants on a per-kilowatt-hour basis (EPA, 2024c). Improving the efficiency and deployment of clean energy technologies will be critical for meeting rising electricity demand while staying within climate targets. Sustainable growth depends on increased energy supply security, which is ensured by improvements in green

energy efficiency (Gao et al., 2023). In addition, increasing green energy efficiency through the implementation of smart grids, green innovations, and new green transportation technologies helps to reduce greenhouse gas emissions, reduce the demand for imported energy, and minimize household and economic energy costs. In terms of pollution management, green energy efficiency also offers enormous potential for every economic sector, including industry, transportation, real estate, and energy generation.

Road electrification is being aggressively promoted by nations worldwide to reduce carbon emissions. Switching from gasoline-powered ICEVs to electric vehicles can reduce vehicle carbon emissions by more than 40%, depending on the electricity source used for charging (Gao et al., 2023). Vehicle electrification significantly lowers the carbon emissions of automobiles over their lifetime. Working from median vehicle carbon emission data covering 2012 to 2021, Gao et al. (2023) found that adding each million EVs to the U.S. fleet produces substantial annual reductions in both total lifecycle and direct fuel-combustion emissions, on the order of millions of metric tons, highlighting how fleet size amplifies the cumulative climate benefit of electrification. Vehicle electrification is an unavoidable trend for achieving carbon neutrality, and EVs will gradually replace ICEVs in road transportation to lower carbon emissions from the transportation sector.

The expansion of renewable energy and the acceptance of electric vehicles are the two main aspects that this study looks at to create an ideal transformation pathway. These factors affect total CO_2 emissions by contributing to emissions from the production of vehicles and electricity. Hence, the following are the main variables examined:

1. Green Energy: Solar and wind contributions to the US electricity grid, and annual growth rates of renewable energy capacity in the US. Other Green is held relatively stable in absolute output, though its share of total generation declines from 25% in 2025 to 13% by 2050 as solar and wind capture most new growth.
2. EV adoption is modeled as a decision variable in the optimization. The annual EV sales share is constrained by realistic policy-based growth ranges, and is multiplied by the actual year-specific total vehicle sales volume (derived from the EIA AEO2026 vehicle stock series at a 4.5% annual retirement rate, averaging approximately 16.3 million vehicles per year) to calculate unit-level adoption and associated emissions.

1.7 Significance of the Study

The results of this study will have major implications in the energy and transportation sectors, particularly in the U.S. This work determines the best renewable energy combination for EV charging infrastructure; hence it offers practical insights for policymakers, energy suppliers, and automakers willing to achieve net-zero emissions by 2050. This analysis enables the fair and efficient integration of renewable resources across the country.

The study also underlines the role of lifecycle assessments in the appraisal of the environmental impact of EVs. The work identifies areas for improvement across the production, use, and disposal stages of electric vehicles by contrasting their lifecycle carbon footprints with those of gasoline cars. Such understanding is key in making the auto industry fit into wider sustainability aims.

The study advances energy security and resilience discussions in addition to emissions reduction. Renewable-powered EV charging infrastructure will reduce dependence on fossil fuels, mitigating the associated risks of price volatility and supply disruption. It will promote local economic development in clean energy technology and infrastructure investment. This work will pave the way for the transition of the U.S. transportation system into a sustainable, low-carbon system while fighting climate change globally.

The study also offers a new perspective by examining the best pacing of EV and renewable deployment, showing that a more gradual transition, if well aligned, may lead to deeper long-term emissions cuts than rapid adoption alone.

CHAPTER TWO LITERATURE REVIEW

2.1 Introduction

This study of the literature attempts to provide a solid foundation for the evaluation of how to incorporate renewable energy into the infrastructure for electric vehicles. The green benefits of EVs are largely determined by the energy sources used to charge them. While EVs lack any tailpipe emissions, the overall carbon footprint of this transportation method is shaped primarily by the composition of the power grid's energy sources. Success is dependent on changing the U.S.'s main feedstock, which is predominantly composed of fossil fuels, into a renewable form of electricity that can be used to power electric vehicles if significant reductions in GHG are desired in the country (Barman et al., 2023).

This chapter discusses the recent status of integrating renewable energy into the U.S. electricity grid and its application for EV charging networks. Solar and wind energies have grown incredibly due to the decline in costs and technological advancements. Solar energy, abundant in sunny regions such as the American Southwest, holds immense potential for decarbonizing EV charging. Similarly, wind power has emerged as one of the leading renewable energy sources, with states like Texas and Iowa contributing much to the national grid. Though it has a very limited geography, hydropower continues to provide steady and carbon-free electricity in the Pacific Northwest. In addition, nuclear energy, while not renewable, provides a significant share of the U.S. low-carbon electricity supply and delivers stable baseload power. Although its share is expected to remain relatively constant over time, it plays a critical role in maintaining the reliability and reducing the carbon intensity of the grid (U.S. Energy Information Administration, 2024c). Together, these sources create the base of a renewable-powered EV ecosystem (Rana et al., 2025). The carbon accounting framework used in this dissertation spans multiple levels of the automotive sector, from enterprise-level Scope 1 and 2 emissions to full product lifecycle and service-cycle accounting (Gao et al., 2023).

The chapter goes on to look at other parts linked to energy storage solutions like lithium-ion batteries and pumped hydro storage to address the intermittency challenges of solar and wind power. Emerging grid technologies, including smart grids and decentralized configurations, are also evaluated for their ability to improve efficiency and flexibility in bringing in renewables to EV infrastructure. This review covers the lifecycle emissions of conventional internal

combustion engine vehicles and compares them with those of EVs; it also brings to the fore the role of renewables in reducing lifecycle emissions (O’ Malley and Slowik, 2024).

Federal policies, along with technological interventions exemplified by the Inflation Reduction Act, and state-level initiatives illustrated by California's Zero-Emission Vehicle program complete the discussion on speeding up the deployment of renewable energy and EVs. This chapter synthesizes the literature to set the scene for subsequent analysis and informs optimal strategies for deploying renewable energy-powered EV charging infrastructure.

Integrating renewable energy into the charging process of EVs is crucial to the development of sustainable energy and transportation. The increasing popularity of electric vehicles around the world has led to a greater appreciation of the importance of clean, renewable energy sources. As a result, the full environmental benefits of electric drives have become more apparent. Chapter 2 discusses the current state of research on this integration; it covers renewable energy technologies, the lifecycle of emissions, optimization strategies, and policy initiatives that comprise the foundation of a renewable-powered EV ecosystem. This chapter supports the methodological foundation for optimizing deployment timing to reduce lifecycle CO_2 emissions under a fixed 2050 target energy mix, a core objective of this dissertation's modeling approach. This chapter first addresses the environmental imperative of integrating renewable energy within the context of EV adoption. This imperative is heightened by the fact that the grid relies heavily on fossil fuels, which makes the shift toward renewable-powered charging systems one of the main factors in GHG reduction. Solar, wind, and hydropower (along with nuclear as a stable low-carbon baseline) have emerged as key contributors due to their scalability, declining costs, and technological advancements. However, their successful deployment within EV infrastructure faces several challenges: intermittency, resource availability disparity across regions, and infrastructure limitations.

A full lifecycle approach to carbon emissions underlines that, environmentally speaking, EVs have their nuances when compared to internal combustion engine vehicles. Tailpipe emissions are eliminated in battery EVs; however, operational emissions remain through the electricity used for charging, yet sizable emissions at the manufacturing and disposal stages, particularly battery production, offset this. Therefore, transitioning to renewable energy on the grid becomes key in ensuring minimal lifecycle emissions from EVs and a maximization of the environmental benefits accruable from them.

This review presents U.S.-focused renewable energy mix models optimized to offer the right balance of resource availability, cost, and reliability. These range from integrated models that combine solar, wind, and hydro with large-scale energy storage technologies, addressing intermittency and grid-energy availability to support charging stations, to more advanced approaches that incorporate smart grid technology and AI-driven solutions.

The main players in accelerating the uptake of renewable energy and EVs are policy interventions. These come in federal and state-level initiatives: tax credits for installing renewable energy and zero-emission vehicle mandates. These policies create a strongly enabling regulatory and economic environment for integration. Meanwhile, technological advancements in energy storage, battery recycling, and decentralized energy systems help overcome technical and economic barriers.

The chapter identifies the research gaps and potential opportunities in this field, including the regional distribution of renewable resources, the refining of lifecycle assessment methods, and the improvement of energy storage efficiency. This chapter first surveys the prior research that has been done on this topic and then highlights the unresolved issues. It provides a thorough understanding of the connection between renewable energy and electric vehicles, and it develops a framework for addressing sustainable transportation and energy issues.

2.2 Renewable Energy Integration for EV Infrastructure

The actual climate benefit of electric vehicles depends largely on where their electricity comes from. An EV running on a coal-dominated grid produces far fewer savings than one charged by renewables, which means that decarbonizing the electricity supply and decarbonizing transportation are fundamentally linked goals (Gao et al., 2023). Solar, wind, hydropower, and nuclear power have all become significant participants in the American electricity grid. Despite their potential, with fossil fuels still accounting for more than 60% of U.S. electricity generation, the share of EV charging powered by low-carbon sources remains relatively small (U.S. Energy Information Administration, 2024a).

High-insolation states such as California, Arizona, and Nevada offer strong potential for solar-powered EV charging, where falling photovoltaic costs and federal tax incentives continue to accelerate deployment. However, solar generation varies by time of day and season, making storage systems essential for reliable supply. To mitigate this, various advanced energy storage

systems like lithium-ion batteries and pumped hydro storage are increasingly being deployed to stabilize supply and store surplus energy for EV charging (Rana et al., 2025). Nuclear power is not classified as a renewable source, yet it greatly helps reduce the carbon footprint in the United States. It provides constant, carbon-free baseload power, which is an ideal supplement to renewable energies such as solar and wind. Since this research considers nuclear power as a consistent contributor to the base, its inclusion will ensure the system's reliability during periods of low natural output.

Wind power, concentrated in states such as Texas, Iowa, and Oklahoma, has become the most rapidly expanding renewable energy source in the United States. Its favorable energy payback ratio makes it well-suited for EV charging infrastructure, particularly in regions with insufficient solar resources (NREL, 2024b). However, like solar power, the variability of wind power requires strong management of the grid plus complementary storage solutions to enable reliability (Rana et al., 2025).

In addition to expanding capacity, the improvements in generation efficiency, reflected in increasing capacity factors (CF), are essential for reducing the lifecycle CO_2 emissions associated with electric vehicle (EV) charging. Under NREL's Advanced Technology Scenario, utility-scale solar capacity factors are projected to rise from about 24% in 2025 to above 30% by 2050, while onshore wind is expected to improve from 34% to 45% over the same timeframe (NREL, 2024b). As generation efficiency increases, lifecycle emissions per kilowatt-hour decrease, bringing EV operational emissions from solar charging down to roughly 11.4 g CO_2/mile and from wind to about 3.1 g CO_2/mile, based on an assumed vehicle efficiency of 0.285 kWh/mile (IPCC, 2014; NREL, 2024b). This study incorporates these gains into its optimization model to explore whether a slower, more efficient transition can achieve lower total CO_2 emissions.

Hydropower remains a cornerstone of renewable energy in the U.S., particularly in the Pacific Northwest, where it is a relatively stable and reliable energy source. Despite its geographic and ecological constraints, hydropower contributes meaningfully to grid flexibility and reliability, helping offset the variability of solar and wind generation and supporting a more consistent electricity supply for EV charging systems (Wang et al., 2025).

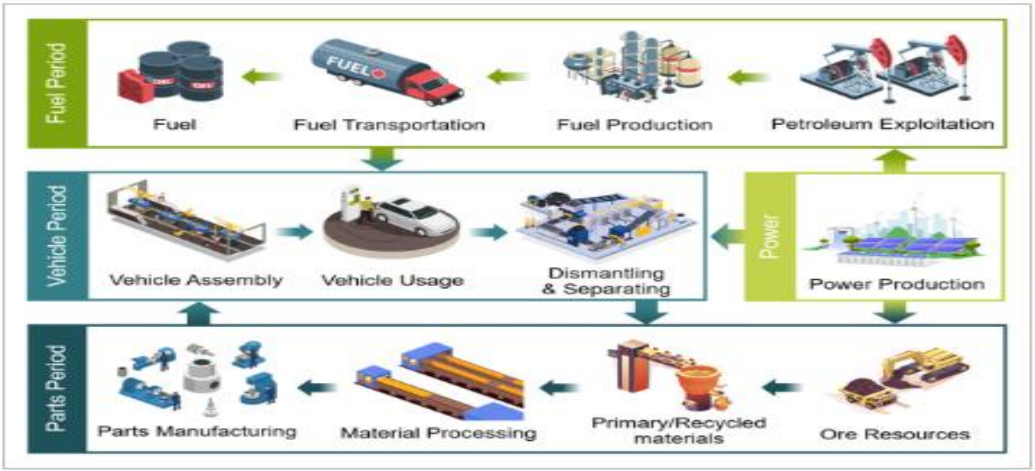

Figure 1: Automobile Lifecycle Carbon Footprint by Country and Powertrain Type. Adapted from Gao et al. (2023).

Current challenges, including variability in generation, regional disparities in renewable resources, and the need for advanced grid technologies, must be overcome to integrate these renewable energy sources into EV charging networks successfully. Smart grids and energy management systems promise to enable real-time energy flow monitoring and optimization. These barriers must be overcome with new storage solutions and grid upgrades if a sustainable, renewable-powered EV infrastructure is to be provided. This goes along with the national objectives of Net Zero Emissions and enhances the decarbonization of transport modes. Integrating renewable energy into EV charging infrastructure is central to decarbonizing transportation and reducing the impact of climate change. While accelerating the adoption of EVs delivers significant environmental benefits, their complete potential could be reached only with the transition to renewable-powered charging systems. In the United States, these range from various initiatives to technological innovations to localized strategies that lay the groundwork for renewable-powered EV infrastructure. Yet infrastructure gaps, intermittency of renewable energy, and uneven regional progress suggest that a coordinated, multi-faceted approach will be needed.

2.2.1 Federal Initiatives and Investment in EV Infrastructure

Federal policy has been central to scaling EV charging infrastructure across the United States. The Bipartisan Infrastructure Law of 2021 directed approximately $7.5 billion toward charging infrastructure with a goal of establishing 500,000 public stations nationwide by 2030, targeting

improved connectivity across urban, rural, and interstate corridors while addressing the range anxiety that constrains EV adoption (U.S. Department of Transportation, 2022).

Based on the above and in support of these objectives, programs such as the National Electric Vehicle Infrastructure (NEVI) Formula Program and the Charging and Fueling Infrastructure Discretionary Grant Program have been implemented to promote standardized, interoperable, and geographically equitable deployment of charging infrastructure. In practice, implementation has been uneven: as of late 2024, only a small fraction of federally funded stations had entered service while the majority of projects remained in planning or construction stages, reflecting ongoing challenges in administrative capacity, jurisdictional coordination, and equitable resource distribution (U.S. Department of Transportation, 2024).

Parallel to infrastructure-focused policies, federal energy legislation has supported the expansion of low-carbon electricity generation through production-based tax credits and long-term financial incentives. Provisions under the Inflation Reduction Act and related clean energy legislation have strengthened economic support for solar, wind, and energy storage projects, improving the feasibility of powering EV charging infrastructure with renewable electricity (U.S. Department of Energy, 2024b). Although nuclear energy contributes a relatively stable and largely fixed share of the national electricity mix, its role as a baseload source enhances grid reliability and facilitates greater integration of variable renewable energy resources. Collectively, these federal guidelines reduce financial and institutional barriers to large-scale adoption of electric vehicles while supporting the broader transition toward a decarbonized electricity system (International Energy Agency, 2023b; U.S. Energy Information Administration, 2024b).

2.2.2 Technological Innovations in Urban Charging

It is known that the urban electric vehicle (EV) charging infrastructure faces persistent challenges related to limited physical space, high population density, and existing demands on urban electricity networks (International Energy Agency, 2023b). In response, a range of technological innovations has emerged to mitigate these constraints, including curbside charging systems that use existing building electricity connections, lamppost-based charging technologies, and compact high-power charging units designed for dense urban environments. Therefore, these solutions not only expand access to charging in space-constrained areas but also reduce reliance

on large-scale grid upgrades by using distributed and modular infrastructure configurations (U.S. Department of Energy, 2023c).

On the other hand, lamppost-based charging systems, in particular, retrofit existing urban lighting infrastructure into EV charging points, offering a cost-effective and relatively rapid deployment pathway compared to traditional standalone chargers (U.S. Department of Energy, 2023c). Such approaches have attracted significant interest from private firms and technology startups, which have played a central role in piloting and scaling new urban charging solutions. Nevertheless, regulatory barriers, permitting complexity, and local grid capacity limitations continue to pose challenges to widespread implementation (U.S. Energy Information Administration, 2024b).

In parallel, the integration of renewable energy into urban charging systems has gained increasing attention. The combination of rooftop solar generation with on-site energy storage enables localized, self-sustaining charging hubs that can operate partially independent of the main grid. These microgrid-based configurations enhance system reliability and resilience, particularly in urban areas vulnerable to grid congestion or outage risks, while also supporting the broader decarbonization of EV charging infrastructure (International Renewable Energy Agency, 2023; 2022).

2.2.3 Grid Modernization and Renewable Energy Integration

Modernizing the electricity grid is essential for accommodating the increased demand associated with EV charging and ensuring the smooth integration of renewable energy sources. The U.S. Department of Energy's Artificial Intelligence for Interconnection (AI4IX) program, launched in 2024, exemplifies efforts to streamline grid connections for renewable energy projects. Through this, the program seeks to use AI to hasten the interconnection application process and shorten the period for connecting renewable energy projects from a few years to months. This addresses one of the major bottlenecks in deploying renewable energy: integrating solar and wind farms onto the grid and into EV infrastructure.

The smart grid technologies also revolutionize the distribution of energy by making it possible to manage dynamic flows of energy and providing demand response in real time. Allowing optimization for renewable generation, storage, and electric vehicle (EV) charging patterns within the utility reduces congestion and makes for a more efficient grid. Vehicle-to-grid technology

can further empower this ecosystem by allowing EVs to discharge stored energy back into the grid during peak periods, functioning as a distributed energy resource. While intermittent renewable sources are emphasized in managing them, nuclear power continues to serve as the anchor for the grid, providing a stable baseline source of carbon-free power enhancing the reliability of modernized grid operations.

2.2.4 Addressing Intermittency and Storage Needs

Intermittency is the largest barrier to achieving very high levels of renewable penetration. Solar energy is highly available in places like California, Nevada, and Arizona, though it fluctuates day-to-day and seasonally; wind energy is central to the Midwest and is weather-dependent. Equally important is the accompanying deployment of advanced energy storage technologies alongside these renewable sources that ensure stable energy supply. Lithium-ion batteries, pumped hydro storage, and emerging solutions such as vanadium flow batteries and solid-state batteries are key to addressing these sorts of variation. That is where technologies store surplus energy during periods of high generation for later use during periods of high demand or low generation.

Hybrid renewable systems mix solar and wind with storage to make the system more reliable, while stable sources like hydropower and nuclear provide a consistent baseload supply for EV charging networks. Indeed, any system that mixes solar with wind farms has one resource cover for the other when there is a lull from one, further flattening the supply curve. In addition, technologies such as dynamic inverters and energy management systems improve efficiency and performance even more in such hybrid systems. However, many major barriers are inhibiting the penetration of renewable energy into electric vehicle infrastructure. Range anxiety, plus the limited number of charging stations, is by far the biggest barrier for potential electric vehicle buyers. The high acquisition costs of electric vehicles and renewable energy infrastructure further limit their use, especially in underserved communities. The political reasons for this include inconsistent policy frameworks and varying state-level priorities, which add to the aforementioned challenges and create many disparities in progress across the country.

These, however, would require the entire spectrum of federal, state, and local governments to come together in unison, where private players should exhibit considerable interest as well. Policies leading PPPs may incentivize investment in renewable energy generation projects and

infrastructure for EV charging. This can be further enhanced by adopting uniform standards for grid interconnection and energy trade, which will make straightforward deployment possible while ensuring access equity. Integration of renewable energy sources into the grid behind-the-meter EV charging is a significant stride toward a sustainable, low-carbon transportation system. Here, federal investment, innovation in urban charging, and grid modernization are all making strides. However, a strong and fair electric vehicle ecosystem on the way will require working through challenges around renewable energy volatility, infrastructure vacuum, and policy incoherence.

2.3 Lifecycle Carbon Emissions of Gasoline Vehicles vs. EVs

Carbon emissions are essentially linked to the lifecycle of EVs in comparison with conventional gasoline-powered vehicles; it is the analysis of environmental benefits that makes it a critical aspect. Though zero tailpipe emissions during operation contribute to a cleaner environment, the overall impact of these vehicles is dependent on the production, use, and disposal stages. The lifecycle assessment is a widely embraced tool that quantifies such emissions while identifying areas needing improvement.

The manufacturing phase of EVs contributes significantly to their overall lifecycle emissions, mainly due to the energy-intensive production of lithium-ion batteries. Much of these emissions result from the extraction and refinement of raw materials such as lithium, cobalt, and nickel. Research highlights that EVs powered by renewable energy can achieve 66 to 74 percent lower lifetime emissions than gasoline vehicles in the United States (O'Malley and Slowik, 2024). Operationally, carbon intensity is a function of the generation mix of the generating station serving the grid. EVs charged from renewable energy, like solar, wind, or hydro and nuclear, yield near-zero operational emissions that considerably reduce their lifecycle carbon footprint. On the other hand, the operational emissions from EVs powered by highly fossil fuel-based grids decrease their environmental benefit. Indeed, EVs powered from grids dominated by coal exhibit lifecycle emissions that are very similar or even higher than those of gasoline-fueled vehicles (O'Malley & Slowik, 2024).

End-of-life emissions are from battery recycling and vehicle disposal. Recycling can recover valuable materials and reduce further resource extraction, because it allows for materials to be reused in other applications and hence reduces the need to extract raw materials. However, the

emission of recycling processes depends on the technologies and energy sources used. Advancement in battery recycling methods and policy measures for a circular economy would be important in minimizing environmental impacts at the end of life of EVs (Rana et al., 2025).
In contrast, compared with gasoline, EVs have the potential to reduce total lifecycle emissions; these reductions are particularly achievable when renewables power them. The largest share of the gasoline car's lifetime emissions comes from the vehicle's operational phase through the combustion processes of fossil fuels. Because gasoline cars' operational-phase emissions from fuel combustion dominate their lifecycle total, their overall lifetime emissions are about four times higher than those of electric cars, even though their manufacturing emissions are lower. One important measure used in gauging the environmental benefit of electric vehicles relative to ICEVs is lifecycle carbon emissions. LCAs consider the emissions at every stage in the life cycle, including manufacturing, operation, and end-of-life disposal. This gives a full understanding of the carbon footprint of EVs and their potential for GHG reductions where their electricity source is renewable.

2.3.1 Manufacturing Emissions

In this case, ICEVs are far less carbon-intensive to produce than EVs, especially given the energy-intensive manufacturing of EV batteries. This is primarily due to the extraction, refinement, and processing of raw materials such as lithium, cobalt, and nickel, which are highly energy intensive. The battery pack is the single largest contributor to manufacturing-phase carbon output, with research placing its share between 40% and 60% of total production emissions (Arshad et al., 2022). However, these emissions are gradually being reduced due to the development of battery production technologies, including solid-state batteries and improved energy efficiency in mining processes. Besides, there is immense scope for further mitigation at the production stage with technological innovation in material recycling, particularly lithium-ion batteries.

2.3.2 Operational Emissions

Unlike ICEVs, EVs produce no tailpipe emissions during operation, which is a significant advantage. However, their operational carbon footprint depends heavily on the energy sources used to recharge them. Where electricity generation is dominated by renewable energy, its

operation yields near-zero direct emissions. In contrast, regions reliant on coal or natural gas produce higher emissions, though still lower than those of ICEVs in most cases.

This study incorporates updated lifecycle emissions data for solar and wind energy to quantify this impact based on efficiency improvements. Generation efficiency is modeled using capacity factor (CF), which measures how effectively a power plant converts its rated capacity into actual electricity over the year. According to the National Renewable Energy Laboratory (NREL, 2024b), the capacity factor for utility-scale solar is projected to rise from 24% in 2025 to over 30% by 2050, while the capacity factor for onshore wind is expected to increase from 34% to 45%.

