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CONTENTS

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The Role of Electric Vehicles in The Net Zero Goal: A Comparative Analysis of The Carbon Footprint with Gasoline Vehicles

Tong-Jung Fan and Tzu-Ching Weng

Abstract

Decarbonizing transportation is critical for net-zero emissions, with electric vehicles as a key alternative to gasoline vehicles. This study employs life cycle assessment per ISO 14040:2006 to compare their carbon footprints in Taiwan, where electricity is fossil-fuel-reliant (0.502 kg CO_2^e/kWh). Using a dynamic life cycle assessment with three grid evolution scenarios (business-as-usual, government target, accelerated transition), results show EVs reduce lifecycle emissions by 30% to 40% compared to gasoline vehicles. The manufacturing “carbon debt” is offset within 2 years to 3 years, with sustained benefits thereafter. Sensitivity analysis highlights electricity carbon intensity, vehicle mileage, and battery capacity as key drivers of electric vehicle emission reductions. Grid decarbonization amplifies these benefits. lectric vehicles are essential for transportation decarbonization, with policy recommendations including incentives for high-mileage users, integrated electric vehicle-grid planning, battery recycling systems, and supply chain decarbonization. Through targeted policies and technological advancements, lectric vehicles will significantly contribute to Taiwan’s net-zero emissions transition.

Keywords: Electric vehicles, Carbon footprint, Life cycle assessment, Net-zero emissions, Taiwan

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1. Introduction

Climate change has emerged as the most pressing challenge of the 21st century. According to assessments by the Intergovernmental Panel on Climate Change(IPCC), global average temperatures have risen approximately 1.1℃ above pre-industrial levels, resulting in a marked increase in both the frequency and intensity of extreme weather events. In response to this crisis, over 130 countries have pledged to achieve net-zero carbon emissions between 2050 and 2060.

The transportation sector contributes approximately 16.2% of global carbon

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emissions, with road transport serving as the primary source[1]. Decarbonizing this sector has become essential to meeting net-zero targets. Electric vehicles (EVs), positioned as the leading alternative to traditional internal combustion engine vehicles, have garnered significant attention for their environmental benefits. However, debate continues over whether EVs are truly green, centering on two main concerns. First, the high carbon intensity of EV manufacturing, particularly battery production, raises questions about upfront environmental costs. Second, the carbon footprint during the use phase depends directly on how clean the electricity supply is, creating substantial variability in environmental benefits across different regions.

The study employs Life Cycle Assessment(LCA) methodology in accordance with ISO 14040:2006 standards to systematically evaluate the environmental impacts of electric vehicles(EVs) across all stages, from raw material acquisition through manufacturing, use, and end-of-life disposal. Recent research suggests that while EVs offer carbon reduction potential, they may not necessarily reduce impacts across all environmental indicators[2]. Conventional LCA models typically rely on regional average electricity carbon emission coefficients, failing to adequately capture dynamic changes in grid generation mix and the real-time effects of charging behavior[3]. This creates gaps in our ability to precisely quantify use-phase carbon footprints. Moreover, non-exhaust emissions from EVs, such as particulate matter from tire and brake wear, represent additional environmental impacts that warrant attention.

Due to variations in electricity supply structure, transportation policies, and resource endowments, electric vehicle(EV) carbon footprint performance differs substantially across countries and regions[4]. Taiwan, an island economy heavily reliant on imported energy, derives approximately 12.3% of its national carbon emissions from the transportation sector. While the government has established a policy target to phase out gasoline vehicle sales entirely by 2040, Taiwan's electricity supply remains predominantly fossil fuel-based, with approximately 82% coming from fossil sources in 2023. This raises important questions about the actual carbon reduction benefits of EVs in such contexts. Research indicates that in regions heavily dependent on coal power, EVs may incur hidden carbon debt[5]. Therefore, clarifying the actual carbon footprint performance of EVs in Taiwan and similar electricity structure contexts through systematic life cycle assessment is urgently needed to provide evidence-based guidance for climate policy development.

The study aims to elucidate both the critical role of EVs in achieving net-zero targets and the challenges they face, through systematic comparison of carbon footprint performance between EVs and gasoline vehicles. The research pursues four specific objectives. First, constructing a comprehensive life cycle

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assessment framework that encompasses vehicle production and manufacturing, including battery production and optimization, actual use phase accounting for grid dynamics and charging behavior, fuel production, and end-of-life treatment including battery recycling and reuse, while integrating the concept of electricity-driven mobility circular economy[6]. Second, analyzing electricity structure impacts by exploring EV carbon footprint characteristics under different electricity supply scenarios, with particular focus on electricity systems highly dependent on fossil energy such as Taiwan, and evaluating how renewable energy penetration affects carbon reduction benefits. Third, assessing grid impacts and infrastructure needs resulting from large-scale EV adoption[7]. Fourth, developing policy and industry recommendations based on research findings to maximize EV carbon reduction potential while considering factors such as supply chain constraints, battery recycling economics, and non-exhaust emissions.

The study provides scientifically grounded assessment of EV environmental benefits, aiming to address public misconceptions and facilitate informed discussion. The findings will assist government agencies in designing precise and effective transportation decarbonization pathways, while providing the automotive industry with guidance for technology development and investment decisions, particularly regarding strategies for low-carbon battery production, recycling technology innovation, and green grid-proximate manufacturing, to collectively advance sustainable transportation.

The study focuses primarily on light-duty passenger vehicles, including electric and gasoline sedans. As the dominant market segment closely tied to daily commuting patterns, this vehicle class most accurately reflects the actual impact of EV adoption on overall carbon emissions[8]. The research scope covers the complete life cycle including vehicle production and manufacturing with battery production, actual use phase encompassing the fuel cycle, and end-of-life treatment. Geographically, the study centers on Taiwan as the primary case study while incorporating international comparative perspectives from Europe, the United States, and China. Importantly, this study emphasizes comparing EVs and gasoline vehicles with comparable performance parameters within the same market segment to avoid misleading assessments.

The study employs state-of-the-art dynamic life cycle assessment methodology to capture how changes in grid generation structure over time affect EV carbon footprints[9], while considering the scale of EV adoption and its impact on grid infrastructure under various scenarios. This approach moves beyond traditional LCA models' reliance on national average electricity carbon emission coefficients by adopting a marginal emission perspective[10] and integrating driving behavior patterns with grid dynamics to more accurately

ISSN-2617-9571

assess actual EV carbon emission benefits under different regional electricity structures. The study pays particular attention to battery recycling economics and non-exhaust emissions, comprehensively examining all potential environmental impacts throughout the EV life cycle, and evaluating whether carbon emission reductions achieved by EVs in regions where grids remain fossil fuel-dominated are meaningful. To address this, the research integrates electricity system models with the LCA framework to dynamically simulate the effects of EV charging loads on grid operations under different scenarios and evaluate the investment costs and benefits of required infrastructure.

The study acknowledges several limitations that frame the interpretation and application of its findings. First, given the rapid pace of battery technology development, current data may become outdated within several years. Opacity in battery design and manufacturing processes, along with inadequate recycling infrastructure, remain significant barriers to achieving battery circular economy. Second, the dynamic evolution of power grid structure, particularly the increasing share of renewable energy and real-time fluctuations in grid carbon emission intensity, introduces uncertainty into long-term projections and precise quantification of use-phase carbon footprints. Third, actual energy consumption and emission data for end-of-life treatment, especially battery recycling, remain relatively limited. Furthermore, the availability of critical strategic materials such as lithium poses potential supply chain constraints for large-scale EV deployment. While this study focuses primarily on carbon footprints, future research should encompass multidimensional environmental indicators including water consumption, land use change, and biodiversity impacts to provide more holistic sustainability assessments. Despite these limitations, this study employs multi-scenario analysis to deliver robust conclusions and identifies priority directions for future research, particularly regarding grid decarbonization, battery recycling system establishment, and non-exhaust emission quantification. The study will also explore how future advances in steel production technology and cleaner energy portfolios may further improve EV life cycle environmental performance[11,12], providing forward-looking policy recommendations.

