COMILLAS
UNIVERSIDAD PONTIFICIA

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GRADO EN INGENIERÍA EN TECNOLOGÍAS INDUSTRIALES

TRABAJO FIN DE GRADO

Decarbonization of Public Transport Fleets in Urban Areas

Autor: Rodrigo Colmenar Cascón

Director: Pablo Frías Marín

Madrid, Agosto de 2025

Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título
"Decarbonization of Public Transport Fleets in Urban Areas"
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Fdo.: Rodrigo Colmenar Cascón Fecha: 27 / 08 / 2025

Autorizada la entrega del proyecto
EL DIRECTOR DEL PROYECTO

Fdo.: Pablo Frías Marín Fecha: 27 / 8 / 2025

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RESUMEN EJECUTIVO

CONTEXTO E INTRODUCCIÓN

El imperativo global de mitigar el cambio climático ha situado la descarbonización del sector del transporte en la vanguardia de la política medioambiental mundial. En la Unión Europea, donde el transporte representa una parte significativa de las emisiones de gases de efecto invernadero, se han establecido objetivos ambiciosos para alcanzar la neutralidad climática.

Este estudio se centra en el papel fundamental de las flotas de transporte público urbano de personas en esta transición, utilizando Madrid, España, como un caso de estudio integral. La extensa y compleja red de transporte público de la ciudad, compuesta por autobuses municipales (EMT), una gran flota de taxis y vehículos de transporte con conductor (VTC), y autocares interurbanos de gestión privada, presenta un entorno ideal para analizar los multifacéticos desafíos y oportunidades de la electrificación.

Aunque las políticas se han centrado tradicionalmente en la restricción a la movilidad de los vehículos privados contaminantes, el creciente uso de las flotas de transporte público ofrece un efecto multiplicador estratégico. Electrificar un solo autobús o taxi produce reducciones, si calculamos las emisiones por personas que movemos, desproporcionadamente grandes tanto de gases de efecto invernadero (CO2) como de contaminantes atmosféricos locales nocivos (NOx, PM).

Este trabajo adopta un límite de emisiones "del depósito a la rueda" (*tank-to-wheel*) para aislar el impacto directo de las elecciones tecnológicas de la flota de la intensidad de carbono más amplia de la red eléctrica nacional, alineándose con la metodología estándar para el análisis de políticas a nivel municipal.

OBJETIVOS DEL ESTUDIO

El objetivo principal de este trabajo es realizar un análisis integrado, cuantitativo y comparativo de las implicaciones medioambientales y económicas de la electrificación de las principales flotas de transporte público de Madrid. El estudio busca ir más allá de los objetivos políticos de alto nivel para proporcionar simulaciones detalladas y basadas en datos que puedan fundamentar la toma de decisiones estratégicas. Para lograrlo, la investigación persigue cinco objetivos específicos:

i. **Modelizar la evolución tecnoeconómica:** Simular la composición cambiante de cada flota, contrastando las vías de adopción impulsadas por políticas (para los autobuses) con la adopción impulsada por el mercado y basada en el Coste Total de Propiedad (TCO) para los operadores privados (taxis/VTC).

ii. **Cuantificar el impacto medioambiental:** Modelizar la trayectoria de reducción interanual de las emisiones de CO2, NOx y PM para cada flota bajo diferentes escenarios de electrificación entre 2025 y 2045.

iii. **Evaluar el impacto en la energía y la infraestructura:** Calcular la demanda eléctrica anual resultante y, de manera crucial, la potencia máxima de recarga necesaria, cuantificando así la potencial presión sobre la red eléctrica de Madrid.

iv. **Determinar las implicaciones financieras:** Realizar un análisis financiero básico de la transición, siguiendo la evolución tanto de los gastos de capital (CAPEX) como de los gastos operativos (OPEX) para los operadores de las flotas

v. **Evaluar la robustez de los resultados:** Analizar la sensibilidad de las conclusiones del modelo a los cambios en variables económicas clave, como los costes de las baterías y los precios de los combustibles.

METODOLOGÍA

Para abordar la complejidad del proceso de transición de las flotas, este estudio emplea un marco de Modelado Basado en Agentes (ABM, por sus siglas en inglés) implementado en MATLAB. Este enfoque computacional ascendente (*bottom-up*) simula las acciones discretas de miles de agentes individuales (vehículos) a lo largo del tiempo, permitiendo la observación de patrones a nivel de sistema en la composición de la flota, las emisiones y los costes. El núcleo de la metodología es su capacidad para modelizar dos paradigmas de toma de decisiones distintas:

i. **Adopción Impulsada por Políticas:** Simula una vía de transición donde la renovación de la flota se adhiere estrictamente a objetivos gubernamentales predefinidos para la adopción de vehículos eléctricos de batería (BEV), un modelo típico de las flotas de control público como los autobuses de la EMT.

ii. **Adopción Impulsada por el Mercado:** Simula un entorno de libre mercado, principalmente para la flota de taxis y VTC, donde las decisiones de compra se rigen por la racionalidad económica de los operadores individuales que buscan minimizar su Coste Total de Propiedad (TCO).