These efficiency improvements directly reduce the lifecycle CO_2 emissions per kilowatt-hour (kWh) of electricity generated, resulting in reduced emission intensity per kilometer of electric vehicle (EV). Using IPCC lifecycle benchmarks (IPCC, 2014; IPCC, 2023) and assuming a fixed EV electricity consumption rate of 0.285 kWh per mile, the resulting CO_2 emissions per mile decline over time as generation efficiency improves. Under these assumptions, solar-based EV emissions decrease from approximately 11.4 g CO_2 per mile in 2025 to 9.0 g CO_2 per mile by 2050, while wind-based EV emissions decline from 3.1 g CO_2 per mile in 2025 to 2.3 g CO_2 per mile over the same period.

$$CO_{t,2} = CO_{2,2025} \times \left(\frac{CF_{2025}}{CF_t}\right)$$

where $CO_{t,2}$ represents lifecycle CO_2 emissions per mile in year **t**, $CO_{2,2025}$ denotes base-year emissions in 2025, CF_t is the capacity factor in year **t**, and CF_{2025} is the capacity factor in the base year. These emissions per mile are dynamically updated within the optimization described in Chapter 3, resulting in emissions trajectories reported in Chapter 4. This formulation enables the model to capture not only the timing of clean-power deployment but also the effect of improvements in production efficiency on cumulative life-cycle EV emissions.

2.3.3 End-of-Life Emissions

The end-of-life stage comprises vehicle disposal and component recycling, especially battery recycling. Recovery technologies are key to the fact that valuable materials, e.g., lithium, cobalt, and nickel, are recovered, and the negative impacts on the environment from the disposal of batteries are reduced. However, emissions do depend on the technology applied to the recycling

process and its energy source. Enhancing recycling efficiency alongside creating new green practices, such as closed-loop recycling systems, will be critical at that stage for the environmental footprint minimization of electric vehicles.

2.3.4 Impact of Integration of Renewable Energy

Integration of renewable energy into the EV infrastructure transforms lifecycle emissions. As the electricity grid shifts toward cleaner generation sources, the operational emissions from EVs decrease significantly. A new EV sold in 2023 is expected to produce about half the total lifetime CO_2 of a comparable gasoline vehicle, a gap that is projected to grow wider as electricity grids continue to decarbonize (IEA, 2023b). And further reductions are expected because of the acceleration in the adoption of renewables. It brings out how energy policies and EV lifecycle emissions play together and how decarbonizing electricity grids becomes more important.

2.3.5 Comparative Studies

Numerous comparative studies emphasize the lifecycle advantages of EVs relative to ICEVs. Multiple independent lifecycle assessments have reached consistent findings on this point. The European Environment Agency (2018), the IEA (2023b), and the Union of Concerned Scientists (2022) all concluded that BEVs produce meaningfully lower total greenhouse gas and air pollutant emissions over their lifetimes than gasoline-powered alternatives, a conclusion that holds even in parts of the United States where fossil fuels still dominate electricity generation. These results consistently show that EVs have better environmental performance, especially when their well-to-wheel emissions are combined with renewable energy supplies.

Major automakers across Europe, North America, and China have announced binding commitments to phase out internal combustion engine vehicles and achieve carbon neutrality between 2030 and 2050. European manufacturers have set the most aggressive near-term targets, with several committing to full electrification of new vehicle sales before 2040. North American automakers have pledged to eliminate gasoline-powered car production by 2035, while Chinese manufacturers are targeting emissions peaks in the mid-2020s with full carbon neutrality by mid-century. These commitments collectively signal a structural shift in the global automotive industry toward electrification as the primary long-term strategy (IEA, 2023a)

2.3.6 Conclusion

Though ICEVs have lower manufacturing-stage emissions, EVs' overall lifecycle emissions are far below those of ICEVs, even accounting for EVs' higher battery-production footprint, especially with renewable energy powering them. As grid decarbonization intensifies and recycling technologies advance, the lifecycle advantages for EVs will further increase. These include regional disparities in electricity generation and integrating renewable energy, which has a great bearing on maximizing the environmental benefits of EVs to further global sustainability goals.

This study highlights the need for renewable energy integration at the EV charging stations. A shift towards a renewable energy grid makes the operational phase of EVs practically emissionless and thus eco-friendly. Challenges on the regional variation in the grid makeup and issues of scalability with recycling technologies have to be addressed to maximize lifecycle emission cuts that EVs can provide. This is necessary for making EV uptake align with global climate targets plus achieving sustainable transport systems.

2.4 Optimization Models for Renewable Energy Mix

Incorporating renewable energy into EV charging infrastructure requires carefully designed optimization frameworks capable of balancing resource availability, cost efficiency, and grid reliability while targeting minimum lifecycle carbon emissions (Barman et al., 2023). Optimization frameworks are designed to correctly balance supply and demand under highly uncertain renewable sources of solar and wind power, focusing on their ability to ensure stability and scalability. Unlike many prior models that focus solely on minimizing cost or emissions under fixed energy targets, this study uniquely explores how the flexible timing of EV and renewable adoption within policy-aligned bounds affects total lifecycle CO_2 emissions.

Most existing optimization frameworks seek to blend solar, wind, and hydropower in proportions that minimize total emissions. Solar carries the largest share of this combination due to its rapidly declining costs and scalability, though its variability during nighttime and overcast conditions requires complementary wind and hydro sources to maintain stable supply (Rana et al., 2025). Hydropower and nuclear enhance grid stability by providing reliable baseload power, particularly in regions with suitable water resources.

Energy storage solutions are a critical component of these optimization models, addressing the intermittency of solar and wind power. Lithium-ion batteries, pumped hydro storage, and even more new options like solid-state batteries are used to make sure there is always enough power. For example, pumped hydro storage helps large systems with renewable energy keep the right balance between how much energy is made and used. Even more advanced models think about the grid infrastructure because of the need for upgrades to handle high levels of renewable energy penetration (Rana et al., 2025).

Another important facet of these models is cost optimization. Whereas the costs of solar and wind have come down, the initial investments needed for storage and grid upgrades are still high. Most models, therefore, contain a cost-benefit analysis that identifies the economically viable pathways for renewable integration. These frameworks also consider policy incentives, such as federal tax credits, which offset costs and accelerate deployment (U.S. Department of Energy, 2021b).

Despite these advancements, most optimization models are limited in one way or another. Most work under ideal conditions and do not consider real-time factors such as fluctuating energy demand, weather variability, and shifting policy conditions. Most of them also lack region-specific customization, which is necessary given the geographic diversity of renewable resources in the United States. For instance, states with rich solar resources, such as California, need different approaches than wind-dominated regions like Texas and Iowa.

These are the gaps that future optimization models should fill by integrating regional data and dynamic factors like real-time energy demand and weather patterns. New technologies such as AI and machine learning promise to help improve models' accuracy and adaptability. These allow an optimization framework to dynamically adjust the energy mixes and storage strategies for a more reliable and efficient renewable-powered EV infrastructure.

Optimization models are indispensable for attaining the full potential of renewable energy integration into the EV charging system, tackling the technical, economic, and regional challenges involved in developing a sustainable and scalable renewable-powered EV infrastructure aligned with climate goals at the national and global levels.

2.5 Policy and Technological Interventions

Renewable energies and EV charging infrastructure would face serious challenges without rigorous policy frameworks and continuous technology innovations. Federal and state-level policies in the US accelerate renewable energy adoption and facilitate EV infrastructure development. Most measures try to overcome these economic and logistic challenges by using renewable-powered systems with more innovation to transcend technical barriers.

The Inflation Reduction Act and the Bipartisan Infrastructure Law together provide the most significant federal commitment to clean energy, directing tax credits toward solar and wind installations, grants for EV charging deployment, and funding for grid modernization. These provisions reduce the upfront cost of clean energy projects and are designed to attract private sector co-investment (U.S. Department of Energy, 2024b). California's ZEV mandate, for example, has set very high targets for EV adoption. Other states have programs similar to New York and Oregon that help align EV adoption with clean energy goals and provide a good environment for bringing in renewable sources onto the grid.

Technological developments are also important to address the challenges of renewable energy integration. Energy storage solutions (currently lithium-ion batteries and possible alternatives such as redox flow batteries) are essential to overcome fluctuations in solar and wind energy supply. Such systems can store excess energy generated during peak production periods for use by electric vehicle charging stations that require a stable power supply. Pumped hydroelectric power plants remain a cost-effective option for large-scale energy storage in areas with special geographical conditions (Rana et al., 2025).

While it is still evolving, the Smart Grid is emerging as one of the tools that help integrate renewables with EV infrastructure. Applying advanced communication and automation systems optimizes energy flow, harmonizes supply and demand, and reduces congestion on smart grids. The system supports real-time monitoring and control of renewable energy generation and EV charging, ensuring efficiency and reliability. In addition, artificial intelligence and blockchain are being studied to improve energy management and ensure secure and transparent transactions in decentralized systems (International Renewable Energy Agency, 2023).

Despite the above progress, several issues still hinder the expansion of renewable energy systems to meet the growing demand for EV charging: high upfront costs for storage and grid expansion, inconsistent government frameworks, and regulatory barriers. For example, the lack of unified

standards for grid connection and energy trading makes smooth integration difficult. Addressing these challenges requires coordinated efforts among federal and state governments, private sector stakeholders, and research institutions.

Public-private partnerships have proved to be a driver for renewable energy projects. These partnerships merge public funding with private sector expertise, enabling the joint development of renewable-powered EV charging infrastructure at lower costs while keeping projects in line with energy demand. For instance, utilities partnered with manufacturers of electric vehicles to provide creative charging solutions using renewable energy sources.

Overall, policy and technological interventions are essential in making the change towards renewable-powered EV infrastructure feasible. Such steps can break down present obstacles, encourage creativity, and build a green, low-carbon transit system in accord with domestic and world climate goals.

2.6 Overview of Green Energy

Since the U.S. electrical consumption has expanded significantly in recent years due to soaring demand from cloud computing centers and other sources, the need for more renewable energy production has become more pressing. Nonetheless, several obstacles still impede implementation, including insufficient grid capacity and lengthy interconnection lines, concerns with permits and siting, exorbitant borrowing rates, and persistent supply chain problems. Federal policy headwinds added further uncertainty during this period, with proposals to restrict wind energy permitting and scale back major clean energy and infrastructure legislation creating new risk for deployment timelines precisely when the sector needed to be moving faster (Bird et al., 2025).

The U.S. is a resource-rich nation with a wealth of renewable energy sources. Renewable energy resources are available in every part of the nation. The gap between the United States' renewable energy potential and its actual use is striking. Brooks (2022) estimated that technically exploitable resources amount to roughly 100 times the country's total annual electricity consumption, yet in 2020 the nation tapped less than 0.2% of that available capacity for power generation, a figure that illustrates how much room remains for expansion. Federally recognized Tribal lands are located within 10 miles of more than 9 percent of the nation’s renewable energy resources. The country’s most plentiful renewable energy sources are solar, wind, and

geothermal (Figure 2). Mid- and low-latitude regions have the highest concentrations of solar energy; the Central Plains and coastal shores are dominated by wind energy, the Pacific Northwest and eastern half are home to biomass and hydropower, the Pacific Coast produces the most ocean energy, and the Western states have the most geothermal resources. The growth of current technological deployment, generation, delivery, and research endeavors will facilitate access to these renewable energy potentials.

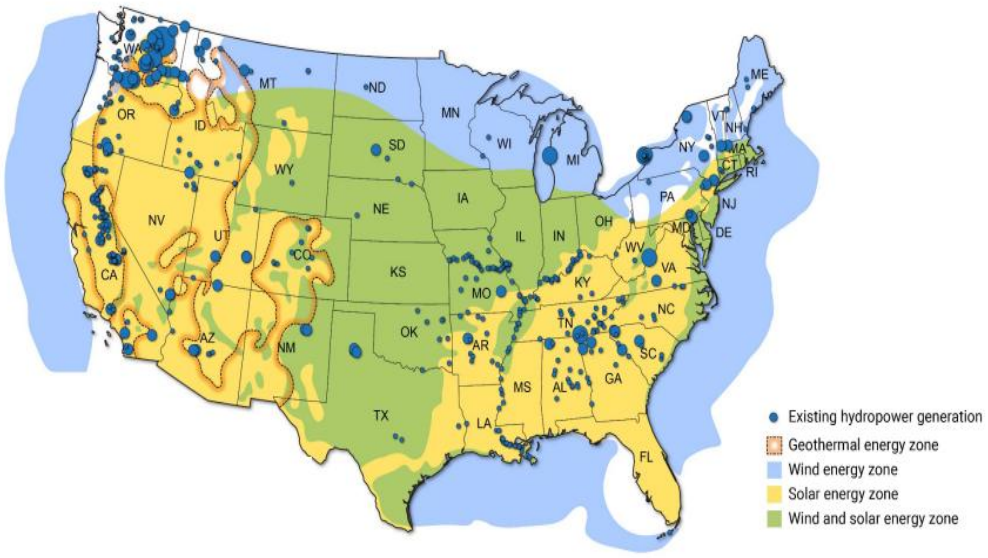

Figure 2: Abundance of clean energy (Source: Brooks, 2022)

After 2023's record-breaking results, 2024 was yet another outstanding year for the U.S.'s deployment of sustainable energy. Given that the great majority of new grid additions come from renewable sources and battery storage, these increased trends indicate that clean electricity sources are becoming an increasingly important component of the American economy and power system (Figure 3). The year 2024 saw solar installations surpass 2023's record installations, adding an anticipated 39.6 gigawatts (GW) of capacity, up from 27.4 GW in 2023. Approximately 220 GW of solar capacity has been installed in the United States, sufficient to supply more than 7% of the country's electricity. With a total installed capacity of over 29 GW, battery storage almost doubled in 2024 and is expected to increase by an additional 47% in 2025 (Bird et al., 2025). With only 5.3 GW of new wind capacity added in 2024, much less than in prior years, onshore wind capacity expansion has slowed. By the end of 2024, installed wind capacity was 153 GW.

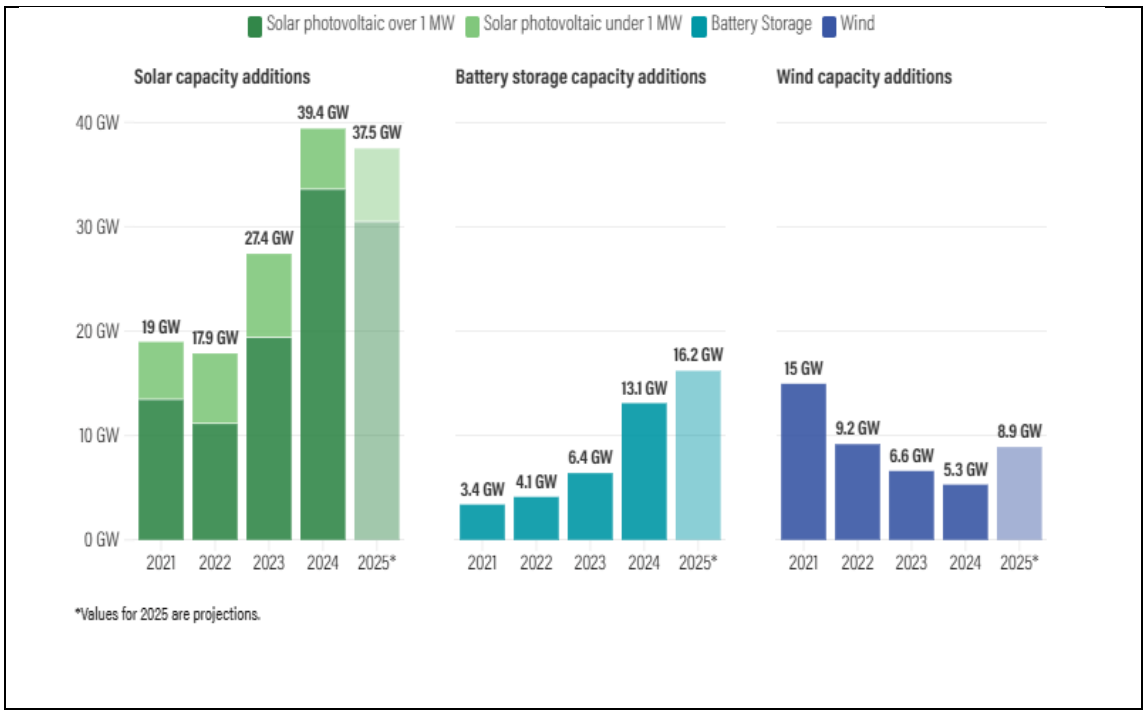

Figure 3: Renewable energy annual capacity additions (Source: Bird et al., 2025)

In 2024, nearly 44% of electricity came from carbon-free sources, including nuclear power, while nearly 25% came from renewables, such as small scale solar. According to Bird et al. (2025), 60–70 GW of new renewable energy sources annually over the next ten years, along with additional carbon-free power sources, would be needed to reach 90% or more carbon-free electricity by 2035, which is a crucial component of creating a clean energy economy. Although the United States made significant headway last year, installing over 45 GW of combined wind and solar power, further increases in carbon-free generation are still required to meet grid decarbonization ambitions.

2.6.1 Wind

As of 2023, the installed capacity of U.S. onshore wind resources was over 144 GW, with a potential capacity of 9,124 GW (Department of Energy (DOE), 2023; Lopez et al., 2021). With a 42 MW current capacity and the potential for 4,249 GW offshore wind resources, the development pipeline included more than 50,000 MW of projects in 2023 (DOE, 2023; Lopez et al., 2022). Due to supply chain strains, rising borrowing rates, interconnection, siting issues, and eliminating the Production Tax Credit (PTC), the United States installed over 8.5 GW of wind power in 2022, the least amount since 2018 (DOE, 2023). Although the PTC has had a

significant impact on wind development, investment fluctuates from year to year due to cycles of legislation enactment and expiration (Center for Sustainable Systems, 2024). The EPA (2025) estimated. U.S. wind turbine in 2022 displaced approximately 3,800 metric tons of CO_2-equivalent emissions annually by substituting for fossil fuel generation on the grid. A total of 404 GW of wind capacity would prevent 12.3 Gt of CO2 emissions by 2050, a 14% decrease from 2013, and meet 35% of the country's electricity consumption (Center for Sustainable Systems, 2024).

2.6.2 Hydroelectric

In 1997, net electricity production from standard hydropower peaked in the United States at 356 TWh/yr; in 2023, hydropower accounted for 240 TWh/yr of U.S. electricity (Center for Sustainable Systems, 2024). Hydroelectricity is almost emission-free, but the decomposition of vegetation in the reservoir releases methane and CO2. Ecological concerns can be addressed through design choices such as run-of-river configurations and more fish-compatible turbine designs, which reduce environmental disruption without significantly compromising hydropower's contribution to low-carbon electricity supply (Center for Sustainable Systems, 2024).

2.6.3 Geothermal

Geothermal energy resources principally hydrothermal steam and hot water from underground reservoirs are concentrated in the western United States, Alaska, and Hawaii, where they can generate baseload electricity with very low lifecycle emissions (Center for Sustainable Systems, 2024). Because subsurface temperatures at shallow depths remain relatively stable year-round, ground source heat pumps (GSHPs) can be deployed across virtually all geographic regions for efficient space heating and cooling. With more than 1.7 million units installed in the U.S., GSHP use has increased by 3% yearly (IEA Geothermal, 2021). By 2050, 28 million households might be served by GSHPs for residential heating and cooling (DOE, 2019). In 2022, the United States had about 4 GW of installed geothermal power capacity, representing roughly one-quarter of the global total (IRENA, 2023). Geothermal electricity generation in the United States is projected to increase from 15.6 billion kWh in 2022 to about 37.2 billion kWh by 2050 (Center for Sustainable Systems, 2023). In addition, the United States had 23 geothermal district heating systems in operation as of 2022, while the long-term economic potential has been estimated at up

to 17,500 geothermal district heating installations by 2050 (U.S. Department of Energy, 2021a; U.S. Department of Energy, n.d.).

2.6.4 Solar

In 2022, the United States produced 1.9% of PV modules and 0.7% of PV cells worldwide (IEA PVPS, 2023). Over the past decade, U.S. solar capacity grew at an average annual rate of approximately 22%, reaching roughly 180 GW by 2022. In 2023 alone, a record 32.4 GW of new solar capacity was added, the first time in eight decades that a single energy technology accounted for the majority (53%) of new U.S. generating capacity (Center for Sustainable Systems, 2024). Over the next ten years, PV deployment is anticipated to quadruple to 673 GW (Solar Energy Industries Association (SEIA), 2024). By 2030, the DOE's SunShot Initiative seeks to cut the cost of solar energy by 50%, which is expected to result in 33% of the United States' electricity demand being supplied by solar power and an 18% reduction in greenhouse gas emissions from the electrical sector by 2050 (Center for Sustainable Systems, 2024).

2.6.5 EV Prevalence

In addition to utilities setting new records for battery storage installations in the power sector, battery electric vehicles are also becoming more popular in the United States. In 2024, 1.3 million EVs were sold, making up around 8.7% of all new automobile sales (Bird et al., 2025). Even though a record number of EVs were sold overall, the growth pace of EV sales is still slower than in prior years. Only 7.3% more EVs were sold in 2024 than in 2023, less than the 49% rise between 2022 and 2023 (Bird et al., 2025). In 2024, the U.S. added more than 37,700 charging connections, including 12,500 fast chargers, further advancing its EV charging infrastructure. According to Bird et al. (2025), the nation has about 204,000 charging stations open. However, additional charging stations are required to fulfill the increasing demand. States gave $330 million to EV charging developers in 2024 as part of the National Electric Vehicle Infrastructure (NEVI) initiative, demonstrating the ongoing public and private investment in this sector.

2.6.6 Electric Capacity Mix Shifts

According to the Annual Energy Outlook 2023, the U.S. power system will almost double in size between 2022 and 2050 to accommodate the growing electricity demand, where the majority of newly constructed capacity will come from renewable energy sources. When constructing new

electricity capacity, renewables are becoming more and more cost-effective when compared to the alternatives due to declining capital costs for solar panels, wind turbines, and battery storage as well as government subsidies like those provided by the Inflation Reduction Act (IRA). Through 2050, the demand for electric power in the United States will continue to expand steadily due to economic expansion and increased electrification in end-use sectors. Throughout the forecast period, renewable energy sources will increasingly meet electricity demand, while nuclear, coal, and natural gas output shares will decrease. In this context, total installed power capacity nearly doubles in most situations, including the Low Economic Growth case, to meet the growing electricity demand (Figure 4). Because solar and wind have lower capacity factors than coal, nuclear, and combined-cycle plants, cases with a more significant proportion of renewables in the generating mix have larger overall grid capacity (Energy Information Administration (EIA), 2023). Although regional resource availability causes different renewable resource mixes across areas, renewable electricity capacity will rise in every region of the United States. Wind will provide for 40–60% of the Mid-Continent region's renewable power capacity in 2050, while the Southeast and the CAISO-managed region (California) will have high solar power and a negligible amount of wind power capacity overall. Across most Independent System Operator regions, solar power makes up a significant portion of renewable capacity, with wind contributing a comparatively minor share.

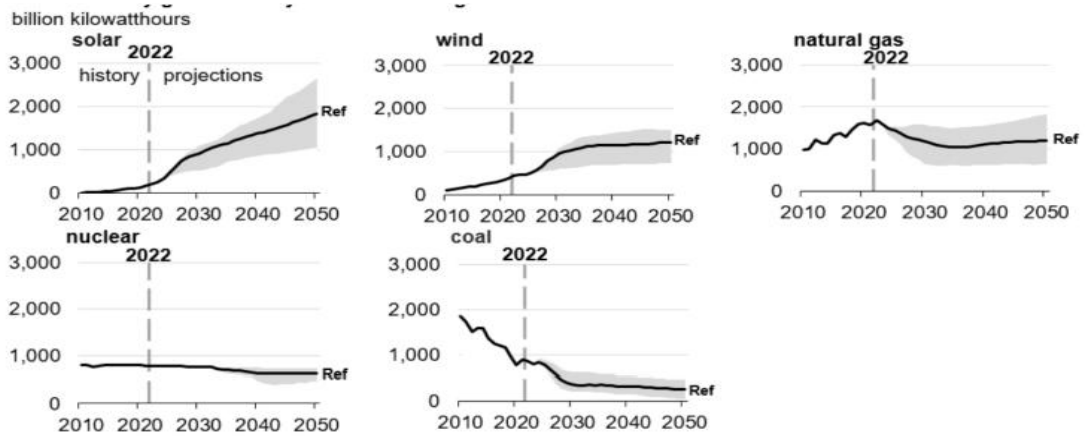

Figure 4: Electricity generation over different technologies (Adapted from U.S. Energy Information Administration [EIA], 2023, Annual Energy Outlook 2023: Narrative).