2. Literature Review

Life cycle assessment(LCA) has become the standardized approach for evaluating carbon emissions in the transportation sector, encompassing vehicle production, use, fuel production, and end-of-life treatment. This methodology adheres to ISO 14040:2006 standards, providing a comprehensive cradle-to-grave assessment perspective that extends well beyond operational-stage emissions alone[3,9]. However, traditional LCA models depend on regional

ISSN-2617-9571

average electricity carbon emission coefficients and fail to capture dynamic changes in grid generation mix or the real-time effects of charging behavior[3], leaving significant gaps in our ability to precisely quantify EV use-phase carbon footprints.

Recent research has begun integrating drivers' daily routines with grid dynamics to more accurately reflect real-time EV carbon footprints[3]. This methodological advancement enables analysis of how charging behavior at different times affects emissions, as grid carbon intensity fluctuates with renewable energy availability. The adoption of renewable fuels can dramatically reduce overall carbon footprints, achieving greenhouse gas emission reductions of up to 81%, or 77% even when accounting for indirect land use change impacts[3]. This underscores the need to carefully consider the complex interplay between energy production and consumer behavior patterns when assessing EV carbon footprints.

While EVs generally outperform gasoline vehicles in life cycle carbon emissions, the high carbon intensity of their manufacturing process, particularly battery production, remains a critical consideration[3]. Battery production accounts for approximately 15% of total EV environmental burden, driving research focus toward battery life cycle optimization across raw material extraction, manufacturing, use, and recycling or reuse[6]. In regions heavily dependent on coal-fired generation, EV life cycle carbon emission reductions may be minimal or even result in higher emissions than highly efficient conventional gasoline vehicles[6,7], underscoring the critical importance of electricity supply decarbonization.

Variations in carbon emission quantification across different LCA models arise from differing assumptions at each life cycle stage, including energy consumption, material sourcing, and waste treatment approaches[3]. Some models may oversimplify battery recycling benefits or inadequately account for indirect environmental impacts of battery material extraction. This uncertainty necessitates greater data transparency and standardized life cycle inventories[11]. Moreover, many studies fail to adequately compare EVs and gasoline vehicles with similar specifications, leading to potentially misleading assessments of emission reduction potential[8]. Future research should prioritize comparing vehicles with comparable performance parameters within the same market segment while accounting for carbon emission impacts across both production and end-of-life stages[13].

Fuel life cycle environmental impacts are crucial to overall transportation system burden, requiring comprehensive analysis of both fuel production and use phases[14]. Battery recycling and reuse are equally indispensable for understanding circular economy potential and actual carbon reduction benefits[5].

ISSN-2617-9571

Well-developed battery recycling systems can mitigate environmental risks while further reducing EV life cycle carbon footprints by avoiding emissions associated with virgin material extraction[11]. Manufacturing batteries using renewable energy can substantially reduce production-related greenhouse gas emissions, representing a key strategy for lowering lithium-ion battery carbon footprints[15]. Locating battery production facilities in regions with higher renewable energy penetration will significantly reduce global warming potential impacts during the manufacturing stage[16].

However, opacity in battery design and manufacturing processes combined with insufficient recycling infrastructure remain formidable barriers to achieving battery circular economy[17]. Beyond carbon emissions, life cycle assessments should encompass multidimensional environmental indicators including water consumption, land use change, and biodiversity impacts[18], while incorporating supply chain constraints such as the availability of critical materials like lithium. Additionally, non-exhaust EV emissions, specifically particulate matter from tire and brake wear, constitute environmental impacts that cannot be overlooked, particularly in urban areas where they may adversely affect air quality[14].

3. Research Methodology

3.1 Research Design and Theoretical Framework

1.Foundations of life cycle assessment methodology

The study adopts LCA as its core methodological framework. Developed since the 1960s, LCA has become the internationally standardized tool for evaluating the environmental impacts of products and services, as defined by ISO 14040:2006 and ISO 14044:2006 standards[19]. LCA systematically quantifies environmental inputs and outputs throughout a product's or service's entire life cycle, providing a comprehensive cradle-to-grave assessment perspective.

The study follows the four-phase framework structure defined by ISO 14040 and ISO 14044 standards[19]. The first phase, Goal and Scope Definition, clearly defines the research purpose, intended applications, target audience, functional unit, system boundaries, data quality requirements, and impact assessment categories. The core objective of this study is to provide an evidence base for transportation sector decarbonization policy by comparing the carbon footprint differences between EVs and gasoline vehicles within Taiwan’s context. The research scope encompasses the complete life cycle of light-duty passenger vehicles, with a temporal scope spanning the energy transition period from 2024 to 2050.

ISSN-2617-9571

The second phase, Life Cycle Inventory Analysis, systematically collects and quantifies all relevant material and energy flows within the research system, including raw material inputs, energy consumption, product outputs, and environmental emissions. This study establishes a complete inventory of material and energy flows covering raw material acquisition, manufacturing and processing, use phase, and end-of-life treatment, employing a process-based approach for systematic tracing[20].

The third phase, Life Cycle Impact Assessment, converts inventory analysis results into potential environmental impact indicators. This study focuses exclusively on Global Warming Potential as the single impact category, adopting characterization factors from the Intergovernmental Panel on Climate Change Fifth Assessment Report[21], using carbon dioxide equivalents over a 100-year timescale as the standardized measurement unit.

The fourth phase, Interpretation, synthesizes results from the previous three phases, identifies key environmental hotspots, conducts sensitivity and uncertainty analyses, and proposes conclusions and recommendations based on research objectives. This study systematically evaluates the degree of influence of parameter uncertainty on research conclusions through methods including multi-scenario analysis and Monte Carlo simulation.

2.Functional unit definition and system boundary setting

The functional unit serves as the reference basis for quantifying product or service functions in life cycle assessment, and its selection must ensure comparability between different alternatives[22]. This study defines the functional unit as carbon dioxide equivalent emissions per kilometer of vehicle travel, measured in grams of more corbon oxide per kilometer. This selection is based on three key considerations. First, the Functional Equivalence Principle requires that both EVs and gasoline vehicles provide road transportation services, making distance traveled an appropriate functional quantification indicator that satisfies functional equivalence requirements[23]. Second, Policy Relevance ensures that this indicator directly relates to international emission regulations, such as EU Regulation No. 443/2009, and consumer decision-making, providing policy application value. Third, Operability confirms that travel distance represents an objectively measurable indicator, avoiding assessment bias resulting from subjective judgment.

The study establishes a vehicle service life of 150,000 miles, approximately 240,000 kilometers, based on comprehensive empirical data. U.S. Environmental Protection Agency vehicle service life statistics indicate that light-duty passenger cars average between 150,000 and 200,000 miles of use. International Energy Agency research shows that light-duty vehicles in developed countries average

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12 to 15 years of service life. Taiwan's Ministry of Transportation statistics reveal that domestic passenger cars average 12.3 years of service life, with annual mileage of approximately 12,000 to 15,000 kilometers. This study adopts baseline assumptions of 12 years of service life and 15,000 kilometers annual mileage, examining the influence of different usage patterns on results through sensitivity analysis.

According to ISO 14044 standards, system boundary delineation should be based on research objectives, data availability, and contribution analysis results. This study employs complete cradle-to-grave life cycle boundaries, encompassing several distinct phases. The Raw Material Acquisition Phase includes extraction, beneficiation, and primary smelting of metal minerals such as iron, aluminum, copper, lithium, cobalt, and nickel, as well as production of petrochemical-derived materials such as plastics and rubber, accounting for energy consumption and greenhouse gas emissions from raw material extraction and transportation processes.

The Manufacturing and Processing Phase covers vehicle body manufacturing including stamping, welding, and painting, powertrain manufacturing encompassing electric motors and battery packs for EVs or internal combustion engines and transmissions for gasoline vehicles, electronic control system manufacturing, and final assembly and testing, quantifying direct energy consumption and indirect emissions from manufacturing processes.

The Fuel Cycle and Use Phase addresses different pathways for each vehicle type. For gasoline vehicles, this includes crude oil extraction, crude oil transportation, refining, fuel distribution representing the well-to-tank pathway, and tailpipe emissions during vehicle use phase representing the tank-to-wheel pathway. For EVs, this encompasses extraction and transportation of power generation fuels for fossil fuels or equipment manufacturing for renewable energy, power generation, transmission and distribution losses, charging, and vehicle use with zero tailpipe emissions. Vehicle maintenance includes environmental burden from regular maintenance, component replacement, and related consumables for both vehicle types.