As coal units continue to be retired and natural gas-fired output grows slowly, the overall percentage of fossil fuel-fired power generation falls from 60% to 44% in the AEO2023 Reference case. In the Reference case, the amount of coal used in the U.S. electric power

industry decreases from 458 million short tonnes (MMst) in 2022 to 189 MMst in 2030 and 131 MMst in 2050. In the Low Zero-Carbon Technology Cost (Low ZTC) scenario, coal disposition, which includes exports and intake by the electric power industry and other end-use sectors, drops to 170 MMst in 2050. The proportion of natural gas in the overall generating mixes falls marginally, from 37% in 2021 to 34% in 2050, despite an absolute increase in natural gas-fired power.

Due to their negligible fuel costs, wind and solar generating outperform other technologies for system dispatch once they are constructed and the resource is available. In 2050, 160 gigawatts (GW) of standalone battery storage capacity will be deployed in the Reference case; in the other situations, deployment ranges from 40 GW to 260 GW (EIA, 2023a). Consequently, by 2050, 44% of the power generated in the United States will come from renewable sources, up from 21% in 2021 (Figure 5). This rise in renewable energy mainly consists of new wind and solar electricity. Until 2050, hydro and nuclear share of the overall power output is stable, while the combined share of other renewable energy sources, such as geothermal and biomass, is still less than 3% (EIA, 2022b). By the early 2030s, the combined contribution of all solar generation, both utility-scale and small-scale rooftop end-use systems, will exceed wind generation. Federal tax credits scheduled to expire or drastically decrease by 2026 are the primary driver of early development in wind and solar, although both short- and long-term growth are greatly influenced by the lowering prices of these technologies.

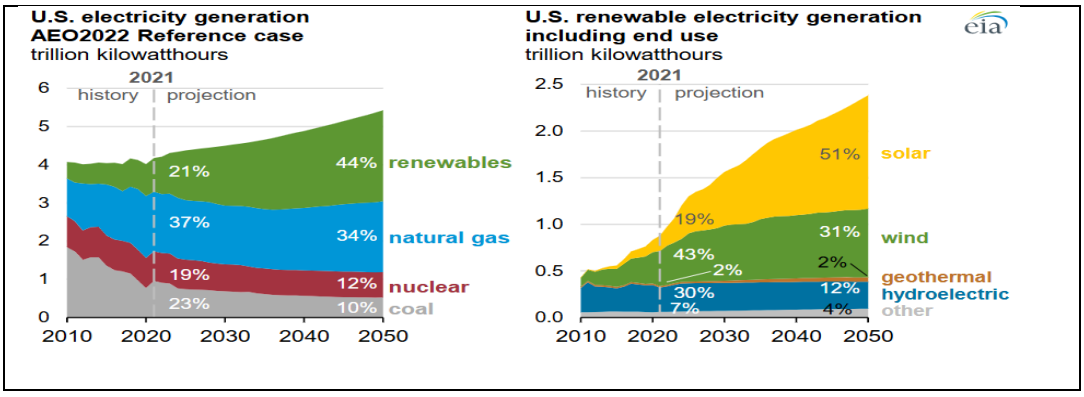

Figure 5: Electricity projections (Source: EIA, 2022b)

The Reference example shows that overall energy consumption, including electricity use and losses associated with electricity, can rise by up to 15% between 2022 and 2050. In this sense, during the projected period, the number of passenger car miles driven in the United States will

rise between 12% and 33% in tandem with population and income. In the Reference example, 2050 vehicle miles are 23% more than 2022. Fuel economy improvements will cause the anticipated energy consumption of light-duty vehicles (LDVs) to decrease until the early 2040s, but for the rest of the forecast period, it will increase due to rising vehicle miles traveled (Figure 6).

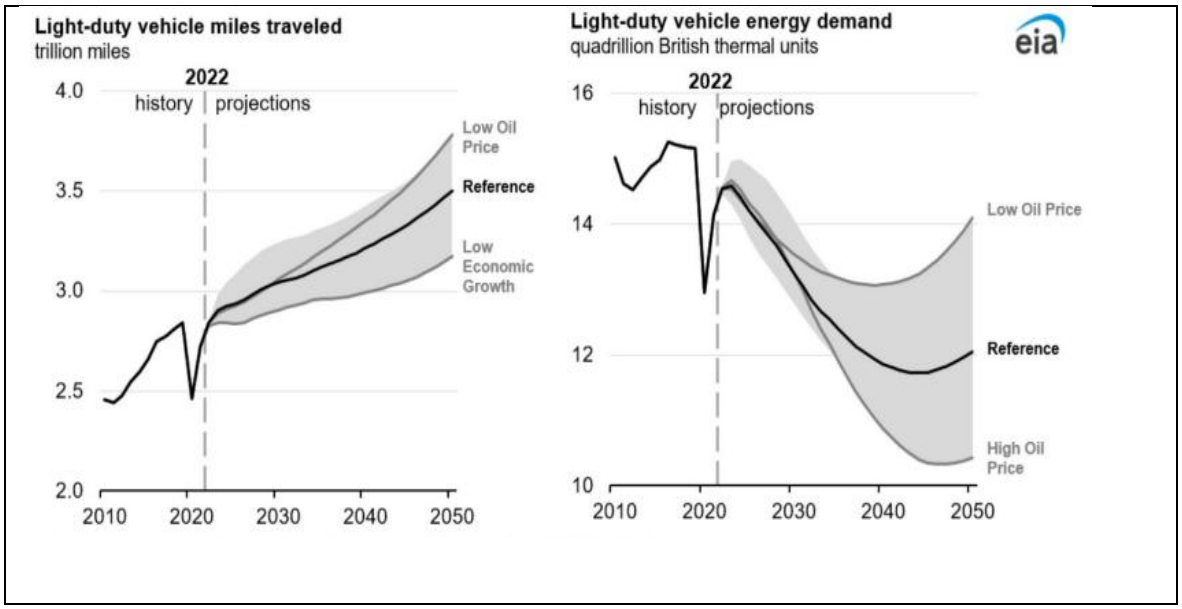

Figure 6: LDV projections (Source: EIA, 2023a)

2.6.7 Total Cars in the U.S.

In 2023, there were 1.4 million new electric car registrations in the U.S., a more than 40% increase over 2022. The demand for electric automobiles and absolute growth remained strong in 2023 despite slower relative annual growth compared to the previous two years. According to the IEA's Global EV Outlook (2023), keeping EV sales growth at the pace seen in the early 2020s would be enough to put U.S. light vehicle CO_2 emissions broadly in line with what a net-zero-by-2050 pathway requires. An estimated 420 million cars are expected to be produced between 2024 and 2050 (Figure 7). It is anticipated that light cars powered by regular petrol will continue to be the most popular vehicle class in the U.S. in 2050, accounting for around 11.36 million sales (Carlier, 2023). Sales of gasoline-powered vehicles are predicted to decline gradually from 2021 to 2050. On the other hand, battery-electric vehicle sales are expected to increase gradually and rank as the second most common fuel type in the United States by 2032.

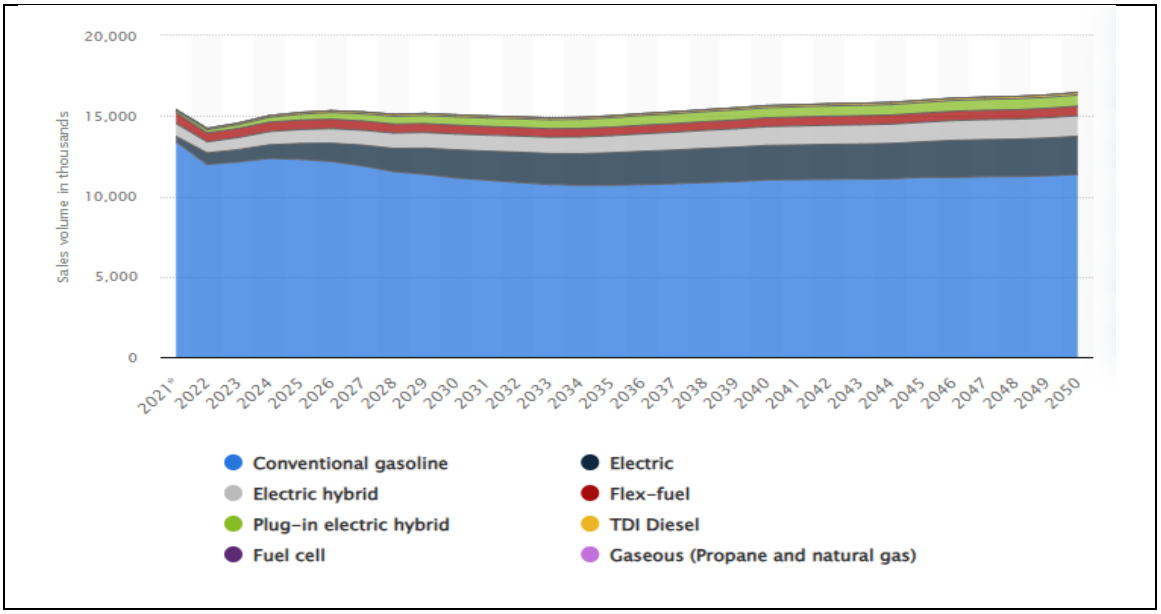

Figure 7: Projected light vehicle sales (Source: Carlier, 2023)

Ideally, up to 90% of American automobiles would be electric by 2050 to fulfill climate targets. It is anticipated that the average car will continue to accumulate more miles during the ensuing decades. However, only 51% of all vehicles on the road in the U.S. will have to be electric by 2050 to fulfill the emissions objectives outlined in the worldwide Paris Accord, assuming travel demand remains unchanged from its current levels. The International Energy Agency set this target in 2017 through its EV30@30 campaign, which called for a 30% share of new automobile sales by 2030. According to Astute Analytics (2024), the worldwide electric vehicle industry is expected to expand at a compound annual growth rate (CAGR) of 21.73% between 2024 and 2050. Although precise slow-growth estimates are not easily accessible in the slow scenario, elements like policy changes may influence a more gradual adoption rate, the state of the economy, and technology improvements.

Approximately 296.6 million automobiles were on American highways as of the last quarter of 2024, up from 292.3 million in 2023 (Carlier, 2024). In the meantime, the U.S. sold roughly 14.5 million new cars and light-duty trucks in 2020. This number increased in 2021 and 2023, and as of right now, just over 16 million new cars are expected to be sold in the U.S. in 2025 (EIA, 2024b). The U.S. light-duty vehicle fleet is projected to grow from approximately 270.3 million vehicles in 2025 to about 334.8 million by 2050 (U.S. Energy Information Administration, 2026).

2.6.8 Gas vs. Electric Cars

In May 2024, gasoline vehicles held 82.4% of new U.S. vehicle sales while battery electric vehicles represented 6.8%. When plug-in hybrids (PHEVs) are added at 1.7% of sales, the combined electrified vehicle share reached 8.5% (Montoya, 2024). However, considering the total number of vehicles in the fleet, the overall percentage of EVs is lower. As discussed above, meeting long-term climate targets would require a substantial share of the fleet to be electric by 2050, though the exact percentage varies depending on which benchmark is used. Regardless of the specific target, achieving it would require a significant annual increase in EV adoption rates. Detailed yearly sales projections are not readily available, but reaching 90% of new car sales by 2050 would require very steep year-over-year growth in EV sales for most of the remaining transition period.

Battery prices dropped to record lows and were projected to fall by another 40% through 2025, with the range of available EV models continuing to grow during that period (Case, 2024). State-level policy also played a reinforcing role, with at least 17 states putting in place zero-emission vehicle requirements stricter than federal standards and strengthening near-term purchase incentives for consumers (Case, 2024). Nearly 60% of used EV postings are under $30,000, indicating that the market is becoming more reasonably priced (Case, 2024). The IEA projected BEV market share to reach between 13% and 14% of new vehicle sales by 2030 on a BEV-only basis; factoring in plug-in hybrid sales would push the total electrified vehicle share toward 50% of the 2030 market (IEA, 2024). The number of EVs in the U.S. is expected to increase sharply over the coming decades, driven by falling battery costs, expanding model variety, and state-level zero-emission mandates (IEA, 2024).

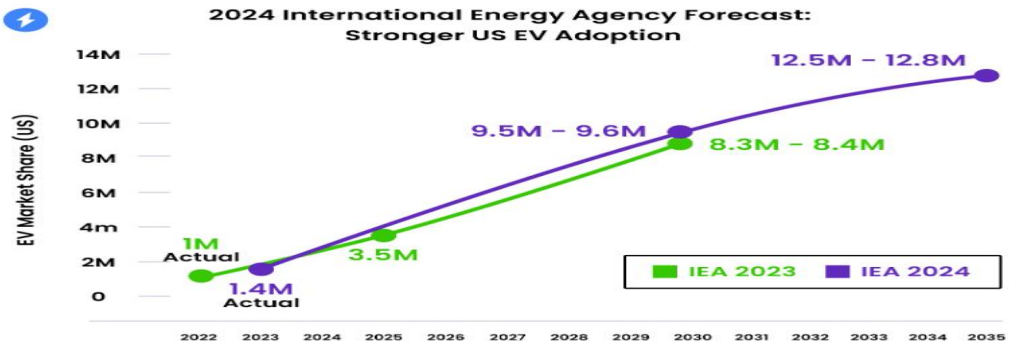

Figure 8: Projected EV market share (Source: Case, 2024)

2.6.9 Miles Driven

The Federal Highway Administration's Highway Statistics 2024, Table VM-1, reports the average miles traveled per light-duty vehicle as 10,787 miles in 2024 (Federal Highway Administration, 2026). For the purposes of this study, this figure is adopted directly and applied equally to both electric and gasoline vehicles.

States have very distinct driving behaviors. At 21,589 miles, Wyoming has the highest average yearly mileage per driver in the U.S., while New York has the lowest average among the 50 states, with drivers traveling 9,548 miles annually. Drivers in Wyoming cover more than twice as much ground as New York drivers (Federal Highway Administration, 2022). Washington, D.C., reported separately from the states, has an even lower figure, with drivers there averaging only 6,694 miles. Some studies report a gap between EV and gasoline-vehicle annual mileage, with EV averages ranging from 6,300 to 12,522 miles depending on region and use case (Zhao et al., 2023). This dissertation nonetheless applies the FHWA's single average of 10,787 miles per year equally to both vehicle types, consistent with the modeling approach described above and carried through Chapters 3 and 4.

In 2019, electricity produced by wind turbines overtook hydropower as the most common source of renewable electricity in the United States. Thus, hydroelectricity, solar power, and wind power are the nation’s top three renewable energy sources. By 2050, any LDV with a charging port will account for 31% of the world’s LDV fleet, or 672 million cars, up from 0.7% in 2020 (EIA, 2021). The global conventional petrol and diesel LDV fleet will peak in 2038 due to a substantial rise in EV sales and sales shares. Therefore, areas with a more significant proportion of renewable energy may have a higher percentage of EV charging, albeit detailed national data remains limited. Significant yearly growth rates in solar, wind, and hydro capabilities are needed to raise the proportion of power generated by renewable energy sources by 2050 (EIA, 2021). Policy choices, technology developments, and investment levels affect specific growth rates.

2.6.10 CO_2 Emissions

Although the sophisticated batteries found in electric cars are made to last a long time, they will inevitably degrade. Several electric vehicle manufacturers provide eight years’ battery warranties and 100,000 miles. Batteries made today can survive anywhere from 12 to 15 years in moderate temperatures and 8 to 12 years in harsh climates. Battery cell chemistry and design, driving and

charging habits, and the vehicle-battery-environment thermal system are additional elements that affect battery longevity and climate. Consequently, modern LDVs (or PHEVs in electric mode) can achieve over 130 miles per gallon of petrol equivalent (MPGe) and 100 miles using only 25 to 40 kWh, depending on how they are driven.

Electricity has a great potential to reduce greenhouse gas emissions. While EVs themselves emit no emissions, the process of producing the electricity needed to run the car is probably going to pollute the air. Compared to today's ICE-powered cars, EVs can cut greenhouse gas emissions by roughly 33% if electricity is produced using the present average production mix in the United States, and transport emissions might be reduced by 26 to 30 percent overall if 56 percent LDV penetration is achieved by 2050. However, the energy required to charge EVs will surpass 270 billion kilowatt-hours by 2030 in the U.S. alone (Ali et al., 2024). Achieving clean and carbon-free transportation systems is hampered by the significant energy requirements for EV charging. According to Life Cycle Assessment (LCA), UK power generation emissions were 43 g CO2 per km, consistent with the 41.2 g CO2/km figure reported by Mehlig et al. (2022). According to the LCA, more than half of the BEV's life cycle emissions came from the vehicle and battery manufacture, which produced CO2 emissions of 48 g/km. Total BEV CO2 emissions would rise by 9.5 g/km, or 11%, assuming the current incremental impact of EV charging continued for the duration of the BEV's life (Mehlig et al., 2022). For context, the LCA's findings remain unchanged because the lifetime emissions of the BEV would need to rise by 142 g/km or 162 g/km, respectively, to match those of petrol and diesel ICE (Mehlig et al., 2022). Hence, every new BEV adds a new load to the electrical grid in the short term, necessitating a rise in output from the only partially operational plants. Over time, every car adds to the total need for BEV charging. Through the construction of additional infrastructure, the energy grid can support the fleet-wide pattern of charging demand captured by the national charging profile.

Vehicle use will continue to account for most CO, NOx, and CO_2 emissions in scenarios where EV expansion follows baseline and slow routes. By 2050, the Fast RE-Baseline EV and Fast RE-Slow EV scenarios ascribe over 75% of CO, 64% of NOx, and 54% of CO_2 emissions to vehicle use (Li et al., 2025). By 2050, fast EV development will cause the vehicle energy supply chain to overtake vehicle use as the primary source of these emissions when renewable electricity (RE) expansion follows baseline, slow, and medium trajectories. Under the Baseline and Slow EV scenarios, on the other hand, vehicle manufacture will continue to be the primary source of

PM2.5, PM10, and SO_2 emissions, but as EV development picks up speed, battery production will take over as the primary source (Li et al., 2025).

2.6.11 Emission factors for vehicle production

Emission considerations for vehicle production include emissions generated throughout the vehicle's manufacture, operation, and disposal. Lifecycle emissions from vehicles include production, transportation, fuel refining, and electricity generation. In addition, the recyclability of components and the proportion of recyclable material used have a substantial impact on lifecycle emissions, while environmental repercussions arise during the extraction, manufacture, refining, transportation, and combustion of the fuels used in petrol and diesel cars.
When ICE-powered and electric vehicles are disposed of, they emit the same amount of pollutants. As a result, the comparison between combustion engine vehicles and EVs is focused on the emissions produced during their manufacturing and operation. Estimates vary considerably by vehicle segment: production of an average compact car emits approximately 2 metric tons of carbon, while a premium or luxury vehicle can emit approximately 17 metric tons (O'Malley & Slowik, 2024). This dissertation adopts the mid-range figures used throughout its model: 10 metric tons of CO2 for ICE vehicle production and 15.3 metric tons for EV production, consistent with the Argonne GREET-based factors applied in Chapter 3. Turning to annual operational use, the average fuel-powered car emits 5.2 metric tons of CO2 per year (O'Malley & Slowik, 2024). The figure was reached by keeping the annual commute distance at 19,300 kilometers (approximately 12,000 miles), consistent with vehicle miles traveled estimates reported by the Federal Highway Administration (2022). In contrast, an electric automobile emits 2.2 metric tons of CO2 for the same distance.

2.6.12 Emission factors for vehicle operation

Road vehicle emissions are influenced by a variety of factors, including automobile model, dimensions, engine design and capability, roadway loads, fuel type and technology, emissions after-treatment technology, driving habits, roadway gradient, and vehicle upkeep. According to the EPA (2024b), the average passenger vehicle releases approximately 400 grams of CO2 per mile, while heavy-duty vehicles produce substantially higher emissions per mile due to engine size and load requirements. LDG vehicles produced more CO2 than gasohol E20, LPG, or NGV.

Separately, Zhang et al. (2022) found that as the methanol blending ratio rises, the quantity of fuel consumed grows under stable circumstances but reduces under NEDC.

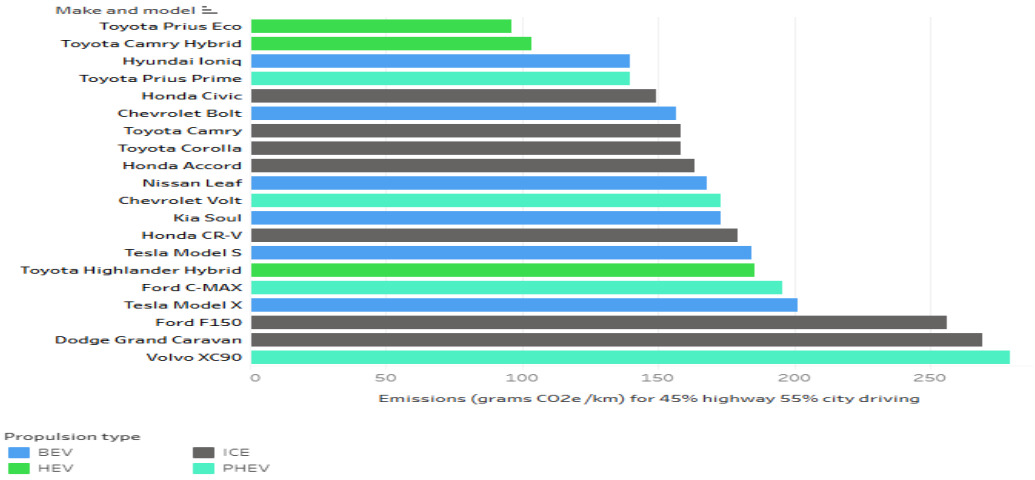

Figure 9: Fuel associated GHG emissions from selected vehicles (Source: EPA, 2024b)

ICE automobiles emit 8,887 grams of carbon dioxide in tailpipe emissions for each gallon of fuel burned. The average passenger vehicle releases approximately 400 grams of CO2 per mile (EPA, 2024b). EVs emit no tailpipe emissions, but they do have an upstream and manufacturing impact (Figure 9). EVs emit as little as 10-20 grams of CO2 each mile, depending on the exact electrical grid mix and manufacturing procedures (O'Malley & Slowik, 2024).

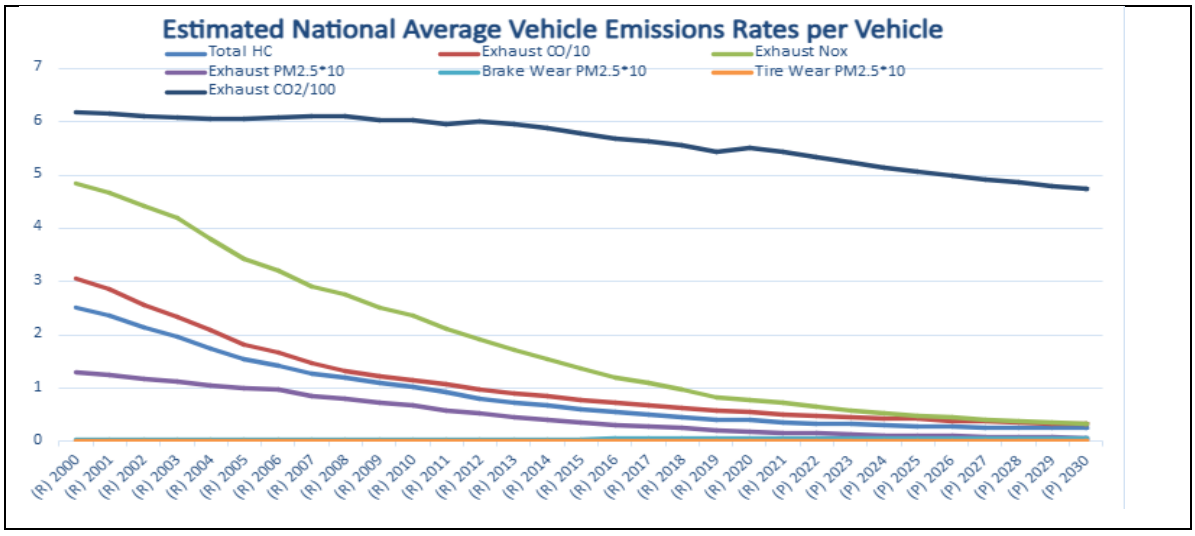

Figure 10: Average vehicle emission in US (Source: Bureau of Transportation Statistics, 2025)

Figure 10 shows the total energy consumption of different vehicles in British thermal units, starting from 2000. For gasoline vehicles, LDV recorded 4791.991 Btu/mile in 2020, which will fall to 3864.218 Btu/mile in 2030, light-duty trucks attained 6236.121 and will fall to 5192.792,

and buses recorded 21,375.366 which will fall to 19,747.427. For EVs, LDV recorded 1192.03 in 2020 and will rise to 1680.883 in 2030, LDT attained 1,669.043 and will deliver 1,680.883 in 2030, while buses attained 9210.619 which will fall to 5876.074 compared to HDD which attained 10,993.44 and will deliver 5666.19 by 2030 (Bureau of Transportation Statistics, 2025).

2.6.13 Emission factors for energy generation

A grid emission factor is a CO_2 emission factor (t CO_2/MWh) that is associated with each unit of power generated by an electricity system. It is a metric used to establish baseline emissions for initiatives in the renewable energy sector (Institute for Global Environmental Strategies, 2025). While residential solar panels typically produce about 41 g CO_2/kWh (NREL, 2022), commercial-scale solar systems tend to have slightly lower lifecycle emissions, averaging 35–40 g CO_2/kWh, due to greater installation efficiency, optimized system design, and higher energy output over time (NREL, 2022). The majority of lifecycle emissions for both systems originate from panel fabrication and are typically offset within the first few years of operation. Solar energy overall demonstrates a lifetime emission reduction of approximately 12 times that of natural gas plants and 20 times that of coal plants. In this regard, the emission factor for commercial solar energy in the United States is estimated at ~40 g CO_2/kWh, compared to 490 g CO_2/kWh for natural gas and 820 g CO_2/kWh for coal (NREL, 2022).

Meanwhile, the average amount of CO_2 emissions per kilowatt-hour (kWh) varies by energy source, with hydropower producing an average of 24 g CO_2eq /kWh, compared to 820 g for coal, 490 g for gas, 40–45 g for solar, 11 g for wind, and 12 g for nuclear (IPCC, 2014; IPCC, 2023). On average, an electric vehicle can drive approximately 3–4 miles per kWh (Federal Highway Administration, 2022), indicating that for every kilowatt-hour of electricity consumed, the vehicle can travel roughly 3 to 4 miles. Using a midpoint value of 3.5 miles per kilowatt-hour, the estimated operational CO_2 emissions amount to approximately 11.4 g CO_2 per mile for electric vehicles charged from a solar-dominated electricity mix, and about 3.1 g CO_2 per mile when powered by wind-based electricity. On an operational basis, these emission levels are substantially lower than the average tailpipe emissions of internal combustion engine (ICE) vehicles, which are estimated at approximately 400 g CO_2 per mile (EPA, 2024b).

2.7 Research Gaps and Opportunities

Though great strides have been made in the uptake of renewable energy into EV infrastructure, research and implementation strategy gaps still exist. Closing these gaps is critical to advancing renewable-powered EV ecosystems as a pathway to meeting long-term climate goals. A central gap in the literature is the limited understanding of how geographic variation in renewable resource availability constrains the scalability and equitability of EV charging infrastructure. Solar-rich states such as California and Arizona face fundamentally different planning challenges than wind-dominant regions in the Central Plains, and states with limited renewable potential or deep fossil fuel dependencies present even greater obstacles. Region-specific optimization models reflecting geographic, climatic, and economic factors would be important to address this inequity.

A related gap concerns the integration of LCA methodology into renewable energy planning for EV infrastructure. While comparative lifecycle studies of ICE and EV vehicles are well represented in the literature, analyses examining how different renewable energy mix compositions affect total lifecycle emissions including manufacturing and end-of-life stages remain limited. A more granular understanding of these interactions would enable more precisely targeted deployment strategies (O'Malley and Slowik, 2024).

This is why existing optimization models have been plagued with problems of adaptability even in real-time, missing the very essence of dynamism brought by factors such as fluctuating demand for energy, weather variability, and policy environments. Setting idealized conditions for most of these models has practically rendered many useless. The use of technologies like artificial intelligence (AI) and machine learning can make these models more accurate and flexible to take on evolving situations and behaviors by users (Rana et al., 2025).

Energy storage and grid constraints represent a third area requiring focused research attention. While lithium-ion and flow battery deployments are growing, further analysis is needed on their scalability, cost trajectories, and environmental footprint at scale. Grid modernization to accommodate high renewable penetration is both technically demanding and expensive, particularly in regions with limited existing infrastructure. Research on cost-effective upgrade pathways for underserved areas is a priority (Horesh & Quinn, 2024).

Policy inconsistency at federal, state, and local levels obstructs the implementation of renewable energy in EV infrastructure. This set-up has states pushing aggressively for clean energy goals

and providing incentives for EVs while others are not so proactive, thus making the situation quite uneven. A study on harmonizing policy frameworks and making incentives for the adoption of renewable energy would help the United States align its growth in electric vehicles with its clean energy objectives.

Issues related to public awareness and behavioral factors in the adoption of electric vehicles (EVs) and the integration of renewables are underexplored. This can be broken down into consumer preferences, charging habits, and usage of infrastructure, plus energy demand. That understanding will lead to better-informed strategies for promoting EV use and systems running on renewable energy.

These identified research gaps open up exciting pathways for knowledge and practice improvements in renewable energy-powered EV infrastructure. Future research focused on developing region-specific approaches, nonlinear deployment optimization models, and solutions to storage and policy challenges can contribute to a sustained and equitable energy transition, helping achieve national and global climate objectives while inspiring innovation in the renewable energy and transportation ecosystem.

2.8 Temporal Optimization Theory in Energy Transitions

Traditional energy transition research has largely assessed decarbonization success through terminal targets, most significantly the achievement of net-zero emissions by a predefined horizon such as 2050. Contemporary climate science, however, increasingly demonstrates that climate impact is governed by cumulative emissions over time rather than by emissions levels in any single year (IPCC, 2014; IPCC, 2023). Indeed, the Intergovernmental Panel on Climate Change shows that long-term temperature change is approximately proportional to the total atmospheric carbon dioxide stock, rather than to the annual emission rate observed at the end of a planning period (IPCC, 2014; IPCC, 2023).

Within this scientific framework, temporal optimization constitutes a central theoretical lens for evaluating energy transitions (Muratori et al., 2023). Temporal optimization refers to the deliberate sequencing and pacing of technological deployment, such as renewable electricity integration and electric vehicle (EV) adoption, to minimize cumulative lifecycle emissions throughout the transition period, rather than optimizing only the final configuration of the energy system. This perspective is consistent with recent system-level analyses indicating that transition

timing can materially shape aggregate emissions outcomes, even when long-term decarbonization targets remain unchanged (Chen & Ma, 2024).

Temporal optimization implies that the timing of electricity grid decarbonization relative to EV diffusion is as consequential as the overall scale of electrification (Arshad et al., 2022). Rapid EV uptake supported by a carbon-intensive electricity mix may generate a temporary yet substantial increase in cumulative emissions, largely driven by manufacturing-stage emissions associated with battery production (Gao et al., 2023). Conversely, postponing EV adoption despite improvements in grid cleanliness may delay near-term mitigation benefits and extend reliance on internal combustion engine vehicles (Horesh & Quinn, 2024).

Accordingly, temporal optimization theory challenges the assumption that faster transitions are inherently superior. Instead, it suggests that well-sequenced and temporally coordinated pathways can deliver lower cumulative emissions, even when identical end-year decarbonization targets are achieved. This theoretical position is the basis for the modeling strategy employed in this dissertation, which evaluates alternative transition pathways based on cumulative lifecycle carbon impacts over the period 2025‑2050 rather than end-state emissions alone (Ali et al., 2024).

2.8.1 Carbon Stock versus Flow Logic in Climate-Energy Systems

A foundational distinction in climate-energy analysis lies between carbon flow and carbon stock perspectives. Carbon flow refers to emissions released within a given period, typically measured on an annual basis, whereas carbon stock denotes the accumulated concentration of emissions in the atmosphere over time (IPCC, 2014; IPCC, 2023). Because carbon dioxide persists for decades to centuries, climate change dynamics are primarily driven by stock accumulation rather than short-term emission flows (IPCC, 2014; IPCC, 2023).

Many policy frameworks and energy models adopt a flow-oriented logic by emphasizing annual emission reductions or terminal-year benchmarks. While useful for monitoring progress, such approaches risk understating the long-term climatic consequences of delayed or poorly sequenced mitigation efforts (Muratori et al., 2023). In contrast, a stock-based logic recognizes that earlier emissions reductions yield disproportionately larger climate benefits, as they prevent cumulative atmospheric buildup at earlier stages of the transition (Congressional Budget Office, 2022).

In the same context, this difference is particularly prominent in connection with the transition to electric vehicles. Although EVs eliminate tailpipe emissions during operation, their lifecycle emissions, particularly those arising from vehicle manufacturing, battery production, and end-of-life processes, are front-loaded during early deployment phases (Arshad et al., 2022). When such emissions coincide with carbon-intensive electricity generation, the resulting increase in atmospheric carbon stock may offset near-term operational gains (Gao et al., 2023).

By adopting a stock-oriented analytical framework, this study evaluates transition pathways according to total cumulative lifecycle emissions, rather than annual profiles or terminal decarbonization levels. This approach aligns with IPCC-endorsed climate metrics and offers a stronger basis for assessing the true mitigation effectiveness of alternative energy transition strategies (Squalli, 2024).

2.9 Transition Dynamics

Energy transitions are inherently non-linear processes shaped by technological inertia, infrastructure constraints, and socio-economic feedbacks (Muratori et al., 2023). Two complementary theoretical perspectives, path dependency and transition management, together provide a coherent framework for explaining why gradual, adaptive transition pathways may outperform abrupt or strictly linear strategies in complex energy-transport systems.

2.9.1 Path Dependency

Path dependency theory posits that early-stage decisions can constrain future system evolution by locking infrastructures, technologies, and markets into specific trajectories (Gao et al., 2023). In the case of transport electrification, rapid deployment of electric vehicles before sufficient decarbonization of the power grid can increase upstream emissions linked to fossil-based power generation and reduce the efficiency of subsequent renewable integration (Horesh & Quinn, 2024).

Once such carbon-intensive pathways become embedded, reversing them entails rising costs due to sunk investments in infrastructure and technology. This perspective underlines the risks associated with poorly sequenced transitions and highlights the importance of synchronizing EV diffusion with parallel reductions in electricity carbon intensity (Muratori et al., 2023).

2.9.2 Transition Management

Transition management theory emphasizes coordinated, phased transformation processes that align technological innovation, infrastructure development, and policy design over time. Rather than maximizing short-term deployment, this approach supports adaptive pathways that evolve in response to system constraints, learning effects, and performance feedback (Chen & Ma, 2024). Within energy and transport systems, transition management favors evaluating strategies based on cumulative emissions outcomes rather than deployment speed alone (Muratori et al., 2023). This view is consistent with policy-oriented analyses indicating that integrated planning of renewable electricity expansion and EV adoption is essential for achieving sustained emissions reductions (Ali et al., 2024).

Transition pathways that align with adaptive, phased deployment are more likely to achieve durable emissions reductions without inducing excessive early-stage manufacturing emissions or infrastructure bottlenecks (Chen & Ma, 2024). Conversely, attempts to force rapid adoption may create short-term inefficiencies and increase cumulative emissions (Gao et al., 2023). Within this theoretical framework, the optimized random search path identified in this study can be interpreted as a balanced and adaptive transition path: rather than imposing a sudden initial push or a rigid linear evolution, the stochastic optimization process explores a wide space of feasible time sequences and converges on a trajectory that aligns the pace of electricity grid decarbonization with EV diffusion dynamics, achieving the lowest cumulative life-cycle emissions over the transition horizon (Ali et al., 2024).

2.10 Summary

This chapter has presented a detailed examination of the integration of renewable energy into electric vehicle (EV) infrastructure as a crucial strategy to reduce greenhouse gas (GHG) emissions and meet global climate goals. Solar, wind, hydro and nuclear have emerged as key drivers of a sustainable EV ecosystem, each offering distinct strengths: solar energy's abundance and falling costs, wind's scalability and efficiency (especially in the Midwest), and hydropower's reliable baseload contribution despite geographical constraints.

A major takeaway is the vital alignment between renewable energy deployment and EV adoption, ensuring that EV operational emissions remain low across their lifecycle. As grids decarbonize and technologies like battery recycling improve, the total lifecycle emissions of

EVs, despite their initially higher manufacturing emissions, can be substantially lower than those of internal combustion engine vehicles.

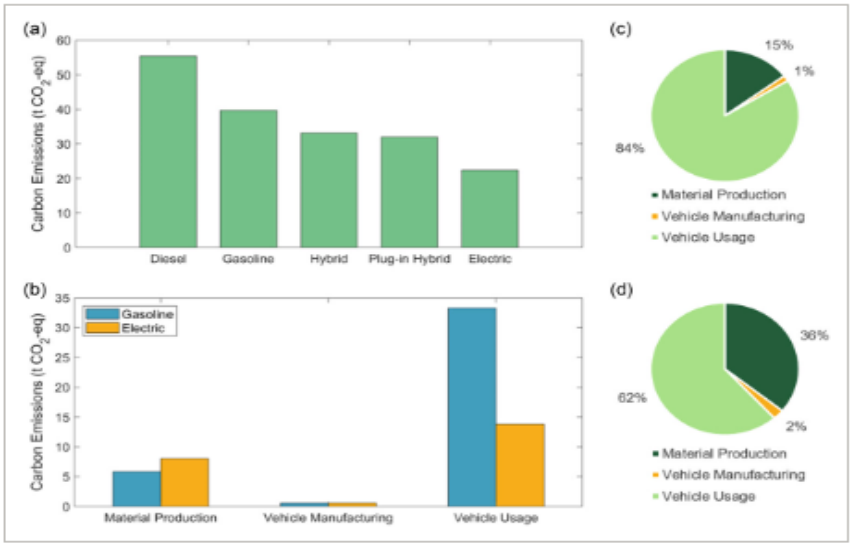

Figure 11: Comparative Lifecycle Carbon Footprint of Passenger Vehicles. Adapted from Gao et al. (2023).

Figure 11 above shows the lifecycle carbon footprint data of passenger cars, which gives a comparison of emissions by electric and gasoline vehicles in production, operation, and disposal. It has been implied that the integration of renewable energy into EV infrastructure would bring environmental benefits.

This points to the importance of continued renewable integration, energy storage innovation, and smart grid development to maximize environmental benefits.

The chapter has further demonstrated that enabling policy frameworks, financial incentives, and technological advances, including AI-assisted grid management and vehicle-to-grid integration, are essential for overcoming longstanding barriers related to infrastructure costs, deployment complexity, and regulatory fragmentation. Addressing the identified research gaps, particularly region-specific optimization and the behavioral dimensions of EV adoption, will be critical for building a resilient and equitable low-carbon transport system.

By synthesizing current literature and identifying both opportunities and persistent challenges, this chapter establishes the conceptual and empirical foundation for the methodological framework and optimization analysis presented in the following chapters.

CHAPTER THREE MATERIALS AND METHODS

3.1 Introduction and Research Design

This study adopts a quantitative computational optimization modeling approach, an advanced methodological framework aimed at analyzing alternative temporal pathways of the energy transition and the transport sector (Bakioglu, 2025), and at identifying the optimal trajectory that achieves the minimum possible level of cumulative carbon dioxide emissions over the period from 2025 to 2050.

Unlike conventional studies that concentrate on meeting fixed targets in a single terminal year (such as 2050), this research is grounded in a fundamental scientific assumption that climatic impact is determined by the cumulative stock of emissions, rather than by emission levels in any single year. This assumption is supported by findings reported in the literature on climate change and long-term environmental impacts (IPCC, 2014; IPCC, 2023).

The objective of the model therefore extends beyond merely attaining a clean electricity grid and low-carbon transport fleets. Instead, it seeks to achieve this transformation according to the most effective temporal sequencing. To accomplish this, the study adopts a multi-path algorithmic framework (Kühnbach et al., 2020), within which three independent algorithms are employed to model the energy transition. This framework enables a comparative assessment of different transition patterns, linear, abrupt, and stochastic, thereby reducing methodological bias associated with reliance on a single transition pathway and strengthening confidence in the results.

3.2 Data Sources and Core Inputs

The computational model employed in this study is based on a set of reliable secondary data sources that serve as the baseline for modeling and optimization. These data sources include the following:

3.2.1 Electric Vehicle Fleet and Market Penetration Data

Data on the number of registered electric vehicles in the United States and their growth rates were derived from Edmunds reports, which document the rapid expansion of the electric vehicle fleet in recent years (Edmunds, 2025).

In addition, data published by the International Council on Clean Transportation (ICCT) regarding electric vehicle sales and market shares up to 2024 were used to calibrate the early-stage adoption trajectory of electric vehicles during the initial years of the modeling period (ICCT, 2025).

To enhance the realism of the trajectories generated by the optimization algorithms, projections from the National Renewable Energy Laboratory (NREL) were also considered. These projections indicate that the number of electric vehicles in the United States could reach between 30 and 42 million vehicles by 2030 under scenarios involving expanded charging infrastructure deployment (NREL, 2023b). These estimates provide contextual grounding for the plausibility of the model's early-stage adoption trajectory rather than serving as a hard ceiling on total EV counts. Because the optimization is explicitly designed to search for the transition pathway that minimizes cumulative emissions by 2050, including trajectories that exceed near-term business-as-usual projections, such as NREL's, the model's resulting EV counts in later years are not bounded by this 2030 estimate.

3.2.2 Vehicle Retirement Rates and End-of-Life Emissions

The model is based on the principle of stock turnover, whereby a proportion of vehicles exiting service is retired each year. The annual retirement rate was adopted on the basis of data from S&P Global Mobility, which reported a vehicle scrappage rate in the United States of approximately 4.5% to 4.6% per year as of 2024 and 2025, reflecting the continued increase in average vehicle age to historically high levels (S&P Global Mobility, 2024; S&P Global Mobility, 2025).

With respect to end-of-life emissions from electric vehicles, the model adopts an estimated value of: EVs_Disposal = 1.3 metric tons of CO_2 per electric vehicle

This estimate accounts for emissions associated with dismantling processes, vehicle transportation, battery treatment, and recycling activities, within a life-cycle assessment (LCA) framework. Incorporating these components ensures that non-operational emissions are not overlooked in the overall emissions accounting.

This value is consistent with end-of-life disposal estimates in the Argonne National Laboratory R&D GREET model (Argonne National Laboratory, 2024b), which accounts for dismantling, battery treatment, and recycling across the full vehicle lifecycle. Consistent with the discussion

in Chapter 2 that internal combustion engine vehicles and electric vehicles emit the same amount at disposal, the model applies the same value to retiring gasoline vehicles: ICEs_Disposal = 1.3 metric tons of CO_2 per vehicle (Argonne National Laboratory, 2024b).

3.2.3 Electricity Generation Mix and Emission Factors for Charging Infrastructure

Electric vehicles are not inherently emission-free, as their operational emission intensity depends on the electricity sources used for charging. The operational emissions of electric vehicles in this study are calculated based on the current and projected U.S. electricity generation mix. Historical data on the distribution of electricity generation sources were obtained from the U.S. Energy Information Administration (EIA, 2024c), alongside projections from the Annual Energy Outlook 2026 extending to 2050 (EIA, 2026). In addition, long-term energy transition studies published by NREL and the International Energy Agency (IEA) were consulted, particularly with regard to projected growth in solar and wind energy capacities (NREL, 2024a; IEA, 2025). Within the model, the electricity generation mix is represented through the following categories:

- Solar %: emissions associated with charging electric vehicles using solar-generated electricity.
- Wind %: emissions resulting from electricity generated by wind power.
- Other Green %: emissions linked to stable, low-carbon generation sources.
- Fossil Fuel %: emissions arising from natural gas and coal-based generation with higher carbon intensity.

3.3 Optimization Algorithms

3.3.1 Objective Function and Model Formulation

Decision variables. The model selects two coupled annual trajectories over the horizon t = 2025, …, 2050: the EV share of the vehicle stock, EV_t, and the electricity generation mix shares for solar (S_t), wind (W_t), Other Green (O_t), and fossil fuel (F_t). Equivalently, the decision variables are the annual changes ΔEV_t, ΔS_t, ΔW_t, ΔO_t, and ΔF_t. All remaining quantities, including fleet size, sales, retirements, and the annual emission terms, are computed from these trajectories and the fixed inputs described in Section 3.2. Table 3.1 defines all notation.

Objective function. The optimization minimizes total cumulative life-cycle emissions TE over the transition horizon:

minimize $TE = \Sigma_{t=2025}^{2050} [\, E_{prod}(t) + E_{oper}(t) + E_{disp}(t) \,]$ (3.1)

where the minimization is taken over the decision variables EV_t, S_t, W_t, O_t, F_t, and the three annual components are computed as:

$$E_{prod}(t) = Sales_{EV}(t) \cdot e_{EV} + Sales_{ICE}(t) \cdot e_{ICE} \quad (3.2)$$

$$E_{oper}(t) = [\, N_{ICE}(t) \cdot m \cdot e_{ICE,op} + N_{EV}(t) \cdot m \cdot I(t) \,] / 10^6 \quad (3.3)$$

$$I(t) = \beta_S \cdot S_t + \beta_W \cdot W_t + \beta_O \cdot O_t + \beta_F \cdot F_t \quad (3.4)$$

$$E_{disp}(t) = D(t) \cdot e_{disp} \quad (3.5)$$

What each component includes. $E_{prod}(t)$ in Eq. (3.2) covers the manufacturing of every new vehicle sold in year t, of both types: each EV sold adds 15.3 t CO_2e, with battery production the dominant contributor, and each ICE vehicle sold adds 10.0 t (Argonne National Laboratory, 2024b). Vehicles already on the road are excluded, since their manufacturing emissions were counted in the year they were sold.

$E_{oper}(t)$ in Eqs. (3.3) and (3.4) covers the driving of the entire on-road fleet in year t, not only new sales. Every ICE vehicle on the road contributes gasoline-combustion emissions at 400 g CO_2 per mile over 10,787 miles (EPA, 2024b; FHWA, 2026). Every EV on the road contributes charging emissions at the grid intensity $I(t)$, which weights the four generation shares by their life-cycle factors of 11.4, 3.1, 6.72, and 173.1 g CO_2 per mile for solar, wind, Other Green, and fossil generation respectively. Because $I(t)$ declines as the grid decarbonizes, the same EV emits less in each successive year, which is the mechanism that makes the timing of grid decarbonization consequential.

$E_{disp}(t)$ in Eq. (3.5) covers the end-of-life processing of every vehicle retired in year t, at 1.3 t CO_2e per vehicle for both types (Argonne National Laboratory, 2024b), with retirements split between EV and ICE vehicles in proportion to their fleet shares. Retirements total 4.5% of the vehicle stock per year (S&P Global Mobility, 2025).

Here $N_{EV}(t) = P(t) \cdot EV_t$ and $N_{ICE}(t) = P(t) \cdot (1 - EV_t)$ are the EV and ICE vehicle stocks in year t; $Sales_{EV}(t) = Q(t) \cdot EV_t$ and $Sales_{ICE}(t) = Q(t) \cdot (1 - EV_t)$ are annual sales, with the sales share tied to the stock share in all scenarios; and $I(t)$ is the charging intensity, in grams of CO_2 per mile,

implied by the year-t generation mix. Production emissions are associated with vehicle manufacturing, operational emissions result from gasoline combustion and from electricity consumption during vehicle use, and end-of-life emissions arise from vehicle retirement and disposal. This formulation reflects a full life-cycle assessment (LCA) perspective across the production, operation, and disposal stages.