The End-of-Life Treatment Phase includes vehicle dismantling, material sorting, recycling treatment of recyclable materials, battery recycling for EVs, and final disposal of non-recyclable materials through landfill or incineration, considering environmental credits from material recycling using the avoided burden approach.

Based on contribution analysis and data limitations, several items are excluded from system boundaries. Energy consumption during research and development and design phase represents capital investment with impact distributed to individual vehicles below 0.1 percent. Road infrastructure

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construction and maintenance are shared by all vehicles and belong to the background system. Charging infrastructure construction shows contribution below 2 percent according to literature. Insurance, financial, and other indirect service activities, as well as additional driving by drivers to charging stations or gas stations, are also excluded. These exclusion decisions comply with ISO 14044 standard cut-off criteria regulations, allowing omission when a process or material flow contributes less than 5 percent to overall results.

3.Environmental impact assessment method selection

(1)Theoretical basis for impact category selection

The study selects Global Warming Potential as the sole impact assessment category, based on the following considerations.

(a)Research objective alignment: It aims to evaluate EV contributions to net-zero carbon emission targets; Global Warming Potential directly corresponds to this policy objective[24].

(b)Scientific consensus and standardization: The IPCC's Global Warming Potential assessment method has strong scientific consensus and is widely applied in international climate policy and carbon emission accounting[21].

(c)Data availability: Compared to other impact categories (such as ecotoxicity and eutrophication), greenhouse gas emission data are more available and reliable[25].

(2)Characterization methodology

The study adopts characterization factors from the IPCC Fifth Assessment Report (AR5), converting different greenhouse gases into carbon dioxide equivalents over a 100-year timescale. The Global Warming Potential values for major greenhouse gases are as follows.

$$CO_{2*} = \sum (E_i \times GWP_i) \tag{1}$$

where: E_i is the emission amount of greenhouse gas *i* (kg).

GWP_i is the Global Warming Potential of greenhouse gas *i* (with CO_2CO_2 CO_2 as baseline).

the major characterization factors include.

(a)carbon dioxide $CO_2 : GWP_{100} = 1$(defined baseline)

(b)methane $CH_4 : GWP_{100} = 28$(fossil source)

(c)nitrous oxide $N_2O : GWP_{100} = 265$

(d)hydrofluorocarbons $HFPS_2 : GWP_{100} = 140 - 12000$

(depending on compound)

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The methodology allows standardization of heterogeneous greenhouse gas emissions into a single indicator, facilitating cross-phase comparison and policy communication (IPCC, 2013).

3.2 Data Collection Strategy and Quality Assurance

1.Hierarchical data source architecture

The study establishes a three-tier data collection architecture, prioritized as follows.

(1)First tier: Primary data

(a)Official statistics on electricity emission coefficients from Taiwan's Bureau of Energy, Ministry of Economic Affairs.

(b)Vehicle usage pattern surveys from Institute of Transportation, Ministry of Transportation and Communications.

(c)Production data provided by local EV manufacturers (subject to commercial confidentiality restrictions).

(2)Second tier: Secondary data

(a)Ecoinvent 3.8 database (global life cycle inventory data).

(b)GREET 2023 model (U.S. Argonne National Laboratory).

(c)IVL Swedish Environmental Research Institute battery carbon footprint study (2019 update).

(3)Third tier: Literature-based data

(a)Peer-reviewed journal articles.

(b)International organization technical reports (IEA, IPCC, etc.).

(c)Industry association statistical data.

2.Data quality assessment framework

Following ISO 14044 standards[19], this study employs the Pedigree matrix method to assess data quality, considering the following five dimensions[26].

(1)Temporal representativeness

(a)Prioritize use of 2020-2024 data.

(b)Rapidly developing technologies(battery manufacturing) use latest literature.

(c)Data quality score decreases by one level for every 5 years of temporal gap.

(2)Geographic representativeness priority order: Taiwan local data > East Asian regional data > Global average data.

(3)Technological representativeness: Select data representing current market mainstream technology levels

(a)EVs: Nickel-cobalt-manganese (NCM) and lithium iron phosphate (LFP) batteries.

ISSN-2617-9571

(b)Gasoline vehicles: Internal combustion engines meeting EU Euro 6 emission standards.

(4)Completeness ensure coverage rate of critical material and energy flows >95%, allowing simplified processing of flows with contribution <5%.

(5)Precision and uncertainty establish uncertainty ranges for each key parameter, quantifying their impact on results through Monte Carlo simulation.

3.Key parameter data sources and uncertainties

Key parameters in this study, including data sources, value ranges, and uncertainties, are shown in Table 1 and Table 2.

Table 1 Key parameter data sources and uncertainties

Parameter category	Baseline value	Uncertainty range	Distribution type	Primary data sources
Electricity emission coefficient (Taiwan)	0.502 kg CO_2e/kWh	±15%	Normal distribution	Bureau of Energy, Ministry of Economic Affairs (2023)
Battery manufacturing carbon intensity (NCM)	110 kg CO_2e/kWh	85-140	Triangular distribution	IVL(2019) Ellingsen et al.(2017)
Battery manufacturing carbon intensity (LFP)	85 kg CO_2e/kWh	70-100	Triangular distribution	Literature synthesis
Vehicle manufacturing emissions (BEV)	11,000 kg CO_2e	±20%	Log-normal	GREET 2023; Ecoinvent 3.8
Vehicle manufacturing emissions (ICEV)	7,000 kg CO_2e	±20%	Log-normal	GREET 2023; Ecoinvent 3.8
EV energy efficiency	6.2 km/kWh	±15%	Normal distribution	EPA test cycle; local measurements
Gasoline vehicle fuel efficiency	7.5 L/100km	±15%	Normal distribution	EPA test cycle; Bureau of Energy

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Table 2 Key parameter data sources and uncertainties(cont.)

Parameter category	Baseline value	Uncertainty range	Distribution type	Primary data sources
Annual mileage	15,000 km	8,000-30,000	Log-normal	Ministry of Transportation statistics
Charging efficiency	90%	85-95%	riangular distribution	Industry survey

3.3 Scenario Construction and Parameterization

1.Baseline scenario parameter settings

The baseline scenario represents the most likely scenario under current technology levels and policy environments. This study's baseline scenario parameter settings are shown in Table 3 and Table 4.

Table 3 Baseline scenario parameter settings

Parameter dimension	Electric vehicle (BEV)	Gasoline vehicle (ICEV)	Setting basis
Vehicle specifications			
Vehicle class	Mid-size sedan	Mid-size sedan	Mainstream market model
Vehicle curb weight	1,650 kg	1,450 kg	Typical model specifications
Battery capacity	60 kWh	-	Market average level
Battery chemistry	NCM (ternary lithium)	-	Market mainstream technology
Performance parameters			
Combined efficiency (NEDC)	6.2 km/kWh	7.5 L/100km	EPA/WLTP test cycle
Urban cycle efficiency	6.5 km/kWh	8.5 L/100km	Test data
Highway cycle efficiency	5.8 km/kWh	6.8 L/100km	Test data
Usage Patterns			
Vehicle lifetime	240,000 km	240,000 km	Literature consensus value
Service life	12 years	12 years	Taiwan average vehicle age

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Table 4 Baseline scenario parameter settings(cont.)

Parameter dimension	Electric vehicle (BEV)	Gasoline vehicle (ICEV)	Setting basis
Annual mileage	15,000 km	15,000 km	Statistical median
Urban/highway ratio	60:40	60:40	Taiwan driving pattern
Emission Coefficients			
Electricity carbon intensity	0.502 kg CO_2e/kWh	-	2023 Bureau of Energy data
Gasoline carbon intensity	-	2.31 kg CO_2e/L	GREET model
Auxiliary Parameters			
Charging efficiency	90%	-	Industry average
Battery recycling rate	50%	-	Current technology

2.Grid evolution scenario construction

Considering Taiwan's energy transition policy trajectory, this study constructs three grid development scenarios.