Constraints. The minimization in Eq. (3.1) is subject to the following constraints, applied identically to every optimized scenario:

Initial conditions (2025):

$$EV_{2025} = 2.078\%; \quad (S, W, O, F)_{2025} = (7\%, 11\%, 25\%, 57\%) \tag{3.6}$$

Terminal conditions (2050):

$$EV_{2050} = 100\%; \quad (S, W, O, F)_{2050} = (45\%, 42\%, 13\%, 0\%) \tag{3.7}$$

Generation-mix identity and nonnegativity, for every year t:

$$S_t + W_t + O_t + F_t = 100\%, \quad S_t, W_t, O_t, F_t \geq 0 \tag{3.8}$$

Annual growth bounds, in percentage points per year, for every year t:

$$+0.25 \leq \Delta S_t \leq +4.31; \quad +0.25 \leq \Delta W_t \leq +2.85; \quad -2.00 \leq \Delta O_t \leq +2.00; \quad -6.20 \leq \Delta F_t \leq -0.50 \tag{3.9}$$

Fleet-turnover (market absorption) constraint, for every year t: the number of EVs added to the stock in a year cannot exceed that year's total new-vehicle sales, and the EV stock is non-decreasing:

$$0 \leq \Delta N_{EV}(t) \leq Q(t) \tag{3.10}$$

The floors in Eq. (3.9) correspond to the slowest deployment years observed in the past decade of EIA generation data, and the ceilings are calibrated so that no single source can complete its full 2025–2050 transition in less than approximately a decade, consistent with the pace of NREL's 100% Clean Electricity by 2035 scenario (National Renewable Energy Laboratory, 2023a). A candidate trajectory is feasible only if it satisfies Eqs. (3.6) through (3.10) simultaneously; infeasible candidates are rejected before evaluation. In the accompanying implementation (Appendix 1), Eq. (3.1) is implemented as the named function objective_function(), whose docstring maps each code term to Eqs. (3.2) through (3.5); the

Random Search algorithm evaluates every candidate pathway by calling this function, and the Linear, Sudden, and Baseline algorithms evaluate the identical expression with each term labeled by its equation number. Eq. (3.9) is encoded in the REALISTIC_BOUNDS_PP constraint set, and Eqs. (3.6), (3.7), and (3.10) are enforced by the trajectory generators, which discard any draw that violates them.

Table 3.1: Notation and Model Parameters

Symbol	**Definition**	**Value / units**	**Source**
t	Model year index (annual steps)	2025–2050	N/A
TE	Total cumulative life-cycle emissions (objective)	metric tons CO_2e	Eq. (3.1)
E_prod(t), E_oper(t), E_disp(t)	Annual production, operational, end-of-life emissions	t CO_2e	Eqs. (3.2)–(3.5)
EV_t	EV share of vehicle stock (decision variable)	2.078% (2025) → 100% (2050)	EIA AEO2026; U.S. Dept. of State (2021)
S_t, W_t, O_t, F_t	Solar, wind, Other Green, fossil generation shares (decision variables)	percent; Eq. (3.8)	EIA (2025 mix); DOE Solar Futures (2050)
ΔX_t	Annual change of variable X	percentage points/yr	Eq. (3.9)
P(t)	Total light-duty vehicle stock	270,313,293 → 334,770,203	EIA AEO2026, Table 39
Q(t)	Total annual new-vehicle sales	≈16.3 million/yr average	Derived: stock and retirement identity
D(t)	Annual vehicle retirements (disposals)	4.5% of P(t) per year	S&P Global Mobility (2025)
m	Annual mileage per vehicle (both types)	10,787 miles/yr	FHWA (2026)

Table 3.1: Continued

Symbol	Definition	Value / units	Source
e_EV	EV production emissions	15.3 t CO_2e/vehicle	Argonne National Laboratory (2024b)
e_ICE	ICE production emissions	10.0 t CO_2e/vehicle	Argonne National Laboratory (2024b)
e_disp	End-of-life emissions (both types)	1.3 t CO_2e/vehicle	Argonne National Laboratory (2024b)
e_ICE,op	ICE operational emission factor	400 g CO_2/mile	EPA (2024b)
β_S, β_W, β_O, β_F	Charging-intensity factors by source	11.4 / 3.1 / 6.72 / 173.1 g CO_2/mile	IPCC (2014); UNECE (2021); NREL (2022)
I(t)	Grid charging intensity	g CO_2/mile; Eq. (3.4)	Computed
N	Monte Carlo trials (Random Search)	75,000 (seed = 42)	Convergence test, Sec. 3.3

1. Linear Transition Algorithm

This algorithm represents a scenario of smooth and uniform transition, in which growth in renewable energy shares and electric vehicle adoption is distributed at a constant annual rate from 2025 to 2050. Average annual mileage is held constant and equal for electric and gasoline vehicles at 10,787 miles per year (Federal Highway Administration, 2026), and the electric-vehicle sales share is tied to the vehicle stock share, both beginning at 2.078% in 2025. It is evaluated as one of three optimized transition pathways relative to the baseline scenario, and it highlights the adverse effects of delaying emissions reductions, even when nominal 2050 targets are ultimately achieved (IPCC, 2014; IPCC, 2023).

2. Sudden Transition Algorithm

This algorithm simulates an intensive early-action scenario, in which electric-vehicle adoption proceeds at the maximum feasible rate the new-vehicle market can sustain for the first five years

(2025‑2030), bounded by total annual vehicle sales, then continues at a constant linear rate through 2050. The five-year window was selected to align with 2030 as the dominant near-term benchmark year used across the policy and industry literature informing this study, including the EV30@30 campaign's target of 30% new-vehicle sales share by 2030 (IEA, 2020), NREL's 2030 National Charging Network infrastructure planning horizon (NREL, 2023b), and state-level zero-emission vehicle mandates structured around the same milestone. The accompanying grid transition follows a front-loaded curve, constrained by the same realistic annual growth bounds applied to the Random Search algorithm. This scenario is grounded in the principle of front-loaded transition dynamics, with EV uptake advancing as rapidly as the market physically allows in the early stage of the study period. It is used to examine whether aggressive early deployment yields lower cumulative life-cycle emissions than a smoother or more gradual alternative.

3. Random Search Optimization Algorithm

This algorithm was based on a Monte Carlo constrained random-search procedure in which 75,000 candidate transition trajectories were generated within predefined model bounds. Feasible scenarios were evaluated using the cumulative-emissions objective function, and the trajectory with the lowest total cumulative CO_2 emissions was selected as the optimal solution. The trial count of 75,000 was set using a direct convergence test rather than chosen in advance: the same search was rerun with the same random seed at increasing trial counts (1,000; 10,000; 30,000; 50,000; 75,000; 100,000; 150,000), and the best result kept improving up through 75,000 trials before remaining unchanged through 150,000. Seventy-five thousand trials is therefore the smallest trial count at which the result stabilizes, which is the strongest practical evidence of convergence available for a heuristic search of this kind; it does not constitute a mathematical guarantee that the global optimum has been found, since no finite number of random trials can provide one. This approach is consistent with the numerical optimization literature on non-linear systems (Dauchet et al., 2018).

The algorithm generated constrained random values for the key study variables affecting cumulative carbon emissions, within predefined annual growth bounds that reflect the technical and practical limitations of the energy system. For the Solar % variable, annual changes were generated within a range of +0.25 to +4.31 percentage points. For the Wind % variable, annual

changes were generated within a range of +0.25 to +2.85 percentage points. The Other Green % variable was allowed to vary within a relatively narrow interval of −2.00 to +2.00 percentage points per year, consistent with a gradual, bounded decline in this category's overall share, from 25% in 2025 to 13% by 2050, as solar and wind capture most new generation growth. By contrast, the Fossil Fuel % variable was assigned negative annual changes within the range of −6.20 to −0.50 percentage points, consistent with the assumed gradual decline of high-carbon fossil energy sources.

The randomly generated values within these bounds were used to construct multiple temporal trajectories of the electricity-generation mix through 2050. For each feasible trajectory, the algorithm computed total cumulative carbon emissions, and the scenario yielding the lowest cumulative total under the imposed system constraints was identified as the optimal outcome. Taken together, this methodology provides an analytical framework that integrates life-cycle assessment, temporal optimization, and multi-path algorithmic modeling. It enables a shift from simple linear projections toward the identification of a more climate-efficient and temporally optimal transition pathway.

CHAPTER FOUR RESULTS AND DISCUSSION

Research Question 1: What is the optimal temporal pathway for the United States' transition to a low-carbon transportation system that minimizes cumulative life-cycle carbon emissions from vehicles (production, operation, and end-of-life) over the period 2025–2050?

To identify the optimal temporal pathway for decarbonizing the U.S. transportation system, three alternative transition algorithms were implemented and benchmarked against the baseline scenario. The primary criterion for comparison was total cumulative vehicle life-cycle carbon emissions over 2025–2050.

The evaluated algorithms were: (1) a rapid (step-change) transition, (2) a linear transition, and (3) an optimized random-search approach (Random Search). Table 4.1 reports the comparative results, including the absolute emissions reductions and the percentage improvements relative to the baseline scenario.

Table 4.1**:** Comparison of Transition Algorithms and Improvement Rates Relative to the Baseline (2025–2050)

Scenario	Total Emissions, 2025–2050 (billion tCO_2e)	Reduction vs. Baseline (billion tCO_2e)	Improvement (%)
Baseline	32.57	N/A	N/A
Sudden Transition	22.29	10.27	31.55
Linear Transition	23.72	8.85	27.17
Random Search	21.66	10.91	33.50

Table 4.1 shows that all alternative transition pathways reduce cumulative emissions relative to the baseline scenario. However, the optimized Random Search algorithm achieves the lowest cumulative emissions and the highest relative improvement, qualifying it as the optimal temporal pathway within the scope of this study.

The optimal pathway produced by the optimized Random Search algorithm reflects a gradual and balanced transition pattern, built on synchronizing power-sector decarbonization with the phased expansion of electric-vehicle (EV) adoption. This pathway avoids abrupt jumps that

could trigger an early rise in manufacturing emissions without delivering commensurate operational benefits.

The pathway follows a front-loaded diffusion curve for EV adoption, reaching approximately 51% of the fleet by 2035 before continuing at a variable pace to full electrification by 2050, reflecting the random search process rather than a smooth or symmetric S-shaped trajectory, accompanied by a steady decline in reliance on high-carbon electricity sources, particularly fossil fuel.

Table 4.2**:** Optimal Temporal Pathway for the Electricity Generation Mix in the Optimized scenario (%)

Year	Solar %	Wind %	Other Green %	Fossil Fuel %
2025	7.00	11.00	25.00	57.00
2026	9.01	12.72	23.93	54.34
2027	10.96	14.53	24.36	50.15
2028	13.08	16.06	25.10	45.76
2029	13.45	16.93	24.79	44.83
2030	13.77	18.71	25.13	42.39
2031	15.91	20.60	25.28	38.21
2032	17.31	22.02	24.24	36.43
2033	19.09	23.09	23.58	34.24
2034	20.54	23.96	23.84	31.66
2035	21.60	24.56	24.40	29.45
2036	22.48	25.11	23.52	28.89
2037	25.03	25.77	23.72	25.48
2038	26.26	26.60	22.60	24.54
2039	27.24	27.50	22.49	22.77
2040	30.00	28.56	20.61	20.83
2041	32.33	29.85	19.83	17.99
2042	33.54	31.05	20.18	15.24
2043	35.47	32.90	18.32	13.31
2044	38.04	33.28	17.31	11.36
2045	40.64	34.80	15.78	8.79

Table 4.2: Continued

Year	Solar %	Wind %	Other Green %	Fossil Fuel %
2046	40.98	36.18	15.96	6.88
2047	41.80	37.25	15.25	5.70
2048	43.12	39.21	13.73	3.95
2049	44.28	41.02	13.89	0.82
2050	45.00	42.00	13.00	0.00

The results indicate that reductions in power-sector carbon intensity begin early in the study horizon, as the share of fossil fuel declines from 57% in 2025 to 0% by 2050. This early shift is a decisive factor in maximizing the climate benefits of transport electrification.

Table 4.3**:** Optimal Temporal Pathway for EV Adoption in the United States

Year	EV Share (%)	ICE Share (%)
2025	2.08	97.92
2026	7.51	92.49
2027	12.81	87.19
2028	18.00	82.00
2029	23.08	76.92
2030	28.02	71.98
2031	32.44	67.56
2032	37.20	62.80
2033	41.84	58.16
2034	46.39	53.61
2035	50.85	49.15
2036	55.25	44.75
2037	59.58	40.42
2038	63.82	36.18
2039	67.99	32.01
2040	72.09	27.91

Table 4.3: Continued

Year	EV Share (%)	ICE Share (%)
2041	75.77	24.23
2042	79.00	21.00
2043	83.02	16.98
2044	83.19	16.81
2045	85.48	14.52
2046	89.52	10.48
2047	93.43	6.57
2048	94.39	5.61
2049	98.12	1.88
2050	100.00	0.00

The findings show that the key inflection point occurs in the mid-2030s, as EVs exceed 50% of the vehicle stock by 2035. This balanced pathway supports a continuous decline in annual emissions and reduces cumulative life-cycle emissions to approximately 21.66 billion tCO_2e over 2025-2050, its lowest level among all scenarios examined.

This reduction is attributable to two interrelated mechanisms:

- Lower operating emissions resulting from the early shift toward low-carbon electricity.
- Managing the pace of EV adoption in a way that limits an early spike in manufacturing emissions.

Accordingly, the study concludes that the optimal temporal pathway for the United States' transition to a low-carbon transportation system over 2025–2050 is a gradual, synchronized transition that begins with early power-sector decarbonization and is accompanied by a controlled acceleration in EV adoption that reaches full dominance by 2050. This outcome confirms that the *timing* of the transition is as important as its *scale* in achieving the minimum cumulative carbon emissions, with important implications for climate policy design and sustainable energy-transition strategies.

This result embodies the logic of *temporal optimization*, which holds that climate success should not be judged solely by reaching a 2050 endpoint, but rather by reducing cumulative emissions

over time. This is because climatic impact is driven more by the accumulation of CO_2 (the carbon stock) than by emissions in any single year (the carbon flow) (IPCC, 2014; IPCC, 2023; Congressional Budget Office, 2022). Accordingly, the superior performance of the Random Search pathway as the lowest in cumulative emissions (21.66 billion tons) relative to the baseline pathway (32.57 billion tons) is directly consistent with evaluating transition pathways using cumulative life-cycle emissions rather than annual indicators or end-year targets alone (Ali et al., 2024).

From a life cycle perspective, the advantage of the Random Search pathway can be explained by a scale effect between fleet size and annual sales. The existing vehicle fleet is far larger than the number of vehicles sold in any single year, so the one-time manufacturing emissions associated with an electric vehicle and its battery are repaid many times over by the operating-emissions savings accumulated across the much larger stock of vehicles already on the road, even while the grid is not yet fully decarbonized (Arshad et al., 2022; Gao et al., 2023). This scale effect is what allows *early, rapid adoption* to remain beneficial in this model's accounting, in contrast to a stricter vintage-based accounting approach that would otherwise penalize early deployment on a still-carbon-intensive grid.

Transition-dynamics theories reinforce this interpretation. Energy-transport transitions are inherently nonlinear and are shaped by infrastructural inertia as well as economic and social feedback mechanisms, which often makes adaptive, incremental trajectories more capable of achieving superior cumulative outcomes than abrupt shifts or rigid linearity (Muratori et al., 2023). Path-dependence theory similarly cautions against “carbon lock-in” when transport electrification outpaces electricity decarbonization, helping to explain why the optimal pathway requires tighter synchronization between the two variables (Horesh & Quinn, 2024). Methodologically, this aligns with the logic of random-search/Monte Carlo approaches, which are designed to explore broad solution spaces and select the pathway that minimizes cumulative outcomes in nonlinear systems (Dauchet et al., 2018).

Taken together, the reported improvement (33.50%) is substantial in absolute terms (a reduction of 10.91 billion tons). Nevertheless, it remains a *conditional optimum* determined by growth constraints, variable bounds, and scenario assumptions. For this reason, it is important to highlight the sensitivity of the findings to changes in constraints or assumptions, rather than presenting the pathway as an unconditional general rule.

Research Question 2: To what extent does the timing of integrating renewable energy sources into the electricity-generation mix affect the effectiveness of reducing electric vehicles' operational emissions during the transition period?

Reducing the operational emissions of electric vehicles (EVs) is a central objective of policies aimed at shifting toward low-carbon transport systems. Achieving this objective, however, does not depend solely on increasing the number of EVs; it is strongly conditioned by when renewable energy is incorporated into the electricity-generation mix that powers EV charging. This question evaluates how the timing of renewable integration influences the efficiency of operational-emissions reductions. This is examined by comparing three transition pathways that differ in the speed of power-sector decarbonization and analyzing the implications for (i) operational-emissions intensity, (ii) reduction rates, (iii) the pace of reaching low-carbon operation, and (iv) the effective scale of EV operation. Comparisons are reported for selected benchmark years across the three scenarios, as shown in the following tables.

Table 4.4**:** EV Operational-Emissions Intensity by Renewable-Integration Timing (g CO_2/mile)

Scenario	2025	2030	2040	2050
Sudden	101.5	73.8	37.6	7.3
Linear	101.5	82.7	45.0	7.3
Random Search	101.5	77.2	41.7	7.3

Emission factors:

- Solar = 11.4 g CO_2/mile
- Wind = 3.1 g CO_2/mile
- Other Green = 6.72 g CO_2/mile
- Fossil = 173.1 g CO_2/mile

Note: The 101.5 g CO_2/mile value reported for 2025 represents the fleet-weighted average EV operational-emissions intensity based on the prevailing U.S. electricity-generation mix. By contrast, the solar value of 11.4 g CO_2/mile shown below reflects the emissions intensity associated specifically with solar-based EV charging. Accordingly, these values are complementary, as they refer to different electricity-supply assumptions.

The results in Table 4.4 indicate that the timing of renewable integration in the electricity mix directly affects EV operational-emissions intensity. Although all pathways begin from a similar operational level in 2025, their subsequent decline rates diverge clearly: The Sudden pathway

delivers a rapid reduction in emissions intensity; the Linear pathway exhibits a slower, incremental decline; and the optimized Random Search pathway lies between the two, reflecting a more balanced improvement over time. To further address the same question, the reduction in operational emissions intensity relative to the 2025 baseline was calculated using the operational intensity values and the following formula:

$$\text{t } \%Reduction = \frac{(\text{ t } EV - Intensity_{2025} - EV - Intensity)}{2025EV - Intensity} \times 100$$

The resulting reductions are summarized in Table 4.5.

Table 4.5**:** Percentage Reduction in Operational-Emissions Intensity Relative to 2025 (%)

Scenario	2030	2040	2050
Sudden	27.3%	62.9%	92.8%
Linear	18.6%	55.7%	92.8%
Random Search	23.9%	58.9%	92.8%

These results reinforce the pattern shown in Table 4.5: early reduction rates are highest under the pathway that integrates renewables sooner, whereas operational gains are delayed under the Linear pathway. Nevertheless, all pathways converge by the end of the study horizon, indicating that the key distinction between scenarios lies not in the final level of reduction, but in *when* that reduction is achieved during the transition.

Overall, the findings demonstrate that the timing of renewable-energy integration into the electricity-generation mix substantially shapes the effectiveness of lowering EV operational emissions during the transition period. Early integration accelerates reductions in operational-emissions intensity, but it does not deliver the full environmental benefit unless it coincides with a material expansion in EV use. Therefore, pathways that temporally coordinate grid decarbonization with accelerating transport electrification are more efficient at reducing operational emissions during the transition than pathways that prioritize one dimension without synchronizing the other.

The results indicate that the impact of renewable integration on EV operational emissions is determined not only by the end-state level of renewables, but also by the *sequence and timing* of changes across the transition years. Differences between pathways widen early (e.g., by 2030) and then gradually narrow as 2050 approaches. This pattern aligns with the literature emphasizing that transport electrification does not guarantee meaningful mitigation unless the

carbon intensity of charging electricity is managed over time and coordinated with the pace of EV diffusion (Cui et al., 2022).

This can be interpreted through a "carbon stock" lens: because CO_2 accumulates and persists for long periods, earlier reductions in grid emissions intensity prevent additional near-term atmospheric accumulation and yield greater climate benefits than delayed reductions, even if pathways ultimately converge at a similar 2050 level (IPCC, 2014; IPCC, 2023; Congressional Budget Office, 2022). EV-focused research further shows that operating EVs on a high-carbon grid can dampen short- to medium-term operational gains and raise cumulative emissions outcomes (Gao et al., 2023).

Path dependence provides an additional explanation. If EV adoption accelerates while grid decarbonization lags, a carbon-intensive trajectory can become "locked in," making later correction difficult due to sunk investments and institutional constraints (Horesh & Quinn, 2024). Hence, the findings are consistent with transition-management perspectives that advocate coordinated, staged pathways that learn and adapt, rather than one-dimensional acceleration (Chen & Ma, 2024).

Taken together, the evidence also suggests that early grid cleaning alone is insufficient unless it translates into large-scale EV operation. Here, charging-infrastructure constraints shape adoption rates and the timing of effective vehicle replacement, thereby influencing overall emissions performance (Tejeida-Padilla et al., 2024).

Research Question 3: How do the temporal dynamics between accelerating electric-vehicle adoption and declining internal-combustion vehicle sales affect cumulative carbon emissions during the transition phase under the best transition scenario?

To address this question, the temporal dynamics of the best-performing scenario are interpreted through three interacting mechanisms:

- **Acceleration in EV adoption** (increases in %_E_CAR and #_EVs_SELL)
- Declining ICE sales within the market (decreases in #_ICE_SELL)
- **Fleet turnover** through vehicle retirement/disposal (# Disposal)

The following table summarizes ICE decline alongside the acceleration in EV adoption (rising %_E_CAR and #_EVs_SELL).

The Random Search (best) scenario demonstrates that emissions reductions during the transition do not arise from "accelerating EV adoption" alone; rather, they are driven by the time-dependent interaction among rising EV sales, declining ICE sales, and the system's capacity to remove ICE vehicles from the fleet through turnover (disposal). At the beginning of the period (2025), EV penetration in the fleet is still very low (%_E_CAR ≈ 2.08%), with clear ICE dominance. This is reflected in a large gap between EV and ICE sales, implying that ICE operational emissions continue to dominate in the early years even as EV sales begin to increase. By 2030, EV adoption rises substantially (%_E_CAR ≈ 28.02%), and EV sales (#_EVs_SELL) expand alongside a gradual decline in ICE sales (#_ICE_SELL). However, the table indicates that the effective pace of ICE decline is also determined by # Disposal: annual retirement is close to total annual sales (roughly 15-17 million, varying by year). Consequently, the ICE stock contracts rapidly only when a large share of new sales becomes "EV instead of ICE" while retirement continues at scale.

Table 4.6: ICE Decline and EV Adoption Dynamics in the Best-Reduction Scenario (Random Search)

Year	%_E_CAR	%_ICE_CAR	#_E_CAR	#_ICE_CAR	Total Cars Sold (EV+ICE)	#_EVs_SELL	#_ICE_SELL	# Disposal
2025	2.08	97.92	5,616,029	264,697,264	14,877,965	309,105	14,568,860	12,164,097
2030	28.02	71.98	80,005,854	205,500,494	16,071,510	4,503,630	11,567,880	12,847,786
2048	94.39	5.61	313,973,133	18,662,762	16,187,823	15,279,594	908,229	14,968,615
2049	98.12	1.88	327,587,074	6,268,029	15,938,580	15,639,338	299,242	15,023,480
2050	100.00	0.00	334,770,203	0	15,979,759	15,979,759	0	15,979,759

To complete the response, an indicator of the decline in ICE sales under the best reduction scenario was computed, as shown in the table below.

Table 4.7**:** Indicator of ICE Sales Decline in the Market (Best-Reduction Scenario)

Year	#_EVs_SELL	#_ICE_SELL	EV/ICE Sales Ratio
2025	309,105	14,568,860	0.02
2030	4,503,630	11,567,880	0.39

Table 4.7: Continued

Year	#_EVs_SELL	#_ICE_SELL	EV/ICE Sales Ratio
2048	15,279,594	908,229	16.82
2049	15,639,338	299,242	52.26
2050	15,979,759	0	Undefined (ICE sales = 0)

Cumulative emissions under the best optimized scenario were also calculated to complete the analysis, as reported below.

Table 4.8**:** Total Cumulative Emissions in the Best-Reduction Scenario (Random Search)

Scenario	Total cumulative emissions
Random Search (Best)	21.66 billion tCO_2e

This dynamic reaches its peak in the final decade (2048–2050), as the EV-to-ICE sales ratio shifts from below one in the early stages to extremely high values (EV/ICE > 10 and then > 25), while %_ICE_CAR falls to marginal levels and disappears entirely by 2050. In practical terms, each additional year late in the transition not only adds new EVs but also prevents the "renewal" of the ICE stock through new sales; with ongoing retirement, the ICE fleet declines rapidly, producing a sharp reduction in ICE-related operational emissions.

Accordingly, the low cumulative emissions total achieved under the best scenario (21,656,848,693 metric tons) can be interpreted as the outcome of a deliberate timing strategy across three phases:

- **Early phase:** Gradual growth in EV sales, with each new EV beginning to accumulate operating-emissions savings against the existing fleet from the outset.
- **Middle phase:** Continued EV expansion with a progressively stronger decline in the ICE stock driven by fleet turnover.
- **Late phase:** EV dominance in both sales and fleet composition, accelerating the elimination of ICE vehicles and reducing the most emissions-intensive source of operational emissions.

The dynamics of the best-performing scenario indicate that cumulative emissions are not determined by a single variable; they are governed by a temporal interaction among accelerated

EV uptake, contraction in ICE sales, and fleet turnover through annual vehicle retirement. This aligns with the theoretical framework, which argues that emissions trajectories emerge from the interaction between EV diffusion and ICE decline within stock-based system dynamics (Muratori et al., 2023).

From a "stock inertia" perspective, rising EV sales do not automatically translate into rapid emissions reductions as long as the ICE fleet remains large and is continually replenished through ongoing sales. The decisive factor therefore becomes the net replacement rate: the point at which the majority of new vehicle sales are EVs, such that the ICE stock is no longer reproduced, while retirement continues to remove older vehicles from the fleet. This interpretation is consistent with path-dependence arguments and with the need to synchronize market policies with energy-system structure and enabling infrastructure (Horesh & Quinn, 2024; Chen & Ma, 2024).

Moreover, the observed pattern, fast early growth followed by a temporary slowdown in the late 2030s and continued growth to full adoption by 2050, reflects the variable pacing produced by the random search process rather than a textbook S-curve, though it shares the broader nonlinear character that transition-diffusion theory would predict, shaped by infrastructure constraints and feedback mechanisms (Muratori et al., 2023). Because charging constraints influence the pace at which EVs enter the fleet, they also shape the timing of ICE decline and, consequently, the cumulative emissions outcome (Tejeida-Padilla et al., 2024).

Finally, a life-cycle perspective provides an additional rationale: although EV manufacturing emissions, especially those associated with batteries, are temporally front-loaded, the analysis indicates that the resulting one-time cost is small relative to the operating-emissions savings accumulated across the existing vehicle fleet, which is why early acceleration remains beneficial under this model's accounting even before the electricity grid becomes fully decarbonized (Arshad et al., 2022; Gao et al., 2023).

Research Question 4: How does the best transition scenario achieve an effective temporal balance between the pace of transport electrification and the reduction of cumulative emissions?

Achieving a balance between the speed of transport electrification and the minimization of cumulative carbon emissions is a core challenge in designing low-carbon transition pathways. An overly rapid transition can trigger an early rise in emissions from EV manufacturing and from operating EVs on an electricity system that has not yet been sufficiently decarbonized.

Conversely, a slow transition keeps internal-combustion vehicles in service for longer, increasing cumulative operational emissions.

In this study, the best-performing scenario addresses this trade-off through deliberate temporal coordination between renewable-energy expansion and the acceleration of EV adoption, thereby attaining the lowest feasible cumulative emissions over the analysis horizon. This balance is achieved by incorporating the following considerations:

First: Aligning the timing of grid decarbonization with growth in electricity demand

The best scenario establishes an effective temporal balance by pairing the pace of power-sector decarbonization with the pace of EV deployment rather than letting either run far ahead of the other. Because the EV charging factor falls every year as the grid cleans up, electrifying earlier against a cleaner grid increases the operating-emissions savings each additional EV accumulates over the remaining study period. In other words, transport electrification is not accelerated in isolation from electricity-system readiness; instead, EV expansion is steered toward periods when the generation mix is cleaner, increasing the cumulative payoff of each additional EV entering the fleet.

Second: Regulating the acceleration of EV adoption in line with fleet-turnover dynamics

The best scenario does not rely on increasing EV sales alone; it synchronizes adoption momentum with the dynamics of fleet turnover. In the early stage, EV sales rise from a small base, so their effect on the overall fleet builds gradually even as the sales mix itself shifts. As the transition advances, rapid growth in EV sales coincides with the continued exit of ICE vehicles through annual retirement, producing a tangible and accelerated contraction of the conventional vehicle stock during the mid-transition phase, the period in which the largest emission-reduction gains are realized.

Third: Finding the right pacing, rather than assuming either a smooth or an abrupt rule is inherently better

Smoothness or abruptness is not itself the deciding factor. The Sudden pathway, which deliberately front-loads EV adoption at the fastest physically feasible rate before settling into a constant rate, outperforms the Linear pathway, which spreads adoption evenly across the entire horizon with no discontinuity at all. The best-performing pathway, Random Search, outperforms both, not because it avoids abrupt change, but because it searches a much wider space of possible timings, smooth and uneven alike, and keeps whichever specific combination minimizes the

cumulative total. This indicates that a rigid assumption about pacing, whether "always smooth" or "always abrupt", is less reliable than searching directly for the combination that performs best under the same physical constraints.

Fourth: Maximizing mitigation gains during the mid-transition phase

The study's results indicate that the mid-transition period is the critical stage in determining the final cumulative emissions outcome. The best scenario achieves effective balance in this phase through the synchronization of three elements: (1) a pronounced reduction in grid emissions intensity, (2) strong acceleration in EV uptake within the market, and (3) a rapid decline in the ICE stock driven by fleet turnover. This concurrence produces a sharp drop in annual emissions, directly lowering cumulative emissions compared with pathways that postpone such synchronization to later stages.

Fifth: The cumulative-emissions outcome

As a consequence of this precise temporal coordination, the best transition scenario achieves the lowest cumulative carbon emissions across the study period without sacrificing the attainment of a near-fully electrified transport system by the end of the time horizon. This demonstrates that temporal balance between the pace of change and the timing of emissions reductions is as important as the overall scale of the transition in designing effective and durable low-carbon pathways.

The best transition scenario achieves an effective temporal balance between transport electrification and cumulative-emissions reduction by:

- aligning grid decarbonization with the expansion of EV use;
- calibrating adoption acceleration to fleet-turnover dynamics;
- searching directly for the best-performing pacing rather than assuming a smooth or an abrupt rule is inherently better; and
- maximizing mitigation gains during the mid-transition phase.

The best transition scenario indicates that "speed" is not an absolute virtue: improving the temporal ordering of actions can yield lower cumulative emissions even when end-point targets are broadly similar. This captures the central premise of temporal-optimization theory, which evaluates pathways on the basis of cumulative life-cycle emissions across the transition horizon (Ali et al., 2024).

In the optimal scenario, temporal balance is expressed through a causal sequence: (1) an early reduction in the carbon intensity of electricity to increase the environmental payoff of EV operation; (2) an acceleration of EV adoption once the generation mix becomes cleaner; and (3) alignment with fleet-turnover processes to speed the contraction of the ICE stock. This sequencing is consistent with a carbon-stock perspective that prioritizes early mitigation to limit the accumulation of emissions (IPCC, 2014; IPCC, 2023; Congressional Budget Office, 2022), and it also reflects warnings in the literature about misalignment between transport electrification and electricity-sector carbon intensity (Gao et al., 2023; Horesh & Quinn, 2024).

This form of balance further accords with transition-management approaches that favor coordinated, staged trajectories capable of learning and adaptation rather than abrupt jumps, and with conceptualizations of the transition as a nonlinear process constrained by infrastructure and feedback dynamics (Chen & Ma, 2024; Muratori et al., 2023).

This points to a policy-design principle: the minimum attainable cumulative emissions are governed by temporal coordination between energy policies (renewable deployment and grid decarbonization) and transport policies (accelerating EV adoption alongside charging-infrastructure expansion), rather than by either policy track in isolation (Cui et al., 2022; Tejeida-Padilla et al., 2024).

Table 4.9**:** Cumulative Emissions at Five-Year Intervals, Optimized Scenarios (Billion Metric Tons CO_2e)

Year	Sudden Transition	Linear Transition	Random Search
2030	7.39	7.61	7.42
2035	12.63	13.27	12.62
2040	16.98	18.03	16.76
2045	20.28	21.62	19.77
2050	22.29	23.72	21.66

Table 4.9 reports cumulative emissions at five-year intervals for the three optimized scenarios, and the comparison shows that an early lead does not decide the final outcome. At 2030, Sudden Transition is ahead of Random Search on both adoption measures, with 29.05% of the fleet electrified against 28.02% and a grid that is 59.8% low-carbon against 57.6%, and its cumulative total at that point is also the lowest of the three. Random Search overtakes it between 2035 and 2040 and holds the advantage through 2050, finishing 636 million metric tons lower despite

trailing on both adoption measures for most of the horizon. A pathway can therefore appear superior at any single checkpoint while still producing a larger cumulative total across the full period, which is the central reason this study evaluates pathways on cumulative rather than end-state or checkpoint performance.

CHAPTER FIVE CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study sought to identify the optimal temporal pathway for the United States' transition to a low-carbon electric transportation system over the period 2025–2050 by minimizing cumulative life-cycle emissions (production-operation-end-of-life), rather than relying solely on end-year indicators. This approach is grounded in temporal optimization, which emphasizes the sequencing and timing of renewable deployment and electric-vehicle (EV) adoption because climate outcomes are driven more by the accumulated carbon stock than by annual emission flows.

The findings indicate that the best-performing transition pathway is the Random Search scenario. It combines early reductions in electricity-sector emissions intensity with a strong but regulated acceleration of EV adoption, while also accelerating the contraction of the internal-combustion engine (ICE) stock through fleet-turnover dynamics. This synchronization produces sustained reductions in annual emissions and lowers cumulative emissions relative to pathways that postpone alignment to later stages.

Overall, the optimal pathway achieves the lowest cumulative emissions across the analysis horizon (2025–2050), at approximately **21.66 billion tCO_2e**, the smallest value among the evaluated scenarios. This confirms that the timing of the transition is as consequential as its scale for achieving minimum cumulative emissions. To place this reduction in perspective, the 10.91 billion metric ton difference relative to the baseline is equivalent to removing all 270.3 million vehicles in the 2025 U.S. fleet from the road for roughly 9.4 years, based on the EPA emission factor of 4.29 metric tons of CO_2 equivalent per passenger vehicle per year (EPA, 2025).

The key message for decision-makers is this: the central question is not only "How much will we electrify?", but also "When and in what order will we decarbonize electricity, scale EV adoption, and phase down ICE vehicles?" Because it is this temporal coordination that ultimately determines the lowest cumulative-emissions pathway.

5.2 Robustness Check: Sensitivity to Real-World Material and Infrastructure Constraints

The optimization results presented in Chapter 4 were generated under the growth bounds described in Chapter 3, which reflect realistic annual rates of change for each variable but do not explicitly model finite physical supply chains for the materials the transition depends on. To

assess whether the study's central conclusion, that temporal sequencing materially affects cumulative emissions, holds up against constraints the core model does not capture, three external robustness checks were conducted after the primary results were finalized. These checks were not incorporated into the optimization itself; rather, each locked scenario's year-by-year trajectory was tested against a physical ceiling derived from independent, real-world supply data to determine whether that ceiling would have been exceeded.

The first check examined copper availability. Cathles and Simon (2024), in a study conducted at Cornell University and the University of Michigan and sponsored by the International Energy Forum, find that a battery electric vehicle requires roughly three to five times as much copper as a comparable internal combustion engine vehicle, and conclude that global mine output cannot expand quickly enough to meet the copper demand of a full vehicle electrification pathway, given that new copper mines typically require upward of two decades to reach production. Applying a conservative estimate of the additional copper the United States could plausibly allocate annually to incremental electric-vehicle content, the maximum feasible year-over-year growth in electric-vehicle unit sales was calculated and compared against each scenario's actual sales growth. The Linear Transition pathway remained within this limit throughout the study horizon. The Random Search pathway exceeded it in three of twenty-five years, and the Sudden Transition pathway exceeded it in five of twenty-five years, with violations concentrated in the earliest years of the transition (2026 to 2029). This finding is directly relevant to the study's central argument: it indicates that the pathways which front-load electric-vehicle adoption most aggressively are also the pathways most exposed to a real, independently documented physical constraint, while the slower, evenly paced pathway is not.

The second check examined battery cell manufacturing capacity, using projections from Argonne National Laboratory and the U.S. Department of Energy's Four-Year Review of Supply Chains for the Advanced Batteries Sector (2024a), which estimate that United States battery cell manufacturing capacity will reach approximately 1,100 to 1,200 gigawatt-hours annually by 2030, shared between electric-vehicle production and grid-scale energy storage. After reserving capacity for projected storage demand and applying an average battery pack size, all three transition pathways were found to exceed available cell manufacturing capacity in the 2040s, once each pathway approaches near-total fleet electrification (Random Search from 2042, Sudden Transition from 2044, Linear Transition from 2045). Unlike the copper result, this

constraint does not differentiate meaningfully between pathways; it instead indicates that achieving near-complete electrification by 2050 under any sequencing strategy requires continued expansion of battery manufacturing capacity beyond what is currently documented through 2030.

The third check examined lithium refining capacity under a deliberately conservative scenario in which the United States relies solely on domestic refining, without import access. Using International Energy Agency demand projections and the Department of Energy's estimate that domestic lithium projects could meet approximately half of projected 2030 U.S. demand, all three pathways were found to exceed domestic-only refining capacity in most years from the early-to-mid 2030s onward. As with the battery cell finding, this result does not distinguish between sequencing strategies; it instead demonstrates that sustained access to international lithium refining capacity is a precondition for full electrification under any of the pathways examined in this study, independent of how quickly or slowly the transition proceeds.

Taken together, these three checks support a differentiated interpretation of the study's findings. The copper constraint, which is sensitive to the pace of early adoption, corroborates the dissertation's central claim that the temporal sequencing of the transition materially affects its feasibility, not only its cumulative emissions outcome. The battery cell and lithium constraints, by contrast, apply broadly across all three pathways and indicate that the ultimate goal of near-total vehicle electrification, rather than any particular route toward it, depends on manufacturing and refining capacity that does not yet exist at the scale required. These findings do not alter the study's core conclusion regarding the emissions advantage of the Random Search pathway, but they identify specific, independently documented supply-chain risks that a full implementation strategy would need to address regardless of which transition pathway is pursued.

5.3 Recommendations

1. **Adopt cumulative life-cycle emissions as an official planning target**
   Rather than prioritizing end-year metrics alone, the study recommends institutionalizing a cumulative life-cycle metric (TE: production + operation + end-of-life) for evaluating policies and pathways. This stock-based indicator reduces the risk of favoring trajectories that appear successful by 2050 yet impose high carbon costs in the early years.

2. **Prioritize early grid decarbonization before large-scale EV expansion**
   The results show that advancing electricity decarbonization increases the operating-emissions savings each EV accumulates from that point forward, since EVs benefit from whatever grid mix is in place in the year they charge, regardless of when they were purchased.
3. **Design phased EV policies synchronized with grid cleanliness**
   Instead of accelerating EV uptake indiscriminately, incentive strength (subsidies, tax exemptions, emissions standards) should be linked over time to measurable improvements in grid carbon intensity. This ensures that the major adoption surge occurs when the generation mix is cleaner, maximizing the environmental return of each additional EV.
4. **Manage fleet turnover to accelerate ICE stock decline**
   The optimal pathway does not depend on higher EV sales alone. It coordinates EV growth with ongoing vehicle retirement and declining ICE sales, since the existing fleet is far larger than annual sales and retirement is what ultimately removes ICE vehicles from the road, securing the greatest mitigation gains in the mid-transition phase.
5. **Address charging-infrastructure bottlenecks as a prerequisite for rapid EV adoption**
   Insufficient charging infrastructure constrains adoption speed and delays the replacement of ICE vehicles within the stock, thereby altering cumulative emissions trajectories. Investment in charging especially fast charging should therefore be treated as a critical temporal driver rather than a secondary component.
6. **Use nonlinear optimization and multi-pathway exploration to support decision-making**
   Because the system is nonlinear and bounded by realistic growth constraints, the study recommends algorithmic approaches that explore thousands of feasible trajectories (Monte Carlo/Random Search) and select the minimum cumulative-emissions pathway under a unified objective function. This shifts planning from a single assumed trajectory to a portfolio of candidate pathways and a defensible selection process.
7. **Formulate the transition roadmap as coordinated, adaptive phases**
   The roadmap should be structured as staged, coordinated packages that evolve with

learning and constraints, rather than seeking maximal early deployment without alignment consistent with transition-management perspectives and the need for adaptive pathways.

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APPENDICES

Appendix No. (1**)**

Python Codes for the Optimized Growth Algorithm

1. Sudden transition algorithm:

```
"""
sudden_transition.py
====================
Sudden Transition Algorithm. EV adoption proceeds at the maximum feasible
rate the new-vehicle market can sustain for 2025-2030 (bounded by total
annual vehicle sales), then continues at a constant linear rate through
2050. Grid mix follows a front-loaded curve (power-law search over a
single shape parameter, gc) toward the same 2050 target used by Linear
Transition and Random Search.

Expected output when run: cumulative total approximately 22.29 billion
metric tons (2025-2050), a 31.55% reduction versus the Baseline.
"""
import numpy as np
import pandas as pd

AVG_EV_MILES = 10787
AVG_ICE_MILES = 10787
ICE_OP_EMISSION_FACTOR = 400
EV_PROD_EMISSION = 15.3
ICE_PROD_EMISSION = 10.0
EV_DISP_EMISSION = 1.3
ICE_DISP_EMISSION = 1.3

EF_SOLAR = 11.4
```

```
EF_WIND = 3.1
EF_HYDRO_NUC = 6.72
EF_GAS_COAL = 173.1

years = np.arange(2025, 2051)
n_years = len(years)

stock_data = np.array([270313293, 273027161, 276130737, 279158936, 282220917,
285506348, 288730072,
291821350, 294999908, 298139465, 301225525, 304159668, 307055237, 309949097,
312836731, 315691467,
318420105, 321030640, 323441864, 325686371, 327725281, 329559509, 331201233,
332635895, 333855103,
334770203])
disposal_data = np.array([12164098, 12286222, 12425883, 12562152, 12699941, 12847786,
12992853,
13131961, 13274996, 13416276, 13555149, 13687185, 13817486, 13947709, 14077653,
14206116, 14328905,
14446379, 14554884, 14655887, 14747638, 14830178, 14904055, 14968615, 15023480,
15064659])
total_sales_data = np.array([14877965, 15389799, 15454081, 15624133, 15985372, 16071510,
16084131,
16310519, 16414553, 16502336, 16489292, 16582754, 16711346, 16835344, 16932389,
16934754, 16939439,
16857603, 16799391, 16694797, 16581866, 16471902, 16338717, 16187823, 15938580,
15979759])

TARGET_2050 = {'Solar': 45.0, 'Wind': 42.0, 'Hydro': 13.0, 'Gas': 0.0}
START_2025 = {'Solar': 7.0, 'Wind': 11.0, 'Hydro': 25.0, 'Gas': 57.0}
```

```
def generate_transition_curve(start_val, end_val, years_idx, curvature):
    t = years_idx / (len(years_idx) - 1)
    curve = t ** curvature
    return start_val + (end_val - start_val) * curve


# CONSTRAINT SET, Eq. (3.9): identical growth bounds as the Random Search algorithm,
# so no scenario can use a physically implausible grid curve.
REALISTIC_BOUNDS_PP = {'solar': (0.25, 4.31), 'wind': (0.25, 2.85), 'hydro': (-2.00, 2.00),
'gas': (-6.20, -0.50)}


def is_feasible(df_sim):
    ev_pct = df_sim['%_E_CAR'].values
    solar = df_sim['Solar %'].values
    wind = df_sim['Wind %'].values
    hydro = df_sim['hydro_nuclear %'].values
    gas = df_sim['natural gas and coal %'].values

    e_car = df_sim['Total LDV Stock'].values * (ev_pct / 100.0)
    yearly_market_cap = total_sales_data[:-1]
    if np.any(np.abs(np.diff(e_car)) > yearly_market_cap + 1e-6):
        return False
    for arr, key in [(solar, 'solar'), (wind, 'wind'), (hydro, 'hydro'), (gas, 'gas')]:
        lo, hi = REALISTIC_BOUNDS_PP[key]
        d = np.diff(arr)
        if np.any(d < lo - 1e-6) or np.any(d > hi + 1e-6):
            return False
    return True
```

```
def run():
    push_years = 5
    e_car = np.zeros(n_years)
    e_car[0] = stock_data[0] * 0.020776
    for i in range(1, push_years + 1):
        e_car[i] = e_car[i-1] + total_sales_data[i-1]
    end_count = stock_data[-1] * 1.0
    remaining_steps = n_years - 1 - push_years
    for i in range(push_years + 1, n_years):
        frac = (i - push_years) / remaining_steps
        e_car[i] = e_car[push_years] + (end_count - e_car[push_years]) * frac
    ev_pct = e_car / stock_data * 100.0

    idx = np.arange(n_years)
    best = None
    for gc in np.arange(0.1, 3.05, 0.02):
        solar = generate_transition_curve(START_2025['Solar'], TARGET_2050['Solar'], idx, gc)
        wind = generate_transition_curve(START_2025['Wind'], TARGET_2050['Wind'], idx, gc)
        hydro = generate_transition_curve(START_2025['Hydro'], TARGET_2050['Hydro'], idx,
gc)
        gas = 100 - (solar + wind + hydro)

        df_sim = pd.DataFrame({'Year': years})
        df_sim['%_E_CAR'] = ev_pct
        df_sim['%_ICE_CAR'] = 100 - ev_pct
        df_sim['Solar %'] = solar
        df_sim['Wind %'] = wind
        df_sim['hydro_nuclear %'] = hydro
        df_sim['natural gas and coal %'] = gas
        df_sim['Total LDV Stock'] = stock_data
        df_sim['#_E_CAR'] = df_sim['Total LDV Stock'] * (df_sim['%_E_CAR'] / 100)
```

```
    df_sim['#_ICE_CAR'] = df_sim['Total LDV Stock'] * (df_sim['%_ICE_CAR'] / 100)
    df_sim['Total Sales'] = total_sales_data
    df_sim['#_EVs_SELL'] = df_sim['Total Sales'] * (df_sim['%_E_CAR'] / 100)
    df_sim['#_ICE_SELL'] = df_sim['Total Sales'] * (df_sim['%_ICE_CAR'] / 100)
    df_sim['Total Disposal'] = disposal_data
    df_sim['Evs_Disposal_Count'] = df_sim['Total Disposal'] * (df_sim['%_E_CAR'] / 100)
    df_sim['ICE_Disposal_Count'] = df_sim['Total Disposal'] * (df_sim['%_ICE_CAR'] / 100)
    df_sim['Evs_Disposal_CO2'] = df_sim['Evs_Disposal_Count'] * EV_DISP_EMISSION
    df_sim['ICE_Disposal_CO2'] = df_sim['ICE_Disposal_Count'] * ICE_DISP_EMISSION
    df_sim['Evs_production_co2'] = df_sim['#_EVs_SELL'] * EV_PROD_EMISSION
    df_sim['ICE_production_co2'] = df_sim['#_ICE_SELL'] * ICE_PROD_EMISSION
    df_sim['Total_Evs_miles'] = df_sim['#_E_CAR'] * AVG_EV_MILES
    df_sim['Total_ICE_miles'] = df_sim['#_ICE_CAR'] * AVG_ICE_MILES
    df_sim['Total_CO2_ICE_Miles'] = (df_sim['Total_ICE_miles'] *
ICE_OP_EMISSION_FACTOR) / 1_000_000
    df_sim['Total_CO2_EV_Solar'] = (df_sim['Total_Evs_miles'] * (df_sim['Solar %']/100) *
EF_SOLAR) / 1_000_000
    df_sim['Total_CO2_EV_Wind'] = (df_sim['Total_Evs_miles'] * (df_sim['Wind %']/100) *
EF_WIND) / 1_000_000
    df_sim['Total_CO2_EV_Hydro'] = (df_sim['Total_Evs_miles'] * (df_sim['hydro_nuclear
%']/100) * EF_HYDRO_NUC) / 1_000_000
    df_sim['Total_CO2_EV_Gas'] = (df_sim['Total_Evs_miles'] * (df_sim['natural gas and coal
%']/100) * EF_GAS_COAL) / 1_000_000
    df_sim['Total Evs_Co2'] = (df_sim['Evs_Disposal_CO2'] + df_sim['Evs_production_co2'] +
                               df_sim['Total_CO2_EV_Solar'] + df_sim['Total_CO2_EV_Wind'] +
                               df_sim['Total_CO2_EV_Hydro'] + df_sim['Total_CO2_EV_Gas'])
    df_sim['Total ICE_Co2'] = (df_sim['ICE_Disposal_CO2'] + df_sim['ICE_production_co2']
+
                               df_sim['Total_CO2_ICE_Miles'])
    # OBJECTIVE FUNCTION, Eq. (3.1): annual TE = E_prod + E_oper + E_disp,
    # summed below over 2025-2050; terms are computed in the columns above
```

```
        # (production Eq. 3.2, operation Eqs. 3.3-3.4, disposal Eq. 3.5). See
        # objective_function() in the Random Search code for the same expression.
        df_sim['Total Co2 in metric ton'] = df_sim['Total Evs_Co2'] + df_sim['Total ICE_Co2']

        if not is_feasible(df_sim):
            continue
        cum = df_sim['Total Co2 in metric ton'].sum()
        if best is None or cum < best[0]:
            best = (cum, gc, df_sim)

    final_cumulative, best_gc, final_df = best
    return final_df, final_cumulative, best_gc



if __name__ == "__main__":
    df, total, gc = run()
    print(f"Sudden Transition total: {total:,.2f}    gc={gc:.2f}")
    for i in range(n_years):
        print(f"{years[i]}\tEV={df['%_E_CAR'][i]:.4f}\tSolar={df['Solar
%'][i]:.4f}\tWind={df['Wind %'][i]:.4f}\tHydro={df['hydro_nuclear %'][i]:.4f}\tGas={df['natural
gas and coal %'][i]:.4f}\tAnnualCO2={df['Total Co2 in metric ton'][i]:,.2f}")
```