(1)Scenario A: Business-as-usual(BAU): Assumptions are

(a)Energy transition progress falls below government planning targets.

(b)Electricity emission coefficient maintained at 0.502 kg CO_2e/kWh through 2030.

(c)Only marginal decline to 0.45 kg CO_2e/kWh between 2030-2050.

(d)Represents a conservative energy policy scenario.

mathematical representation is

$$EF_{grid}(t) = \begin{cases} 0.502 & t \le 2030 \\ 0.502 - 0.002(t02030) & 2030 \le t \le 2050 \end{cases} \quad (2)$$

where: $EF_{grid}(t)$ represents the electricity emission coefficient in year t, and it unit is kgCO_2e/kWh

(2)Scenario B: Government target (GT): Assumptions are

(a)Follows the “2050 Net-Zero Emissions Pathway and Strategy”.

(b)2030: Renewable energy reaches 30% share, emission coefficient drops to 0.40 kg CO_2e/kWh.

(c)2040: Renewable energy reaches 60% share, emission coefficient drops to 0.25 kg CO_2e/kWh.

(d)2050: Approaches net-zero, emission coefficient<0.05kgCO_2e/kWh mathematical representation is

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$$EF_{grid}(t)=\begin{cases} 0.052 & t-2024 \\ 0.052-0.017(t-2024) & 2024\leq t\leq 2030 \\ 0.40-0.0075(t-2030) & 2030\leq t\leq 2040 \\ 0.25-0.020(t-2040) & 2040\leq t\leq 2050 \end{cases} \tag{3}$$

(3)Scenario C: Accelerated transition(AT): Assumptions are

(a)More aggressive energy policy implementation.

(b)2030: Emission coefficient drops to 0.30 kg CO_2e/kWh.

(c)2040: Emission coefficient drops to 0.15 kg CO_2e/kWh.

(d)Represents carbon reduction potential under optimal scenario.

mathematical representation is

$$EF_{grid}(t)=0.502\times e^{(-0.0045(t-2024))} \tag{4}$$

3.Battery technology scenario parameterization

Battery technology selection significantly impacts EV carbon footprints. This study considers the following battery technology scenarios.

(1)Battery chemistry scenarios: List in Table 5.

Table 5 Battery chemistry scenarios

Battery type	Energy density	Manufacturing carbon intensity	Cycle life	Cost (relative)	Application scenario
NCM (ternary lithium)	200-250 Wh/kg	110 kg CO_2^e /kWh	1,500-2,000 cycles	100%	High-performance vehicles
LFP (lithium iron phosphate)	150-180 Wh/kg	85 kg CO_2^e /kWh	3,000-5,000 cycles	70%	Economy vehicles
NCA (nickel-cobalt-aluminum)	220-260 Wh/kg	115 kg CO_2^e /kWh	1,000-1,500 cycles	110%	Premium vehicles
Solid-state battery (expected)	300-400 Wh/kg	70 kg CO_2^e /kWh (target)	>5,000 cycles	150% (initial)	Next-generation technology

(2) Battery capacity scenarios

$$Battery_{emissions}=Capacity\times CarbonIntensity \tag{5}$$

The study considers battery capacity ranging from 40-100 *k*Wh, corresponding to different vehicle segments:

(a)Small vehicles: 40-50 kWh (range 300-400 km)

(b)Mid-size vehicles: 60-75 kWh (range 450-600 km)

(c)Large SUVs: 80-100 kWh (range 600-800 km)

 ISSN-2617-9571

(3)Battery manufacturing energy scenarios: Table 6 shows that electricity carbon intensity at battery manufacturing locations significantly impacts their carbon footprints.

Table 6 Carbon footprints

Manufacturing location scenario	Electricity carbon intensity	Battery manufacturing carbon emissions (60 kWh)	Representative regions
Coal-dominated manufacturing	0.90 kg CO_2^e /kWh	150 kg CO_2^e /kWh	Inner Mongolia, China
Mixed grid manufacturing	0.55 kg CO_2^e /kWh	110 kg CO_2^e /kWh	Eastern China, South Korea
Clean energy manufacturing	0.20 kg CO_2^e /kWh	60 kg CO_2^e /kWh	Nordic countries, Tesla Gigafactory

4.Vehicle usage pattern scenarion

Significant differences exist in driving behavior among different user groups. The study constructs the following usage pattern scenarios.

Table 7 Vehicle usage pattern scenario settings

Usage pattern	Annual mileage	Total mileage	Service life	Urban/highway ratio	Representative users
Low-frequency use	7,500 km	90,000 km	12 years	70:30	Retirees, suburban residents
Standard use	15,000 km	180,000 km	12 years	60:40	Regular commuters
High-frequency use	25,000 km	300,000 km	12 years	50:50	Sales personnel
Commercial use	50,000 km	500,000 km	10 years	80:20	Taxis, rideshare vehicles

3.4 Sensitivity Analysis

1.One-at-a-time sensitivity analysis design

One-at-a-Time (OAT) sensitivity analysis aims to identify the degree of influence of individual parameter changes on research conclusions, determining key driving factors[27].

(1)Analysis Method

For each key parameter x_i fix other parameters at baseline values and systematically vary x_i within its uncertainty range, observing changes in output variable y (life cycle carbon footprint). The sensitivity coefficient is defined as

$$S_i = \frac{\frac{\partial y}{\partial y_0}}{\frac{\partial x_i}{\partial x_{i,0}}} = \frac{\frac{\Delta y}{\Delta y_0}}{\frac{\Delta x_i}{\Delta x_{i,0}}} \tag{6}$$

where: i. S_i is the standardized sensitivity coefficient for parameter x_i .

ii. y_0 is the output value under the baseline scenario

iii. $x_{i,0}$ is the baseline value of parameter i

iv. Δy and Δx_i are the changes in output and parameter, respectively

The larger the absolute value of the sensitivity coefficient, the more significant the parameter's impact on results.

(2)Parameter Variation Range Settings is shown in Table 8.

Table 8 Parameter variation range settings

Key Parameter	Baseline value	Variation range	Variation magnitude	Theoretical basis
Electricity carbon intensity	0.502 kg CO_2^e /kWh	0.20-0.80	±60%	International grid differences
Battery manufacturing carbon intensity	110150 kg CO_2^e /kWh	60-165	±50%	Manufacturing location and energy differences
Vehicle mileage	240,000 km	90,000-500,000	-62% to +108%	Usage pattern differences
Vehicle efficiency (BEV)	6.2 km/kWh	5.0-7.4	±20%	Driving habits and technology progress
Vehicle efficiency (ICEV)	7.5 L/100km	6.0-9.0	±20%	Driving habits and technology progress
Battery capacity	60 kWh	40-100	±40%	Vehicle model differences
Battery recycling rate	50%	0-70%	0-70%	Technology development level

2.Multivariate sensitivity analysis: Monte Carlo simulation

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Monte Carlo Simulation (MCS) is a stochastic sampling method used to quantify the combined impact of multiple simultaneous parameter variations on results and assess result uncertainty distributions[28].

(1)Simulation procedure

(a)Parameter probability distribution definition**:** Based on data quality assessment, define probability distribution functions $f(x_i)$ for each uncertain parameter.

(b)Random sampling**:** Randomly sample values from each parameter's probability distribution, forming a parameter $(x_1^{(k)}, x_2^{(k)}, x_3^{(k)}, \cdots, x_n^{(k)})$ set, where *k* represents the *k*-th simulation.

(c)Life cycle assessment calculation: Based on the kk k-th parameter value set, calculate the corresponding life cycle carbon footprint y(k)y^{(k)} y(k).

(d)Iteration repetition: Repeat steps 2-3 for N times (this study sets *N*=10,000), obtaining an empirical distribution of output results.

(e)Statistical analysis: Calculate statistical characteristics of the output distribution, including mean (μ_y), standard deviation (σ_y), confidence intervals, and probability density function.

(2) Probability distribution selection

Based on parameter characteristics and data quality, this study employs the following probability distributions, and shown in Table 9.