2. Linear transition algorithm:

```
"""
linear_transition.py
=====================
Linear Transition Algorithm. Both EV adoption and grid mix move at a
constant annual rate for all 26 years, 2025-2050, with no discontinuity.

Expected output when run: cumulative total approximately 23.72 billion
metric tons (2025-2050), a 27.17% reduction versus the Baseline.
```

```
"""
import numpy as np
import pandas as pd
from dataclasses import dataclass
from typing import List, Tuple

YEARS: List[int] = list(range(2025, 2051))

TOTAL_LDV_STOCK_2025_2051: List[int] = [
    270313293, 273027161, 276130737, 279158936, 282220917, 285506348, 288730072,
    291821350, 294999908, 298139465, 301225525, 304159668, 307055237, 309949097,
    312836731, 315691467, 318420105, 321030640, 323441864, 325686371, 327725281,
    329559509, 331201233, 332635895, 333855103, 334770203, 334770203,
]
# EIA AEO2026, Table 39, Counterfactual Baseline case (cb2026.d021826b). Final value
repeated
# for the implicit 2051 boundary used to compute 2050's disposal, matching the original pattern.

TOTAL_ANNUAL_SALES_2025_2050 = [14877965, 15389799, 15454081, 15624133,
15985372, 16071510, 16084131,
    16310519, 16414553, 16502336, 16489292, 16582754, 16711346, 16835344, 16932389,
16934754, 16939439,
    16857603, 16799391, 16694797, 16581866, 16471902, 16338717, 16187823, 15938580,
15979759]
# Derived from the stock series above using a 4.5%/year retirement rate (S&P Global Mobility,
2025).

AVG_EV_MILES_PER_YEAR_2025 = 10_787
AVG_ICE_MILES_PER_YEAR_2025 = 10_787

EV_DISPOSAL_TON_PER_VEH = 1.3
```

```
ICE_DISPOSAL_TON_PER_VEH = 1.3
EV_PRODUCTION_TON_PER_VEH = 15.3
ICE_PRODUCTION_TON_PER_VEH = 10.0
ICE_USE_G_PER_MILE = 400.0
EV_SOLAR_G_PER_MILE = 11.4
EV_WIND_G_PER_MILE = 3.1
EV_HYDRO_NUCLEAR_G_PER_MILE = 6.72
EV_GAS_COAL_G_PER_MILE = 173.1

MIX_START_2025 = dict(solar=0.07, wind=0.11, hydro_nuclear=0.25, gas_coal=0.57)  # EIA-confirmed actual 2025 mix
MIX_TARGET_2050 = dict(solar=0.45, wind=0.42, hydro_nuclear=0.13, gas_coal=0.00)



@dataclass(frozen=True)
class ScenarioParams:
    ev_stock_share_2025: float = 0.020776
    ev_stock_share_2050: float = 1.0
    ev_sales_share_2025: float = 0.020776   # tied to stock share start
    ev_sales_share_2050: float = 1.0
    ev_miles_factor_2050: float = 1.0
    ice_miles_factor_2050: float = 1.0



def _linear(start, end, n):
    return start + (end - start) * np.linspace(0.0, 1.0, n)



def _energy_mix_series(n):
    solar = _linear(MIX_START_2025["solar"], MIX_TARGET_2050["solar"], n)
    wind = _linear(MIX_START_2025["wind"], MIX_TARGET_2050["wind"], n)
```

```
    hydro = _linear(MIX_START_2025["hydro_nuclear"],
MIX_TARGET_2050["hydro_nuclear"], n)
    gas = _linear(MIX_START_2025["gas_coal"], MIX_TARGET_2050["gas_coal"], n)
    mix = np.vstack([solar, wind, hydro, gas]).T
    mix = np.clip(mix, 0.0, None)
    mix_sum = mix.sum(axis=1, keepdims=True)
    mix_sum = np.where(mix_sum == 0, 1.0, mix_sum)
    mix = mix / mix_sum
    return mix[:, 0], mix[:, 1], mix[:, 2], mix[:, 3]


def compute_scenario(params: ScenarioParams) -> Tuple[pd.DataFrame, float]:
    years = np.array(YEARS, dtype=int)
    n = len(years)
    stock = np.array(TOTAL_LDV_STOCK_2025_2051[:n], dtype=float)
    stock_next = np.array(TOTAL_LDV_STOCK_2025_2051[1:n+1], dtype=float)

    sales_total = np.array(TOTAL_ANNUAL_SALES_2025_2050, dtype=float)
    avg_ev_miles = np.full(n, float(AVG_EV_MILES_PER_YEAR_2025))
    avg_ice_miles = np.full(n, float(AVG_ICE_MILES_PER_YEAR_2025))

    ev_stock_share = np.clip(_linear(params.ev_stock_share_2025, params.ev_stock_share_2050,
n), 0.0, 1.0)
    ice_stock_share = 1.0 - ev_stock_share
    ev_sales_share = np.clip(_linear(params.ev_sales_share_2025, params.ev_sales_share_2050,
n), 0.0, 1.0)
    ice_sales_share = 1.0 - ev_sales_share

    ev_miles_factor = _linear(1.0, params.ev_miles_factor_2050, n)
    ice_miles_factor = _linear(1.0, params.ice_miles_factor_2050, n)
    avg_ev = avg_ev_miles * ev_miles_factor
```

```
    avg_ice = avg_ice_miles * ice_miles_factor

    solar, wind, hydro, gas = _energy_mix_series(n)

    e_cars = stock * ev_stock_share
    ice_cars = stock * ice_stock_share
    ev_sell = sales_total * ev_sales_share
    ice_sell = sales_total - ev_sell
    disposal = np.maximum((stock + ev_sell + ice_sell) - stock_next, 0.0)

    ev_disposal_co2 = disposal * ev_stock_share * EV_DISPOSAL_TON_PER_VEH
    ice_disposal_co2 = disposal * ice_stock_share * ICE_DISPOSAL_TON_PER_VEH
    total_ev_miles = e_cars * avg_ev
    total_ice_miles = ice_cars * avg_ice
    # E_prod(t), Eq. (3.2): manufacturing of all new vehicles sold in year t
    ev_prod_co2 = EV_PRODUCTION_TON_PER_VEH * ev_sell
    ice_prod_co2 = ICE_PRODUCTION_TON_PER_VEH * ice_sell
    # OBJECTIVE FUNCTION, Eq. (3.1): the block below evaluates TE components
    # E_prod (Eq. 3.2), E_oper (Eqs. 3.3-3.4), and E_disp (Eq. 3.5) per year;
    # the cumulative total is their sum over 2025-2050. See objective_function()
    # in the Random Search code for the identical expression as a named function.
    # E_oper(t), Eqs. (3.3)-(3.4): driving emissions of the entire on-road fleet
    ice_use_co2 = (ICE_USE_G_PER_MILE * total_ice_miles) / 1_000_000.0
    ev_solar_co2 = (total_ev_miles * solar) * EV_SOLAR_G_PER_MILE / 1_000_000.0
    ev_wind_co2 = (total_ev_miles * wind) * EV_WIND_G_PER_MILE / 1_000_000.0
    ev_hydro_co2 = (total_ev_miles * hydro) * EV_HYDRO_NUCLEAR_G_PER_MILE /
1_000_000.0
    ev_gas_co2 = (total_ev_miles * gas) * EV_GAS_COAL_G_PER_MILE / 1_000_000.0

    total_ev_co2 = ev_disposal_co2 + ev_prod_co2 + ev_solar_co2 + ev_wind_co2 +
ev_hydro_co2 + ev_gas_co2
```

```
    total_ice_co2 = ice_disposal_co2 + ice_prod_co2 + ice_use_co2
    total_co2 = total_ev_co2 + total_ice_co2
    cumulative_co2 = float(total_co2.sum())

    df = pd.DataFrame({"Year": years, "Total Co2 in metric ton": total_co2,
                       "%_E_CAR": ev_stock_share*100, "avg_ev_miles": avg_ev, "avg_ice_miles":
avg_ice,
                       "Solar %": solar*100, "Wind %": wind*100, "Hydro %": hydro*100, "Gas %":
gas*100})
    return df, cumulative_co2


def optimize_best_scenario():
    # EV endpoint fixed at 100% (not a searched range) and mileage factors fixed at 1.0
    # (no decline) to match the shared spec across all three algorithms. The search
    # structure is kept intentionally -- each grid has exactly one value, so nothing
    # is actually being searched (Linear is meant to be the "no clever sequencing" case).
    ev_stock_end_grid = np.array([1.0])
    ev_sales_end_grid = np.array([1.0])
    ev_miles_grid = np.array([1.0])
    ice_miles_grid = np.array([1.0])

    best_params = None; best_df = None; best_cum = None
    for ev_stock_end in ev_stock_end_grid:
        for ev_sales_end in ev_sales_end_grid:
            if ev_sales_end < ev_stock_end:
                continue
            for ev_m_end in ev_miles_grid:
                for ice_m_end in ice_miles_grid:
                    params = ScenarioParams(
                        ev_stock_share_2025=0.020776, ev_stock_share_2050=float(ev_stock_end),
```

```
                ev_sales_share_2025=0.020776, ev_sales_share_2050=float(ev_sales_end),
                ev_miles_factor_2050=float(ev_m_end),
ice_miles_factor_2050=float(ice_m_end),
            )
            df, cum = compute_scenario(params)
            if best_cum is None or cum < best_cum:
                best_params, best_df, best_cum = params, df, cum
    return best_params, best_df, best_cum


def run():
    best_params, best_df, best_cum = optimize_best_scenario()
    return best_df, best_cum, best_params


if __name__ == "__main__":
    df, total, params = run()
    print(f"Linear Transition total: {total:,.2f}")
    print(f"Chosen params: {params}")
```

3. Random search algorithm (both EV adoption and grid mix randomized):

```
"""
random_search.py
==================
Random Search Algorithm. 75,000 randomly generated combinations of EV
adoption timing AND grid-mix timing (both randomized), each respecting
realistic annual growth bounds. The combination with the lowest cumulative
total is kept. Seed = 42 for reproducibility.

A convergence test across 1,000 to 150,000 trials found the best result
stops improving from 75,000 trials onward; 75,000 is the smallest trial
```

count at which that plateau begins.

Expected output when run: cumulative total approximately 21.66 billion
metric tons (2025-2050), a 33.50% reduction versus the Baseline,
the lowest of all four scenarios.
"""
import numpy as np

YEAR = list(range(2025, 2051))
n_years = len(YEAR)

# EIA AEO2026, Table 39 (Light-Duty Vehicle Stock), Counterfactual Baseline case (cb2026.d021826b).
TOTAL_LDV_STOCK = np.array([270313293, 273027161, 276130737, 279158936,
282220917, 285506348, 288730072,
291821350, 294999908, 298139465, 301225525, 304159668, 307055237, 309949097,
312836731, 315691467,
318420105, 321030640, 323441864, 325686371, 327725281, 329559509, 331201233,
332635895, 333855103,
334770203], dtype=float)

# Derived from TOTAL_LDV_STOCK using a 4.5%/year retirement rate (S&P Global Mobility, 2025).
TOTAL_CARS_SELL = np.array([14877965, 15389799, 15454081, 15624133, 15985372,
16071510, 16084131,
16310519, 16414553, 16502336, 16489292, 16582754, 16711346, 16835344, 16932389,
16934754, 16939439,
16857603, 16799391, 16694797, 16581866, 16471902, 16338717, 16187823, 15938580,
15979759], dtype=float)
EV_STOCK_SHARE_2025 = 0.020776
AVG_EV_MILES_2025 = 10787.0

```
AVG_ICE_MILES_2025 = 10787.0

EV_PROD_TON_PER_VEHICLE = 15.3
ICE_PROD_TON_PER_VEHICLE = 10.0
ICE_USE_G_PER_MILE = 400.0
EV_CHG_SOLAR_G_PER_MILE = 11.4
EV_CHG_WIND_G_PER_MILE = 3.1
EV_CHG_HYDRO_G_PER_MILE = 6.72
EV_CHG_GAS_G_PER_MILE = 173.1
G_TO_METRIC_TON = 1_000_000.0



def compute_disposal(stock, total_sell):
    d = np.zeros_like(stock, dtype=float)
    for i in range(len(stock) - 1):
        d[i] = stock[i] + total_sell[i] - stock[i + 1]
    d[-1] = total_sell[-1]
    return d



def sample_bounded_sum(n, lo, hi, total, rng):
    if total < n * lo - 1e-12 or total > n * hi + 1e-12:
        raise ValueError("Infeasible bounded-sum constraints")
    x = np.full(n, lo, dtype=float)
    remaining = total - n * lo
    cap = np.full(n, hi - lo, dtype=float)
    w = rng.random(n); w = w / w.sum()
    inc = w * remaining
    for _ in range(80):
        over = inc > cap + 1e-12
        if not over.any():
```

```
            break
        excess = float((inc[over] - cap[over]).sum())
        inc[over] = cap[over]
        avail = cap[~over] - inc[~over]
        if excess > float(avail.sum()) + 1e-12:
            raise ValueError("Redistribution failed")
        w2 = rng.random(avail.size); w2 = w2 / w2.sum()
        inc[~over] += w2 * excess
    x = x + inc
    diff = total - float(x.sum())
    if abs(diff) > 1e-10:
        x[0] = min(hi, max(lo, x[0] + diff))
    if abs(float(x.sum()) - total) > 1e-6:
        raise ValueError("Could not satisfy sum constraint")
    return x


# CONSTRAINTS, Eqs. (3.6)-(3.9): grid boundary conditions (2025 actual mix to the
# 2050 target), the mix identity (shares sum to 100%), and the growth bounds passed
# in as bounds_pp. Any draw that cannot satisfy all of them is rejected before evaluation.
def generate_feasible_mix_path(rng, start, end, bounds_pp):
    s0, w0, h0, g0 = start
    sT, wT, hT, gT = end
    n_steps = 25
    lo_s, hi_s = bounds_pp["solar"][0] / 100.0, bounds_pp["solar"][1] / 100.0
    lo_w, hi_w = bounds_pp["wind"][0] / 100.0, bounds_pp["wind"][1] / 100.0
    lo_h, hi_h = bounds_pp["hydro"][0] / 100.0, bounds_pp["hydro"][1] / 100.0
    lo_g, hi_g = bounds_pp["gas"][0] / 100.0, bounds_pp["gas"][1] / 100.0

    ds = sample_bounded_sum(n_steps, lo_s, hi_s, sT - s0, rng)
    dw = sample_bounded_sum(n_steps, lo_w, hi_w, wT - w0, rng)
```

```
    dh = sample_bounded_sum(n_steps, lo_h, hi_h, hT - h0, rng)
    s = s0 + np.cumsum(np.r_[0.0, ds])
    w = w0 + np.cumsum(np.r_[0.0, dw])
    h = h0 + np.cumsum(np.r_[0.0, dh])
    g = 1.0 - s - w - h
    dg = np.diff(g)
    if np.any(dg < lo_g - 1e-12) or np.any(dg > hi_g + 1e-12):
        raise ValueError("Gas YoY outside bounds")
    if np.any(s < 0) or np.any(w < 0) or np.any(h < 0) or np.any(g < 0):
        raise ValueError("Negative share")
    if not (abs(s[-1]-sT) < 1e-6 and abs(w[-1]-wT) < 1e-6 and abs(h[-1]-hT) < 1e-6 and abs(g[-1]-
gT) < 1e-6):
        raise ValueError("Endpoint mismatch")
    return s, w, h, g


# CONSTRAINTS, Eqs. (3.6), (3.7), (3.10): EV boundary conditions (2.078% in 2025,
# 100% in 2050) and the fleet-turnover cap (EV additions in any year cannot exceed
# that year's total vehicle sales; the EV stock is non-decreasing).
def sample_ev_path(rng, stock, total_market_per_year, ev_share_2025, ev_share_2050):
    n_steps = len(stock) - 1
    e_car_start = stock[0] * (ev_share_2025 / 100.0)
    e_car_end = stock[-1] * (ev_share_2050 / 100.0)
    lo, hi = 0.0, float(total_market_per_year.min())
    total = e_car_end - e_car_start
    d = sample_bounded_sum(n_steps, lo, hi, total, rng)
    e_car = e_car_start + np.cumsum(np.r_[0.0, d])
    ev_pct = e_car / stock * 100.0
    return ev_pct
```

```
def objective_function(ev_share, solar, wind, other_green, fossil,
                       stock, total_sell, disposal_data,
                       avg_ev_miles, avg_ice_miles):
    """OBJECTIVE FUNCTION, Eq. (3.1): TE = sum over 2025-2050 of
    [E_prod(t) + E_oper(t) + E_disp(t)], evaluated for one candidate pathway.

    E_prod(t), Eq. (3.2): manufacturing emissions of all NEW vehicles sold in
       year t: EV sales x 15.3 t/vehicle plus ICE sales x 10.0 t/vehicle (GREET).
    E_oper(t), Eqs. (3.3)-(3.4): driving emissions of the ENTIRE fleet on the
       road in year t: ICE stock x miles x 400 g/mile (gasoline combustion)
       plus EV stock x miles x I(t), where I(t) is the grid charging intensity
       implied by that year's generation mix.
    E_disp(t), Eq. (3.5): end-of-life emissions of all vehicles RETIRED in
       year t: retirements x 1.3 t/vehicle, both vehicle types.

    Inputs: ev_share and the four mix shares as fractions (0-1), per year.
    Returns (annual_emissions_array, TE_total). The search MINIMIZES the
    returned TE, subject to constraints Eqs. (3.6)-(3.10), which are enforced
    by the trajectory generators above (infeasible candidates are rejected).
    """
    ice_share = 1.0 - ev_share
    e_cars = stock * ev_share
    ice_cars = stock * ice_share
    ev_sell = total_sell * ev_share
    ice_sell = total_sell * ice_share
    ev_disp = disposal_data * ev_share
    ice_disp = disposal_data * ice_share

    # E_prod(t), Eq. (3.2)
    e_prod = ev_sell * EV_PROD_TON_PER_VEHICLE + ice_sell *
ICE_PROD_TON_PER_VEHICLE
```

```
    # E_oper(t), Eqs. (3.3)-(3.4)
    intensity = (EV_CHG_SOLAR_G_PER_MILE * solar + EV_CHG_WIND_G_PER_MILE *
wind +
                 EV_CHG_HYDRO_G_PER_MILE * other_green + EV_CHG_GAS_G_PER_MILE
* fossil)
    e_oper = (ice_cars * avg_ice_miles * ICE_USE_G_PER_MILE) / G_TO_METRIC_TON \
             + (e_cars * avg_ev_miles * intensity) / G_TO_METRIC_TON
    # E_disp(t), Eq. (3.5)
    e_disp = (ev_disp + ice_disp) * 1.3

    annual = e_prod + e_oper + e_disp
    return annual, float(annual.sum())



def find_best_mix_and_ev(n_iter, seed, start_mix, end_mix, bounds_pp,
                         stock, total_sell, disposal_data,
                         ev_share_2025, ev_share_2050,
                         avg_ev_miles, avg_ice_miles):
    rng = np.random.default_rng(seed)
    best = {"cumulative_total": float("inf"), "ev_pct": None,
            "solar": None, "wind": None, "hydro": None, "gas": None, "feasible_found": 0}

    for _ in range(n_iter):
        try:
            ev_pct = sample_ev_path(rng, stock, total_sell, ev_share_2025, ev_share_2050)
            s, w, h, g = generate_feasible_mix_path(rng, start_mix, end_mix, bounds_pp)
        except ValueError:
            continue

        # Evaluate the OBJECTIVE FUNCTION, Eq. (3.1), for this candidate pathway.
        _, total = objective_function(ev_pct / 100.0, s, w, h, g,
```

```
                        stock, total_sell, disposal_data,
                        avg_ev_miles, avg_ice_miles)

        best["feasible_found"] += 1
        if total < best["cumulative_total"]:
            best["cumulative_total"] = total
            best["ev_pct"] = ev_pct.copy()
            best["solar"], best["wind"], best["hydro"], best["gas"] = s.copy(), w.copy(), h.copy(),
g.copy()

    if best["ev_pct"] is None:
        raise RuntimeError("No feasible (EV path, grid path) combination found.")
    return best


def run(n_iter=75000):
    # CONSTRAINT SET, Eq. (3.9): annual growth bounds, percentage points per year.
    # Floors: slowest EIA deployment years of the past decade. Ceilings: no source
    # can complete its full 2025-2050 transition faster than about 2035 (NREL 2023a).
    bounds_pp = {"solar": (0.25, 4.31), "wind": (0.25, 2.85), "hydro": (-2.00, 2.00), "gas": (-6.20, -
0.50)}
    start_mix = (0.0700, 0.1100, 0.2500, 0.5700)
    end_mix = (0.4500, 0.4200, 0.1300, 0.0000)
    disposal_data = compute_disposal(TOTAL_LDV_STOCK, TOTAL_CARS_SELL)

    best = find_best_mix_and_ev(
        n_iter=n_iter, seed=42, start_mix=start_mix, end_mix=end_mix, bounds_pp=bounds_pp,
        stock=TOTAL_LDV_STOCK, total_sell=TOTAL_CARS_SELL,
disposal_data=disposal_data,
        ev_share_2025=EV_STOCK_SHARE_2025*100, ev_share_2050=100.0,
        avg_ev_miles=AVG_EV_MILES_2025, avg_ice_miles=AVG_ICE_MILES_2025,
```

```
    )
    return best


if __name__ == "__main__":
    best = run(75000)
    print(f"Random Search total: {best['cumulative_total']:,.2f}")
    print(f"Feasible draws: {best['feasible_found']:,}/75,000")
```

4. Baseline scenario algorithm (EIA AEO2026 Counterfactual Baseline case):

```
"""
baseline_transition.py
======================
Baseline scenario: U.S. Energy Information Administration, Annual Energy
Outlook 2026 (AEO2026), Counterfactual Baseline case -- the no-new-policy
current-law projection, as distinct from the three optimized scenarios,
which target the federal government's stated 2050 decarbonization goal.

SOURCE: EIA AEO2026, Supplemental Table 39 (Light-Duty Vehicle Stock by
Technology Type), NEMS run cb2026.d021826b, Counterfactual Baseline case.
This is the same official source EIA itself names for stock and sales
projections (eia.gov/tools/faqs/faq.php?id=93&t=3). Vehicle stock and the
year-by-year EV stock share are taken directly from this table, not
interpolated. Total annual sales and retirements are derived from this
same stock series using a 4.5%/year retirement rate (S&P Global Mobility,
2025), since EIA's "Fleet" sales table (Table 44) covers only commercial
fleets of 10+ vehicles (about 2.7 million/year), not the total market
(about 16 million/year) this model requires:
  Sales[year] = (Stock[year+1] - Stock[year]) + Retirements[year]
  Retirements[year] = Stock[year] x 0.045
This produces a sales series averaging 16.3 million/year, consistent with
```

real-world U.S. new light-duty vehicle sales.