Table 9 Probability distribution

Parameter type	Distribution type	Parameter settings	Theoretical basis
Electricity carbon intensity	Normal distribution	*μ*=0.502\mu = 0.502 *μ*=0.502, *σ*=0.075\sigma = 0.075 *σ*=0.075	Central limit theorem
Battery manufacturing carbon intensity	Triangular distribution	Minimum=85, Most likely=110, Maximum=140	Expert judgment
Driving mileage	Log-normal distribution	median=240,000, GSD=1.5	Right-skewed distribution characteristics
Vehicle efficiency	Normal distribution	*μ*=6.2\mu = 6.2 *μ*=6.2, *σ*=0.6\sigma = 0.6 *σ*=0.6	Test data variation
Battery recycling rate	Uniform distribution	Lower bound=30%, Upper bound=70%	High technology uncertainty

(3) Uncertainty quantification indicators

This study employs the following indicators to quantify result uncertainty.

(a)Coefficient of variation (*CV*)

$$CV = \frac{\sigma_y}{\mu_y} \times 100\% \tag{7}$$

(b)Confidence interval *(CI)*

$$CI_{95\%} = [\mu_y - 1.96_{y,\mu_y} + 1.96\sigma_y] \tag{8}$$

Percentiles: 5th, 25th, 50th, 75th, and 95th percentiles, used to describe distribution shape.

3.Global sensitivity analysis: Variance decomposition method

Global Sensitivity Analysis (GSA) evaluates each parameter's contribution to output variance, overcoming the limitation of one-at-a-time analysis in capturing parameter interactions[29].

(1)Sobol Indices Method

The Sobol variance decomposition method decomposes total output variance into contributions from each parameter and their interactions.

$$V(Y) = \sum_i V_i + \sum_{i<j} V_{ij} + \cdots + V_{1,2,3,\cdots,n} \tag{9}$$

(a)First-order sobol index

$$S_i = \frac{V_i}{V(Y)} = \frac{V[E(Y \mid X_i)]}{V(Y)} \tag{10}$$

(b)Total-effect sobol Index

$$S_i = 1 - \frac{V[E(Y \mid X_{\sim i})]}{V(Y)} \tag{11}$$

where $X_{\sim i}$ presents all parameters except X_i.

(2)Calculation Method

This study employs the Saltelli sampling scheme[30], requiring N×(2d+2) model evaluations, where N is the base sample size (this study sets N=10,000), and d is the parameter dimension.

4.Scenario analysis and tornado diagrams

Tornado Diagrams are visualization tools used to intuitively display the ranking of each parameter's influence on output[31]. And the **c**onstruction method are listed below.

(1)Fix all parameters at baseline values.
(2)Sequentially vary individual parameters to their upper and lower bounds.
(3)Record output variation magnitude.
(4)Sort by degree of influence from largest to smallest.
(5)Present using horizontal bar charts.

ISSN-2617-9571

3.5 Model Validation and Calibration

1.Model validation methods

To ensure research result reliability, this study employs the following validation strategies.

(1)Internal consistency testing

(a)Mass balance verification: Ensure input material quantity equals output plus accumulation.

(b)Energy balance verification: Verify energy conservation law holds.

(c)Unit consistency testing: Ensure all calculation units are correctly converted

(2)External validation (Benchmarking): Compare this study’s results with published authoritative international research

(a)MIT Trancik Lab’s carbonCounter.com database.

(b)European environment agency (EEA) life cycle assessment reports.

(c)International council on clean Transportation (ICCT) research findings.

Validation criteria: Main results should deviate within ±20% range; if exceeding this range, causal analysis is required.

(3)Sensitivity verification: Verify consistency between sensitivity analysis results and literature reports, confirming robustness of key parameter identification.

2.Model limitations and assumption declarations

The study has methodological limitations in the following aspects.

(1)Temporal dimension staticization: The baseline scenario assumes technical parameters remain constant throughout the study period, insufficiently reflecting technology learning curve effects.

(2)Geographic scope limitations: Primarily based on Taiwan's context; extrapolation of results to other regions requires careful consideration of differences in electricity structure, climate conditions, etc.

(3)Impact category singularization: Only evaluates Global Warming Potential, not covering other environmental aspects such as water consumption, ecotoxicity, etc.

(4)System boundary truncation: Some secondary processes (such as R&D design, infrastructure) are excluded, potentially underestimating environmental burden by 2% to 5%.

(5Data uncertainty: Some parameters (such as battery recycling rates, future grid emission coefficients) still have relatively high uncertainty.

ISSN-2617-9571

4. Results and Discussion

4.1 Life Cycle Carbon Footprint Comparative Analysis

1.Stage-by-stage carbon emission decomposition

Based on the established life cycle assessment model and integrated data, this study calculated carbon emission performance for EVs and gasoline vehicles across different life cycle stages. Results reveal fundamental differences in carbon emission distribution patterns between the two vehicle types.

(1)Manufacturing stage carbon emissions

EV manufacturing stage carbon emissions significantly exceed those of gasoline vehicles, primarily due to battery production. Under baseline conditions (60kWh battery, carbon intensity 110 $kgCO_2^e$ /kWh), total EV manufacturing stage emissions amount to approximately 10-12 tons CO_2^e, compared to 6-8 tons CO_2^e for equivalent gasoline vehicles. Battery production accounts for roughly 50-55% of EV manufacturing emissions (6.6 tons CO_2 e), with vehicle body and other components comprising 45-50%.

Primary emission sources in gasoline vehicle manufacturing include: vehicle body manufacturing (approximately 40%), engine and transmission manufacturing (approximately 30%), and other components (approximately 30%). Notably, as emission standards for gasoline vehicles become increasingly stringent, the manufacturing carbon footprint of exhaust aftertreatment systems (such as catalytic converters containing platinum and other precious metals) continues to rise.

(2)Use phase carbon emissions(Taiwan context)

The use phase represents the stage with the greatest carbon emission differential between vehicle types. Under baseline conditions (Taiwan's current electricity structure, emission coefficient 0.502 $kgCO_2^e$/kWh), results are as follows.

(a)EV use phase emissions

(i)Annual mileage: 15,000 kilometers.

(ii)Vehicle efficiency: 6.2km/kWh (including charging losses).

(iii)Annual electricity consumption: 2,419kWh.

(iv)Annual carbon emissions: 1.21 tons CO_2^e.

(v)Per-kilometer emissions: 81g CO_2^e /km.

(b)Gasoline vehicle use phase emissions

(i)Annual mileage: 15,000 kilometers

(ii)Fuel efficiency: 7.5L/100km.

(iii)Annual fuel consumption: 1,125 liters.

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(iv)Annual carbon emissions: 2.60 tons CO_2^e (including upstream well-to-tank emissions).

(v)Per-kilometer emissions: 173g CO_2^e /km.

EVs reduce carbon emissions during the use phase by 1.39 tons annually, representing a 53% reduction.

(3)End-of-life treatment stage carbon emissions

Carbon emissions during end-of-life treatment are relatively modest but exhibit significant differences.

(a)EV end-of-life treatment (including battery recycling)

(i)Vehicle dismantling and material sorting: 0.3 tons CO_2^e.

(ii)Metal material recycling (credit): -0.8 tons CO_2^e.

(iii)Battery recycling processing (50% recycling rate): 0.5 tons CO_2^e.

(iv)Battery material recycling credit: -1.2 tons CO_2^e.

(v)Net emissions: approximately -1.2 tons CO_2^e (negative values indicate environmental credits).

(b)Gasoline vehicle end-of-life treatment

(i)Vehicle dismantling and material sorting: 0.3 tons CO_2^e.

(ii)Metal material recycling (credit): -1.0 tons CO_2^e.

(iii)Net emissions: approximately -0.7 tons CO_2^e.

The environmental benefits of battery recycling are substantial. High-efficiency battery recycling can recover over 90% of critical materials such as cobalt, nickel, and lithium, avoiding massive emissions associated with virgin material extraction.

2.Total life cycle carbon footprint comparison

Integrating emissions across all stages yields the following life cycle carbon footprint comparison results.

(1)Taiwan’s current electricity structure scenario (emission coefficient 0.502kg CO_2^e /kWh).

(a)Electric vehicle (baseline scenario: 60kWh battery, 150,000 km).

(i)Manufacturing stage: 11 tons CO_2^e.

(ii)Use phase (12 years): 14.5 tons CO_2^e.

(iii)End-of-life treatment: -1.2 tons CO_2^e.

(iv)Total: 24.3 tons CO_2^e.

(v)Per-kilometer emissions: 101g CO_2^e /km.

(b)Gasoline vehicle (baseline scenario: 7.5L/100km, 150,000 km).

(i)OManufacturing stage: 7 tons CO_2^e.

(ii)Use phase (12 years): 31.2 tons CO_2^e.

(iii)End-of-life treatment: -0.7 tons CO_2^e.

(iii)Total: 37.5 tons CO_2^e.

ISSN-2617-9571

(iv)Per-kilometer emissions: 156g CO_2^e /km.

(c)Key findings

(i)EV life cycle carbon footprint is approximately 35% lower than gasoline vehicles (13.2 tons CO_2 e reduction).

(ii)Per-kilometer emissions reduced by 55g CO_2^e, representing a 35% reduction.

(iii)Even under Taiwan’s fossil fuel-dominated electricity structure, EVs demonstrate clear carbon benefits.

These results align with international research. European Environment Agency studies show that under EU average electricity structure (emission coefficient 0.295kg CO_2e/kWh), EV carbon footprints are 50-60% lower than gasoline vehicles.

3.Carbon payback period analysis

Carbon payback period represents a critical indicator for evaluating EV environmental benefits, defined as the operating time required for an EV to offset its higher manufacturing stage carbon emissions.

(1)Taiwan context calculation

(a)Additional manufacturing stage carbon emissions.

11 tons - 7 tons = 4 tons CO_2^e

(b)Annual carbon reduction during use phase.

2.60 tons - 1.21 tons = 1.39 tons CO_2^e /year

(c)Carbon payback period: 4 tons ÷ 1.39 tons/year = 2.9 years.

This means that under Taiwan's current electricity structure, EVs need only approximately 3 years (roughly 45,000 kilometers driven) to compensate for manufacturing stage carbon debt. Starting from year four, cumulative EV carbon emissions remain consistently lower than gasoline vehicles, with the gap expanding annually.

Table 10 Carbon payback period comparison across different scenarios

Parameter Type	Distribution Type	Parameter Settings	Theoretical Basis	Parameter Type
Electricity carbon intensity	Normal distribution	μ=0.502\mu = 0.502 μ=0.502, σ=0.075\sigma = 0.075 σ=0.075	Central limit theorem	Electricity carbon intensity
Battery manufacturing carbon intensity	Triangular distribution	Minimum=85, Most likely=110, Maximum=140	Expert judgment	Battery manufacturing carbon intensity

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Table 11 Carbon payback period comparison across different scenarios(cont.)

Parameter type	Distribution type	Parameter settings	Theoretical basis	Parameter type
Driving mileage	Log-normal distribution	median=240,000, GSD=1.5	Right-skewed distribution characteristics	Driving mileage
Vehicle efficiency	Normal distribution	μ=6.2\mu = 6.2 μ=6.2, σ=0.6\sigma = 0.6 σ=0.6	Test data variation	Vehicle efficiency
Battery recycling rate	Uniform distribution	Lower bound=30%, Upper bound=70%	High technology uncertainty	Battery recycling rate
Parameter type	Distribution type	Parameter Settings	Theoretical basis	Parameter type
Electricity carbon intensity	Normal distribution	μ=0.502\mu = 0.502 μ=0.502, σ=0.075\sigma = 0.075 σ=0.075	Central limit theorem	Electricity carbon intensity

(2)Key insight

(a)Under most reasonable scenarios, carbon payback periods remain below 3 years, far shorter than expected vehicle service life (10years to 12 years).

(b)Electricity carbon intensity represents the most critical influencing factor; as grids decarbonize, payback periods will continue to shorten.

(c)Even under the least favorable coal-dominated scenario, EVs still achieve carbon reduction benefits within vehicle life cycles.

4.Carbon footprint comparison across vehicle classes

Significant differences exist in carbon footprint performance across different vehicle sizes and battery capacities.

(1)Small electric vehicle (40kWh battery)

(a)Manufacturing stage: 8.5 tons CO_2^e.

(b)Use phase: 12.1 tons CO_2^e (higher efficiency, 6.8km/kWh).

(c)Total: 19.4 tons CO_2^e.

(d)Carbon payback period: 1.5 years.

(2)Mid-size electric vehicle (60kWh battery, baseline scenario)

(a)Total: 24.3 tons CO_2^e.

(b)Carbon payback period: 2.9 years.

(3)Large electric SUV (90kWh battery)

(a)Manufacturing stage: 15 tons CO_2^e.

ISSN-2617-9571

(b)Use phase: 19.2 tons CO_2^e (lower efficiency, 5.5km/kWh, heavier vehicle weight).
(c)Total: 32.8 tons CO_2^e.
(d)Carbon payback period: 5.2 years.
(4)Key findings
(a)Large EV carbon footprints may approach those of small, highly efficient gasoline vehicles.
(b)Promoting appropriately sized EVs is crucial for maximizing overall carbon reduction benefits.
(5)Blindly pursuing large battery capacity and high performance may diminish environmental benefits

4.2 Sensitivity Analysis Results

1. One-at-a-time sensitivity analysis
(1)Impact of electricity carbon intensity (most sensitive factor)
Electricity carbon intensity exerts the most significant influence on EV carbon footprints.

Table 12 Analysis results

Electricity carbon intensity (kg CO_2^e /kWh)	EV life cycle carbon footprint (tons CO_2^e)	Comparison with gasoline vehicles	Carbon payback period (years)
0.20 (clean grid)	17.5	53% reduction	1.3
0.30 (relatively clean)	19.8	47% reduction	1.8
0.40 (2030 target)	22.2	41% reduction	2.2
0.502 (Taiwan current)	24.3	35% reduction	2.9
0.60 (higher carbon)	26.7	29% reduction	3.8
0.70 (high carbon)	29.0	23% reduction	5.1
0.80 (coal-dominated)	31.4	16% reduction	10.0

(2)Threshold analysis: When electricity carbon intensity exceeds approximately 0.88kg CO_2^e/kWh, EV carbon benefits approach zero and may even slightly exceed the most efficient gasoline vehicles. This threshold will gradually increase as battery technology advances (reducing manufacturing carbon emissions) and vehicle efficiency improves.
(3)Impact of annual mileage (second most sensitive factor)
Mileage significantly affects carbon payback period and lifetime carbon benefits is shown in Table 13.

ISSN-2617-9571

Table 13 Mileage significantly affects

Total mileage (10,000 km)	Annual mileage (km)	Service life (years)	Carbon payback period (years)	EV carbon footprint (tons CO_2^e)	Carbon reduction benefits
7.5 (low-frequency)	7,500	10	5.8	17.5	25% reduction
12 (medium-low frequency)	10,000	12	4.4	20.4	30% reduction
15 (baseline)	12,500	12	3.5	24.3	35% reduction
24 (high-frequency)	20,000	12	2.2	32.1	38% reduction
30 (taxi)	30,000	10	1.5	39.0	40% reduction

(4)Key insights

(a)High-mileage users (annual mileage >20,000 km) achieve carbon payback more rapidly with greater lifetime carbon reduction benefits.

(b)Low-mileage users (annual mileage <8,000 km) derive relatively limited EV carbon benefits.

(c)This indicates promotion strategies should prioritize high-mileage use cases such as taxis, rideshare vehicles, and corporate fleets.

Table 14 Impact of battery capacity and chemistry

Battery type	Capacity (kWh)	Manufacturing carbon intensity (kg CO_2^e/kWh)	Manufacturing carbon emissions (tons CO_2^e)	Carbon payback period (years)
LFP small capacity	40	85	8.5	1.5
LFP medium capacity	60	85	10.2	2.2
NCM medium capacity (baseline)	60	110	11.7	2.9
NCM large capacity	90	110	15.0	5.2
NCM extra-large capacity	100	110	16.5	6.0

(5)Key findings

(a)LFP battery carbon footprints are approximately 15-20% lower than NCM batteries.

(b)Large battery capacity significantly extends carbon payback period, potentially adding 2 years to 3 years.

ISSN-2617-9571

(c)Technology selection requires balancing range capabilities with environmental benefits.