Grid mix SOURCE: EIA AEO2026 narrative (eia.gov/outlooks/aeo/narrative/)
and EIA, "Electricity in the United States" for the 2025 actual mix.

2025 starting point:
  EV stock share: 2.078% (EIA AEO2026 Table 39, exact)
  Solar 7%, Wind 11%, Other Green 25% (nuclear+hydro+biomass+geothermal),
  Fossil 57% (natural gas+coal+petroleum+other)

2050 endpoint:
  EV stock share: 46.13% (EIA AEO2026 Table 39, exact -- not a midpoint
  estimate; the year-by-year EV curve below is the actual table series,
  not a straight line between endpoints)
  Solar 20%, Wind 20%, Other Green 20%, Fossil 40%
"""
```
import numpy as np

years = np.arange(2025, 2051)
n_years = len(years)

# EIA AEO2026, Table 39, Counterfactual Baseline case (cb2026.d021826b)
# "Total Stock, Cars and Light Trucks", millions converted to vehicles.
stock_data = np.array([270313293, 273027161, 276130737, 279158936, 282220917,
285506348, 288730072,
291821350, 294999908, 298139465, 301225525, 304159668, 307055237, 309949097,
312836731, 315691467,
318420105, 321030640, 323441864, 325686371, 327725281, 329559509, 331201233,
332635895, 333855103,
334770203], dtype=float)
```

```
# Same table, "Electric" row / "Total Stock" row x 100, exact year-by-year EV share.
ev_pct_data = np.array([2.0776, 2.6359, 3.4310, 4.6583, 6.2205, 8.1762, 10.4602, 13.0337,
15.6296,
18.1781, 20.6673, 23.0622, 25.3875, 27.6267, 29.7784, 31.8194, 33.7608, 35.5968, 37.3239,
38.9362,
40.4312, 41.7962, 43.0496, 44.1943, 45.2204, 46.1318], dtype=float)

# Derived from stock_data above using a 4.5%/year retirement rate (S&P Global Mobility,
2025).
disposal_data = np.array([12164098, 12286222, 12425883, 12562152, 12699941, 12847786,
12992853,
13131961, 13274996, 13416276, 13555149, 13687185, 13817486, 13947709, 14077653,
14206116, 14328905,
14446379, 14554884, 14655887, 14747638, 14830178, 14904055, 14968615, 15023480,
15064659], dtype=float)

# Derived: (stock[t+1]-stock[t]) + disposal_data[t]. Averages 16.3M/year, consistent with
# real-world U.S. new light-duty vehicle sales.
total_sales_data = np.array([14877965, 15389799, 15454081, 15624133, 15985372, 16071510,
16084131,
16310519, 16414553, 16502336, 16489292, 16582754, 16711346, 16835344, 16932389,
16934754, 16939439,
16857603, 16799391, 16694797, 16581866, 16471902, 16338717, 16187823, 15938580,
15979759], dtype=float)

AVG_EV_MILES, AVG_ICE_MILES = 10787.0, 10787.0
EV_PROD, ICE_PROD, EV_DISP, ICE_DISP, ICE_OP = 15.3, 10.0, 1.3, 1.3, 400.0
EF_SOLAR, EF_WIND, EF_OTHER, EF_FOSSIL = 11.4, 3.1, 6.72, 173.1
G2T = 1_000_000.0
```

```
GRID_START = {'solar': 7.0, 'wind': 11.0, 'other': 25.0, 'fossil': 57.0}  # EIA-confirmed actual 2025 mix
GRID_END   = {'solar': 20.0, 'wind': 20.0, 'other': 20.0, 'fossil': 40.0}  # EIA AEO2026 Counterfactual Baseline


def run():
    idx = np.arange(n_years)
    ev_pct = ev_pct_data.copy()  # real EIA table series, not interpolated
    solar = np.linspace(GRID_START['solar'], GRID_END['solar'], n_years)
    wind = np.linspace(GRID_START['wind'], GRID_END['wind'], n_years)
    other = np.linspace(GRID_START['other'], GRID_END['other'], n_years)
    fossil = 100.0 - (solar + wind + other)

    ice_pct = 100 - ev_pct
    e_cars = stock_data*(ev_pct/100); ice_cars = stock_data*(ice_pct/100)
    ev_sell = total_sales_data*(ev_pct/100); ice_sell = total_sales_data*(ice_pct/100)
    ev_disp = disposal_data*(ev_pct/100); ice_disp = disposal_data*(ice_pct/100)
    ev_disp_co2 = ev_disp*EV_DISP; ice_disp_co2 = ice_disp*ICE_DISP
    ev_prod_co2 = ev_sell*EV_PROD; ice_prod_co2 = ice_sell*ICE_PROD
    ev_miles = e_cars*AVG_EV_MILES; ice_miles = ice_cars*AVG_ICE_MILES
    ice_use_co2 = (ice_miles*ICE_OP)/G2T
    ev_solar_co2 = (ev_miles*(solar/100)*EF_SOLAR)/G2T
    ev_wind_co2 = (ev_miles*(wind/100)*EF_WIND)/G2T
    ev_other_co2 = (ev_miles*(other/100)*EF_OTHER)/G2T
    ev_fossil_co2 = (ev_miles*(fossil/100)*EF_FOSSIL)/G2T
    total_ev =
ev_disp_co2+ev_prod_co2+ev_solar_co2+ev_wind_co2+ev_other_co2+ev_fossil_co2
    total_ice = ice_disp_co2+ice_prod_co2+ice_use_co2
    total = total_ev+total_ice
    return float(total.sum()), ev_pct, solar, wind, other, fossil
```

```
if __name__ == "__main__":
    total, ev_pct, solar, wind, other, fossil = run()
    print(f"Baseline (EIA AEO2026 Counterfactual Baseline case) total: {total:,.2f}")
    print(f"EV: {ev_pct[0]:.2f}% -> {ev_pct[-1]:.2f}%")
    print(f"Grid 2025: Solar {solar[0]:.1f} / Wind {wind[0]:.1f} / Other {other[0]:.1f} / Fossil
{fossil[0]:.1f}")
    print(f"Grid 2050: Solar {solar[-1]:.1f} / Wind {wind[-1]:.1f} / Other {other[-1]:.1f} / Fossil
{fossil[-1]:.1f}")
```

Appendix No. (2)

Detailed Tables of the Optimized Scenario Data

Sudden Transition Algorithm -- Full Variables Table (2025-2050)

Total cumulative emissions for this scenario: 22,293,130,797 metric tons

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2025	2.08	97.92	7.0	11.0	25.0	57.0	270313293	5616029	264697264	1487796 5	309105	14568860	12164098	13144950 19.09
2026	7.51	92.49	10.29	13.68	23.96	52.06	273027161	20493994	252533167	1538979 9	1155191	14234608	12286222	12862548 38.53
2027	13.0	87.0	12.57	15.55	23.24	48.64	276130737	35883793	240246944	1545408 1	2008292	13445789	12425883	12518919 91.23
2028	18.39	81.61	14.59	17.19	22.6	45.62	279158936	51337874	227821062	1562413 3	2873309	12750824	12562152	1216593439.99
2029	23.73	76.27	16.44	18.7	22.02	42.84	282220917	66962007	215258910	1598537 2	3792818	12192554	12699941	1181672569.35
2030	29.05	70.95	18.18	20.12	21.47	40.23	285506348	82947379	202558969	1607151 0	4669212	11402298	12847786	1142170711.44
2031	33.09	66.91	19.85	21.48	20.94	37.73	288730072	95538520	193191552	1608413 1	5322113	10762018	12992853	1111301411.2
2032	37.05	62.95	21.44	22.78	20.44	35.34	291821350	108129661	183691689	1631051 9	6043598	10266921	13131961	1081424426.83
2033	40.92	59.08	22.98	24.04	19.95	33.02	294999908	120720803	174279105	1641455 3	6717216	9697337	13274996	1049551350.29
2034	44.71	55.29	24.48	25.26	19.48	30.78	298139465	133311944	164827521	1650233 6	7378958	9123378	13416276	1016406689.71
2035	48.44	51.56	25.94	26.45	19.02	28.59	301225525	145903085	155322440	1648929 2	7986835	8502457	13555149	980880569.56

Sudden Transition Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2036	52.11	47.89	27.36	27.61	18.57	26.46	304159668	158494226	145665442	16582754	8641089	7941665	13687185	945166476.84
2037	55.72	44.28	28.75	28.75	18.13	24.37	307055237	171085367	135969870	16711346	9311246	7400100	13817486	908902081.01
2038	59.26	40.74	30.12	29.86	17.7	22.32	309949097	183676509	126272588	16835344	9976661	6858683	13947709	871757518.30
2039	62.74	37.26	31.46	30.95	17.28	20.31	312836731	196267650	116569081	16932389	10623050	6309339	14077653	833427887.02
2040	66.16	33.84	32.77	32.03	16.86	18.34	315691467	208858791	106832676	16934754	11203889	5730865	14206116	792885663.71
2041	69.55	30.45	34.07	33.08	16.45	16.4	318420105	221449932	96970173	16939439	11780781	5158658	14328905	751031677.80
2042	72.9	27.1	35.35	34.12	16.05	14.48	321030640	234041073	86989567	16857603	12289704	4567899	14446379	706684207.85
2043	76.25	23.75	36.6	35.15	15.65	12.59	323441864	246632215	76809649	16799391	12809940	3989451	14554884	661020024.11
2044	79.59	20.41	37.85	36.16	15.26	10.73	325686371	259223356	66463015	16694797	13287880	3406917	14655887	613207051.62
2045	82.94	17.06	39.07	37.16	14.87	8.89	327725281	271814497	55910784	16581866	13752957	2828909	14747638	563620686.72
2046	86.3	13.7	40.28	38.15	14.49	7.07	329559509	284405638	45153871	16471902	14215041	2256861	14830178	512438713.32
2047	89.67	10.33	41.48	39.13	14.11	5.28	331201233	296996779	34204454	16338717	14651353	1687364	14904055	459339735.79
2048	93.07	6.93	42.67	40.1	13.74	3.5	332635895	309587921	23047974	16187823	15066187	1121636	14968615	404345468.13
2049	96.5	3.5	43.84	41.05	13.37	1.74	333855103	322179062	11676041	15938580	15381154	557426	15023480	346204482.68

Sudden Transition Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2050	100.0	0.0	45.0	42.0	13.0	0.0	334770203	334770203	0	1597975	15979759	0	15064659	290456105.04

Linear Transition Algorithm -- Full Variables Table (2025-2050)

Total cumulative emissions for this scenario: 23,717,284,457 metric tons

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2025	2.08	97.92	7.0	11.0	25.0	57.0	270313293	5616029	264697264	1487796 5	309105	14568860	12164097	1314495017.79
2026	5.99	94.01	8.52	12.24	24.52	54.72	273027161	16366602	256660559	1538979 9	922541	14467258	12286223	1299450438.56
2027	9.91	90.09	10.04	13.48	24.04	52.44	276130737	27368400	248762337	1545408 1	1531715	13922366	12425882	1279908933.39
2028	13.83	86.17	11.56	14.72	23.56	50.16	279158936	38602902	240556034	1562413 3	2160550	13463583	12562152	1259527841.13
2029	17.75	82.25	13.08	15.96	23.08	47.88	282220917	50080621	232140296	1598537 2	2836634	13148738	12699941	1239720986.65
2030	21.66	78.34	14.6	17.2	22.6	45.6	285506348	61846614	223659734	1607151 0	3481423	12590087	12847786	1216054807.64
2031	25.58	74.42	16.12	18.44	22.12	43.32	288730072	73854196	214875876	1608413 1	4114156	11969975	12992853	1189526582.25
2032	29.5	70.5	17.64	19.68	21.64	41.04	291821350	86075252	205746098	1631051 9	4810930	11499589	13131961	1163172192.04

Linear Transition Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2033	33.41	66.59	19.16	20.92	21.16	38.76	294999908	98567635	196432273	16414553	5484557	10929996	13274996	1133898130.82
2034	37.33	62.67	20.68	22.16	20.68	36.48	298139465	111294461	186845004	16502336	6160267	10342069	13416276	1102446068.21
2035	41.25	58.75	22.2	23.4	20.2	34.2	301225525	124245167	176980358	16489292	6801266	9688026	13555149	1067721560.8
2036	45.16	54.84	23.72	24.64	19.72	31.92	304159668	137369018	166790650	16582754	7489345	9093409	13687185	1031959768.48
2037	49.08	50.92	25.24	25.88	19.24	29.64	307055237	150703791	156351446	16711346	8201987	8509359	13817486	994662101.62
2038	53.0	47.0	26.76	27.12	18.76	27.36	309949097	164264492	145684605	16835344	8922269	7913075	13947710	955420883.58
2039	56.91	43.09	28.28	28.36	18.28	25.08	312836731	178048348	134788383	16932389	9636924	7295465	14077653	913905422.03
2040	60.83	39.17	29.8	29.6	17.8	22.8	315691467	192038403	123653064	16934754	10301587	6633167	14206116	869124394.82
2041	64.75	35.25	31.32	30.84	17.32	20.52	318420105	206170446	112249659	16939439	10967937	5971502	14328904	822137487.59
2042	68.66	31.34	32.84	32.08	16.84	18.24	321030640	220435150	100595490	16857603	11575245	5282358	14446379	771788558.76
2043	72.58	27.42	34.36	33.32	16.36	15.96	323441864	234759694	88682170	16799391	12193288	4606103	14554884	719465311.5
2044	76.5	23.5	35.88	34.56	15.88	13.68	325686371	249145592	76540779	16694797	12771290	3923507	14655887	664327771.74
2045	80.42	19.58	37.4	35.8	15.4	11.4	327725281	263541989	64183292	16581866	13334394	3247472	14747638	606917230.26
2046	84.33	15.67	38.92	37.04	14.92	9.12	329559509	277925496	51634013	16471902	13891153	2580749	14830178	547490048.37

Linear Transition Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2047	88.25	11.75	40.44	38.28	14.44	6.84	331201233	292282809	38918424	16338717	14418805	1919912	14904055	485773272.38
2048	92.17	7.83	41.96	39.52	13.96	4.56	332635895	306577891	26058004	16187823	14919703	1268120	14968615	421923742.14
2049	96.08	3.92	43.48	40.76	13.48	2.28	333855103	320778346	13076757	15938580	15314282	624298	15023480	354820169.29
2050	100.0	0.0	45.0	42.0	13.0	0.0	334770203	334770203	0	15979759	15979759	0	15979759	291645735.04

Random Search Algorithm (Best -- Lowest Cumulative Emissions) -- Full Variables Table (2025-2050)

Total cumulative emissions for this scenario: 21,656,848,693 metric tons

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2025	2.08	97.92	7.0	11.0	25.0	57.0	270313293	5616029	264697264	14877965	309105	14568860	12164097	1314495017.79
2026	7.51	92.49	9.01	12.72	23.93	54.34	273027161	20493994	252533167	15389799	1155191	14234608	12286223	1287086192.15
2027	12.81	87.19	10.96	14.53	24.36	50.15	276130737	35371959	240758778	15454081	1979646	13474435	12425882	1254409627.81
2028	18.0	82.0	13.08	16.06	25.1	45.76	279158936	50249924	228909012	15624133	2812418	12811715	12562152	1220105786.13
2029	23.08	76.92	13.45	16.93	24.79	44.83	282220917	65127889	217093028	15985372	3688931	12296441	12699941	1189758222.51
2030	28.02	71.98	13.77	18.71	25.13	42.39	285506348	80005854	205500494	16071510	4503630	11567880	12847786	1154623296.74

Random Search Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2031	32.44	67.56	15.91	20.6	25.28	38.21	288730072	93671934	195058138	16084131	5218132	10865999	12992853	1118058932.55
2032	37.2	62.8	17.31	22.02	24.24	36.43	291821350	108549899	183271451	16310519	6067086	10243433	13131961	1081964401.78
2033	41.84	58.16	19.09	23.09	23.58	34.24	294999908	123427864	171572044	16414553	6867844	9546709	13274996	1042975956.25
2034	46.39	53.61	20.54	23.96	23.84	31.66	298139465	138305829	159833636	16502336	7655375	8846961	13416276	1001448365.44
2035	50.85	49.15	21.6	24.56	24.4	29.45	301225525	153183794	148041731	16489292	8385386	8103906	13555149	958000106.48
2036	55.25	44.75	22.48	25.11	23.52	28.89	304159668	168061759	136097909	16582754	9162710	7420044	13687185	918992566.06
2037	59.58	40.42	25.03	25.77	23.72	25.48	307055237	182939724	124115513	16711346	9956414	6754932	13817486	870781243.55
2038	63.82	36.18	26.26	26.6	22.6	24.54	309949097	197817689	112131408	16835344	10744761	6090583	13947710	829302041.18
2039	67.99	32.01	27.24	27.5	22.49	22.77	312836731	212695654	100141077	16932389	11512221	5420168	14077653	783712477.44
2040	72.09	27.91	30.0	28.56	20.61	20.83	315691467	227573619	88117848	16934754	12207816	4726938	14206116	735197970.88
2041	75.77	24.23	32.33	29.85	19.83	17.99	318420105	241280474	77139631	16939439	12835734	4103705	14328904	685412158.69
2042	79.0	21.0	33.54	31.05	20.18	15.24	321030640	253628098	67402542	16857603	13318236	3539367	14446379	637740261.11
2043	83.02	16.98	35.47	32.9	18.32	13.31	323441864	268506063	54935801	16799391	13946056	2853335	14554884	582823515.62
2044	83.19	16.81	38.04	33.28	17.31	11.36	325686371	270931612	54754759	16694797	13888049	2806748	14655887	572424536.95

Random Search Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2045	85.48	14.52	40.64	34.8	15.78	8.79	327725281	280137229	47588052	1658186	14174061	2407805	14747638	531870813.64
2046	89.52	10.48	40.98	36.18	15.96	6.88	329559509	295015194	34544315	1647190 2	14745323	1726579	14830178	470941897.05
2047	93.43	6.57	41.8	37.25	15.25	5.7	331201233	309438872	21762361	1633871 7	15265143	1073574	14904055	413703217.46
2048	94.39	5.61	43.12	39.21	13.73	3.95	332635895	313973133	18662762	1618782 3	15279594	908229	14968615	389884857.69
2049	98.12	1.88	44.28	41.02	13.89	0.82	333855103	327587074	6268029	1593858 0	15639338	299242	15023480	319489495.0
2050	100.0	0.0	45.0	42.0	13.0	0.0	334770203	334770203	0	1597975 9	15979759	0	15979759	291645735.04

Baseline Algorithm (EIA AEO2026 Counterfactual Baseline Case) -- Full Variables Table (2025-2050)

Total cumulative emissions for this scenario: 32,567,373,811 metric tons

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2025	2.08	97.92	7.0	11.0	25.0	57.0	270313293	5616029	264697264	1487796 5	309105	14568860	12164098	1314495019.09
2026	2.64	97.36	7.52	11.36	24.8	56.32	273027161	7196723	265830438	1538979 9	405660	14984139	12286222	1326816761.01
2027	3.43	96.57	8.04	11.72	24.6	55.64	276130737	9474046	266656691	1545408 1	530230	14923851	12425883	1334217546.90

Baseline Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2028	4.66	95.34	8.56	12.08	24.4	54.96	279158936	13004061	266154875	15624133	727819	14896314	12562152	1338599195.76
2029	6.22	93.78	9.08	12.44	24.2	54.28	282220917	17555552	264665365	15985372	994370	14991002	12699941	1341982055.44
2030	8.18	91.82	9.6	12.8	24.0	53.6	285506348	23343570	262162778	16071510	1314039	14757471	12847786	1339706255.74
2031	10.46	89.54	10.12	13.16	23.8	52.92	288730072	30201743	258528329	16084131	1682432	14401699	12992853	1333020242.75
2032	13.03	86.97	10.64	13.52	23.6	52.24	291821350	38035119	253786231	16310519	2125864	14184655	13131961	1324901950.96
2033	15.63	84.37	11.16	13.88	23.4	51.56	294999908	46107306	248892602	16414553	2565529	13849024	13274996	1314940496.43
2034	18.18	81.82	11.68	14.24	23.2	50.88	298139465	54196090	243943375	16502336	2999811	13502525	13416276	1304367127.33
2035	20.67	79.33	12.2	14.6	23.0	50.2	301225525	62255183	238970342	16489292	3407891	13081401	13555149	1292316394.68
2036	23.06	76.94	12.72	14.96	22.8	49.52	304159668	70145911	234013757	16582754	3824348	12758406	13687185	1281080514.38
2037	25.39	74.61	13.24	15.32	22.6	48.84	307055237	77953648	229101589	16711346	4242593	12468753	13817486	1270125311.34
2038	27.63	72.37	13.76	15.68	22.4	48.16	309949097	85628707	224320390	16835344	4651050	12184294	13947709	1259324219.08
2039	29.78	70.22	14.28	16.04	22.2	47.48	312836731	93157773	219678958	16932389	5042195	11890194	14077653	1248443951.98
2040	31.82	68.18	14.8	16.4	22.0	46.8	315691467	100451131	215240336	16934754	5388537	11546217	14206116	1236855340.11
2041	33.76	66.24	15.32	16.76	21.8	46.12	318420105	107501175	210918930	16939439	5718890	11220549	14328905	1225308001.35

Baseline Algorithm - Full Variables Table: Continued

Year	%_E_CAR	%_ICE_CAR	Solar %	Wind %	Other Green %	Fossil %	Total LDV Stock	#_E_CAR	#_ICE_CAR	Total Cars Sell	#_EVs_SELL	#_ICE_SELL	#_Disposal	Annual Total CO2 (metric tons)
2042	35.6	64.4	15.84	17.12	21.6	45.44	321030640	114276635	206754005	1685760 3	6000767	10856836	14446379	1212892247.95
2043	37.32	62.68	16.36	17.48	21.4	44.76	323441864	120721118	202720746	1679939 1	6270188	10529203	14554884	1200749093.11
2044	38.94	61.06	16.88	17.84	21.2	44.08	325686371	126809897	198876474	1669479 7	6500320	10194477	14655887	1188276104.04
2045	40.43	59.57	17.4	18.2	21.0	43.4	327725281	132503264	195222017	1658186 6	6704247	9877619	14747638	1175903398.24
2046	41.8	58.2	17.92	18.56	20.8	42.72	329559509	137743352	191816157	1647190 2	6884629	9587273	14830178	1163977454.89
2047	43.05	56.95	18.44	18.92	20.6	42.04	331201233	142580806	188620427	1633871 7	7033752	9304965	14904055	1152088660.20
2048	44.19	55.81	18.96	19.28	20.4	41.36	332635895	147006105	185629790	1618782 3	7154095	9033728	14968615	1140289504.34
2049	45.22	54.78	19.48	19.64	20.2	40.68	333855103	150970613	182884490	1593858 0	7207490	8731090	15023480	1127720253.05
2050	46.13	53.87	20.0	20.0	20.0	40.0	334770203	154435521	180334682	1597975 9	7371750	8608009	15064659	1118976710.87

VITA

Muhammed Aljohani was born in Yanbu, Saudi Arabia, and received his Bachelor of Science degree in Electromechanical Engineering Technology from Middle Tennessee State University in 2013. He then obtained a Master of Science degree in engineering management from the University of Tennessee at Chattanooga in 2015 and a Master of Science degree in engineering technology from Middle Tennessee State University in 2016. In 2019, he began his Ph.D. studies in Industrial and Systems Engineering at the University of Tennessee Space Institute. During his doctoral studies, he worked as a lecturer in the Engineering Technology Department at Middle Tennessee State University. He completed his Doctor of Philosophy degree in Industrial and Systems Engineering at the University of Tennessee Space Institute in August 2026.