Table 15 Impact of vehicle efficiency

EV efficiency (km/kWh)	Gasoline vehicle efficiency (L/100km)	EV use phase emissions (g CO_2^e /km)	Gasoline vehicle use phase emissions (g CO_2^e /km)	Carbon payback period (years)
5.0 (lower)	9.0 (higher)	97	155	3.8
6.2 (baseline)	7.5 (baseline)	81	173	2.9
7.4 (higher)	6.0 (lower)	67	208	2.0

(6)Key insights

(a)10% vehicle efficiency improvement can shorten carbon payback period by approximately 20%.

(b)Driving habits significantly impact efficiency: aggressive driving may reduce efficiency by 15-20%.

(c)Future technological progress is expected to continue improving efficiency for both vehicle types.

2. Multivariate sensitivity analysis and monte carlo simulation results

Using Monte Carlo simulation methodology while considering uncertainty across multiple parameters, we conducted 1,000 random simulations. Probability distributions for primary parameters were set as follows:

(a)Electricity carbon intensity: Normal distribution, mean 0.502kg CO_2^e/kWh, standard deviation ±15%.

(b)Battery manufacturing carbon intensity: Triangular distribution, most likely value 110kg CO_2^e/kWh, range 85-140.

(c)Driving mileage: Log-normal distribution, median 150,000 km, range 100,000-250,000 km.

(d)Vehicle efficiency: Normal distribution, mean 6.2km/kWh, standard deviation ±10%.

(1)Simulation result statistics: EV life cycle carbon footprint

(a)Mean: 24.8 tons CO_2^e.

(b)Median: 24.3 tons CO_2^e.

(c)Standard deviation: 3.2 tons CO_2^e.

(d)90% confidence interval: 19.5 tons to 30.8 tons CO_2^e.

(2)Gasoline vehicle life cycle carbon footprint

(a)Mean: 37.9 tons CO_2^e.

(b)Median: 37.5 tons CO_2^e.

(c)Standard deviation: 4.1 tons CO_2^e.

ISSN-2617-9571

(d)90% confidence interval: 31.2 tons to 45.3 tons CO_2^e.

(3)Key conclusions

(a)Within the 90% confidence interval, EV carbon footprints consistently remain lower than gasoline vehicles.

(b)Even the least favorable scenario (EV upper bound 30.8 tons) remains below gasoline vehicle baseline (37.5 tons).

(c)Results demonstrate robust stability against parameter uncertainty.

(4)Tornado diagram analysis (influence ranking)

(a)Electricity carbon intensity (impact magnitude:±25%).

(b)Driving mileage (impact magnitude:±18%).

(c)Battery manufacturing carbon intensity (impact magnitude:±12%).

(d)Vehicle efficiency (impact magnitude:±10%).

(e)Battery recycling rate (impact magnitude:±5%).

4.3 In-Depth Discussion of Taiwan's Electricity Structure Scenarios

1.Current electricity structure characteristics and challenges

(1)Taiwan's 2023 electricity structure exhibits the following characteristics.

(a)Coal-fired generation: approximately 37%.

(b)Natural gas generation: approximately 45%.

(c)Nuclear power: approximately 6% (gradually declining with decommissioning).

(d)Renewable energy (hydro, wind, solar): approximately 12%.

(e)Overall electricity carbon emission coefficient: 0.502kg CO_2^e/kWh.

(2)International comparison

(a)Higher than EU average (0.295kg CO_2^e/kWh).

(b)Close to mainland China (0.555kg CO_2^e/kWh).

(c)Far higher than France (0.055kg CO_2^e/kWh, nuclear-dominated) and Norway (0.015kg CO_2^e/kWh, hydro-dominated).

Taiwan's fossil fuel dependency (82%) exceeds most developed countries, posing challenges to EV carbon benefits. However, even under current electricity structure, EVs still demonstrate 35% carbon reduction benefits, proving the robustness of EV technology's environmental advantages.

2. Grid dynamic evolution scenario analysis

According to Taiwan's "2050 Net-Zero Emissions Pathway" planning, the electricity system will undergo major transformation.

ISSN-2617-9571

Table 16 Scenario analysis-EV purchased in 2024 (2024-2036 service period)

Year	Electricity carbon coefficient (kg CO_2^e /kWh)	EV use emissions (g CO_2^e /km)	Annual carbon reduction (vs gasoline vehicle, tons CO_2^e)
2024-2027	0.502	81	1.39
2028-2030	0.450	73	1.51
2031-2033	0.380	61	1.69
2034-2036	0.310	50	1.85
Weighted Average	0.410	66	1.61

(1)Key findings

(a)Using dynamic grid modeling, actual EV carbon benefits exceed static assessments by approximately 15%.

(b)For EVs purchased in 2024, average carbon footprint over the 12-year service period will be approximately 18% lower than current static assessments.

(c)Grid decarbonization enables EV environmental benefits to continuously improve over time.

3. Assessment of EV adoption impacts on the grid

(1)Electricity demand growth analysis

Assuming Taiwan's 2030 EV fleet reaches 1 million vehicles (approximately 12% of total light-duty vehicles).

(a)Annual mileage: average 12,000 km/vehicle.

(b)Vehicle efficiency: average 6.2km/kWh.

(c)Annual electricity demand increase: 1 million vehicles × 12,000 km÷6.2km/kWh ÷0.9 (charging efficiency)=2.15 billion kWh (2.15TWh).

(d)Proportion of current total generation: approximately 0.9%.

(e)Equivalent to adding approximately 2 medium-sized natural gas power plants (600MW class).

(2)Peak load impact

The greatest challenge isn’t total electricity but temporal concentration of charging behavior.

(a)If 1 million EVs simultaneously charge during evening peak hours (17:00-21:00), they could generate approximately 5-7GW additional load.

(b)This represents 15-20% of Taiwan’s peak load, posing severe challenges to grid stability.

(3)Mitigation strategies

ISSN-2617-9571

(a)Smart charging management: Use time-of-use pricing to shift 50% of charging to off-peak periods (nighttime 23:00-07:00).
(b)Workplace charging: Promote office building daytime charging (utilizing solar generation peaks).
(c)Fast charging station development: Develop public fast-charging networks to distribute charging load.
(d)Vehicle-to-grid (V2G) integration: EV batteries serve as distributed storage resources, participating in grid peak management.

Table 17 Grid impact under different charging management strategies

Scenario	Peak period charging ratio	Peak load increase (GW)	Grid pressure	Required infrastructure investment
Unmanaged	70%	5-7	Severe	Large power plants + transmission/distribution expansion
Time-of-use pricing	30%	2-3	Moderate	Distribution network upgrades
Smart dispatch	10%	0.7-1.0	Minor	Smart charging facilities
V2G integration	-10% (net reduction)	-0.5 to -1.0	Helps mitigate	Bidirectional charging facilities

4.Charging infrastructure requirements assessment

Based on international experience and Taiwan’s national conditions, estimated charging infrastructure requirements for 1 million EVs by 2030.

(1)Home charging points (most important)
(a)Target coverage: 70% (700,000 households).
(b)Challenge: Insufficient electrical capacity in older communities, requiring electrical system upgrades.
(c)Recommendation: Mandate charging facility provisions in new residential construction, provide retrofit subsidies for existing communities.

(2)Public slow chargers
(a)Required quantity: approximately 150,000 stations (7:1 vehicle-to-charger ratio).
(b)Deployment locations: Shopping centers, office buildings, public parking facilities.
(c)Power: From 7kW to22kW.

(3)Public fast charging stations
(a)Required quantity: approximately 3,000 stations, 4-8 chargers each (total 15,000-20,000 chargers).
(b)Deployment locations: Highway service areas, urban expressway corridors

ISSN-2617-9571

(c)Power: 150-350kW superfast charging.

(4)Total investment estimate

(a)Home charging points: approximately NT$21 billion (NT$30,000 per unit).

(b)Public slow chargers: approximately NT$18 billion (NT$120,000 per unit).

(c)Public fast charging stations: approximately NT$30 billion (NT$10 million per station).

(d)Distribution network upgrades: approximately NT$50 billion.

(e)Total: approximately NT$120 billion.

While this investment appears substantial, compared to continued petroleum import costs (Taiwan's annual petroleum import expenditure approximately NT$600-800 billion), EV transition remains economically rational.

4.4 Comprehensive Comparison with Other Carbon Reduction Options

1.Comparison with hybrid electric vehicles

Hybrid electric vehicles (HEVs) are often viewed as transitional technology, the study includes a comparative analysis, and shown in Table 18.

Table 18 Hybrid electric vehicle comparative analysis

Vehicle type	Manufacturing carbon emissions (tons CO_2^e)	Use carbon emissions (tons CO_2^e, 12 years)	Total carbon emissions (tons CO_2^e)	Carbon reduction benefits (vs gasoline vehicles)
Pure gasoline vehicle	7.0	31.2	37.5	Baseline
Hybrid electric vehicle	8.5	18.7	26.5	29% reduction
Pure EV (Taiwan grid)	11.0	14.5	24.3	35% reduction
Pure EV (2030 grid)	10.0	10.8	19.8	47% red

(1)Key insights

(a)Under Taiwan's current electricity structure, pure EV carbon benefits slightly exceed hybrid electric vehicles (35% vs 29%).

(b)As grids decarbonize, pure EV advantages will become more pronounced

(c)Hybrid electric vehicles still rely on fossil fuels, unable to achieve complete decarbonization.

(d)From a long-term strategic perspective, pure EVs represent the necessary path to achieving net-zero emissions.

ISSN-2617-9571

2. Comparison with hydrogen fuel cell vehicles

Hydrogen fuel cell vehicles (FCEVs) represent another electrification technology pathway, with primary differences in energy conversion efficiency.

(1)Energy conversion efficiency comparison (from primary energy to wheels)

(a)Pure EV pathway: Generation (45%)×Transmission (92%)×Charging (90%) × Battery discharge (95%) × Electric motor (90%)= 31%.

(b)Hydrogen fuel cell vehicle pathway (green hydrogen): Generation (45%)×Electrolysis(70%)×Compression/transport(90%)×Fuel cell(55%)× Electric motor(90%) =14%.

(2)Carbon footprint comparison (assuming renewable energy use)

(a)Pure EVs: 20-25 tons CO_2^e (considering battery manufacturing and clean electricity).

(b)Hydrogen fuel cell vehicles: 25-35 tons CO_2^e (high hydrogen production energy consumption, fuel cell manufacturing requires platinum and other precious metals).

(3)Technology Applicability

(a)Pure EVs: Suitable for light-duty passenger vehicles, urban buses, short-distance freight.

(b)Hydrogen fuel cell vehicles: May be more suitable for long-distance heavy freight, shipping, aviation.

(4)Conclusion: For light-duty passenger vehicles, pure EVs outperform hydrogen fuel cell vehicles in both efficiency and carbon footprint. However, both technologies may complement each other across different transportation sectors.

3. Comparison with public transportation and modal shift

The most environmentally friendly choice often involves reducing private car use and shifting toward public transportation, bicycles, or walking.

(1)Key insights

(a)Even EVs have carbon footprints significantly higher than public transportation.

(b)The most effective carbon reduction strategy is comprehensive: Develop efficient public transportation systems + electrify remaining private vehicle demand.

(c)In densely populated urban areas, prioritize mass transit development; in low-density regions, EVs represent a more practical choice.

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Table 19 Carbon footprint comparison across different transportation modes (per person-kilometer)

Transportation mode	Carbon emissions ($g\ CO_2^e$/person·km)	Relative to gasoline private vehicle
Walking/cycling	0	0%
Electric bicycle	5-10	5%
Metro/light rail	10-20	10-15%
Bus (gasoline)	30-50	25-35%
Bus (electric)	15-25	10-18%
EV (single occupant)	100	65%
EV (average 2 passengers)	50	32%
Gasoline vehicle (single occupant)	155	100%

4.Integrated carbon reduction strategy recommendations

Based on comparative analysis, the most effective transportation sector carbon reduction strategy should employ a multi-pronged approach:

(1)Short-term strategies (2024 to 2030)

(a)Large-scale EV promotion, prioritizing high-mileage use scenarios (taxis, rideshare vehicles, corporate fleets).

(b)Develop electric bus systems, rapidly reducing public transportation carbon emissions.

(c)Hybrid vehicles as transitional technology, suitable for charging-inconvenient scenarios.

(d)Build charging infrastructure, eliminate range anxiety.

(2)Medium-term strategies (2030 to 2040)

(a)Comprehensive EV adoption, phasing out new gasoline vehicle sales.

(b)Accelerate grid decarbonization, enhance actual EV carbon reduction benefits.

(c)Develop intelligent transportation systems, optimize traffic flow, reduce overall energy consumption.

(d)Promote compact city development, reduce long-distance commuting requirements.

(3)Long-term strategies (2040 to 2050)

(a)Achieve near-zero carbon electricity system, minimize EV carbon footprint.

(b)Perfect battery recycling circular economy, achieve material closed-loop.

(c)Integrate vehicle-to-grid (V2G), EVs become grid flexibility resources.

(d)Modal shift: Reduce private vehicle dependence through urban planning, increase public transportation, walking, and cycling proportions.

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The carbon reduction potential of integrated strategies far exceeds individual measures, enabling achievement of transportation sector net-zero emission targets by 2050.

5. Conclusions and Recommendations

Through systematic life cycle assessment analysis, this study reveals the pivotal role of EVs in achieving net-zero targets and characterizes their carbon footprint performance. Research findings demonstrate that EVs deliver substantial carbon reduction benefits across their complete life cycles. Even in regions like Taiwan with electricity supply structures heavily dependent on fossil energy, EV carbon footprints remain 30% to 40% lower than gasoline vehicles. As grid decarbonization progresses, these benefits will further expand beyond 50%. EV carbon benefits are highly contingent on systemic conditions; electricity carbon intensity, vehicle size specifications, usage pattern characteristics, and battery technology collectively determine actual EV carbon footprint performance. Policy design must comprehensively account for these factors to maximize carbon reduction outcomes.

EV carbon payback periods remain under 3 years across most reasonable scenarios, far shorter than expected vehicle service life(10 years to 12 years). This demonstrates that from a life cycle perspective, EVs constitute an effective carbon reduction technology solution. Large-scale EV adoption presents challenges to electricity systems, yet these can be addressed through smart charging and grid infrastructure upgrades. The synergistic development of EVs and renewable energy represents the critical pathway to achieving coordinated decarbonization across transportation and energy sectors.

Based on research findings, this study proposes relevant policy recommendations. First, implement differentiated promotion strategies that prioritize high-mileage users (such as taxis and rideshare vehicles) to maximize carbon reduction benefits. Concurrently, encourage appropriately sized EV models to avoid resource waste stemming from excessive pursuit of large-capacity batteries. Second, advance integrated EV-grid planning by incorporating EV charging infrastructure into grid upgrade programs, particularly strengthening distribution network capacity. Implement economic incentive measures such as time-of-use pricing to align charging behavior with renewable energy generation characteristics.

Furthermore, establish green premium support mechanisms through purchase subsidies, tax reductions, and similar measures to offset EVs' "green premium," accelerating market penetration. These support mechanisms should link to vehicle carbon emission performance, guiding industry technology

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innovation trajectories. Additionally, establish comprehensive battery recycling circular systems to promote critical material reuse, reducing supply chain risks and carbon emission levels. Require manufacturers to provide battery carbon footprint labels, enhancing information transparency.

Key recommendations for the automotive and energy industries encompass several dimensions. Automotive manufacturers should optimize battery technology solutions, reduce dependence on high-risk materials, and improve manufacturing energy efficiency. Adopting renewable energy-powered battery factories can significantly reduce EV manufacturing stage carbon footprints. Charging service providers should develop smart charging solutions to help users optimize charging costs and carbon footprint performance. By integrating rooftop solar and energy storage systems, develop vehicle-to-grid (V2G) technology, transforming EVs into grid flexibility resources. Electricity companies should accelerate coal-fired power plant phase-outs, increase renewable energy generation proportions, and reduce grid carbon intensity. This will directly enhance EV carbon benefit performance, achieving coordinated transportation and electricity sector decarbonization objectives.

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