Al ejecutar estas simulaciones en paralelo, el estudio crea un “entorno de simulación digital” para probar hipótesis, comparar la eficacia de diferentes palancas políticas y, lo que es más importante, cuantificar la brecha potencial entre la ambición política y la realidad del mercado.

RESULTADOS CLAVE

Según los resultados se observa lo siguiente sobre la dinámica de la descarbonización de las flotas:

i. **El TCO (Total Cost of Ownership) es el factor determinante en la adopción por parte de las flotas privadas:** Para los operadores comerciales, como los conductores de taxi y VTC, la decisión de electrificar está dictada de forma abrumadora por la viabilidad económica. Las simulaciones demuestran que, a menos que un vehículo eléctrico de batería (BEV) ofrezca una clara ventaja en el TCO frente a su homólogo de motor de combustión interna (MCI), la adopción por parte del mercado se quedará considerablemente rezagada respecto a los objetivos políticos.

ii. **Existe un desajuste entre las políticas y la dinámica del mercado:** Los planes gubernamentales suelen diseñarse en torno a objetivos de adopción lineales, mientras que el mercado responde de forma no lineal a los puntos de inflexión económicos. Esto crea un riesgo de dos fallos estratégicos: «Fallo de Ambición», donde los objetivos políticos no se alcanzan porque el argumento económico no es convincente, y «Fallo de Preparación», donde una mejora repentina en la economía de los BEV (una fuerte caída del precio) provoca que la adopción por parte del mercado supere masivamente el despliegue planificado de la infraestructura de recarga.

iii. **El déficit de infraestructura de recarga es un riesgo principal:** Un escenario hipotético que contemplaba la llegada masiva de BEV de bajo coste demostró que una transición rápida e impulsada por el mercado podría crear un grave déficit de infraestructura de recarga, con un pico de casi 27 MW. Esto revela que la planificación de la infraestructura debe ser proactiva y anticipar los puntos de inflexión del mercado, en lugar de simplemente reaccionar a los plazos establecidos por las políticas.

iv. **El argumento económico para la electrificación marca la evolución del parque:** Un segundo escenario hipotético, una «Crisis de Durabilidad de las Baterías», demostró que un único coste imprevisto a largo plazo (como la sustitución prematura de la batería) puede invertir por completo el cálculo del TCO, haciendo que los BEV sean económicamente inviables y estancando, o incluso revirtiendo, la transición. Esto subraya la importancia de la fiabilidad tecnológica a largo plazo y de la confianza del operador.

CONCLUSIÓN Y ESTRATEGIAS RECOMENDADAS

Este estudio concluye que una transición exitosa y eficiente hacia un sistema de transporte público de cero emisiones requiere un cambio fundamental en la formulación de políticas, pasando de mandatos rígidos a un enfoque más dinámico y modelador del mercado.

CONCLUSIONES PRINCIPALES:

i. Para las flotas comerciales privadas, alcanzar la paridad en el Coste Total de Propiedad (TCO) es el requisito previo más crítico para la adopción generalizada de los vehículos eléctricos de batería (BEV).

ii. La naturaleza lineal y basada en objetivos de la formulación de políticas está a menudo desalineada con el comportamiento no lineal e impulsado por el TCO del mercado, lo que crea riesgos estratégicos significativos.

iii. Una planificación de infraestructuras proactiva, e incluso «sobredimensionada», es esencial para garantizar la resiliencia frente a una rápida adopción tecnológica impulsada por el mercado.

iv. La viabilidad económica a largo plazo de la electrificación es sensible a los riesgos tecnológicos, y generar confianza en los operadores respecto a la fiabilidad y el coste de propiedad a largo plazo es tan crucial como abordar el precio de compra inicial.

RECOMENDACIONES ESTRATÉGICAS

Basando en estas conclusiones, se extraen las siguientes recomendaciones:

i. Para los responsables políticos municipales y regionales:

- Adoptar políticas centradas en el TCO: Pasar de imponer porcentajes de adopción a gestionar activamente el TCO para los operadores mediante subvenciones dinámicas, precios competitivos de la electricidad para la recarga comercial e incentivos fiscales que amplifiquen las ventajas en OPEX de los BEV.
- Planificar la infraestructura de forma proactiva: Desarrollar planes de despliegue de infraestructuras basados en pruebas de estrés del mercado y escenarios hipotéticos («what-if»), con el objetivo de crear capacidad antes de los puntos de inflexión del mercado previstos.
- Reducir el riesgo de la propiedad a largo plazo: Implementar políticas que generen confianza en los operadores, como programas de garantía extendida respaldados por el gobierno para los BEV comerciales o el apoyo a modelos de «Batería como Servicio» (BaaS) que separan los costes del vehículo y de la batería.

ii. Para las Autoridades de Transporte Público (EMT):

- Acelerar la electrificación de la flota pública: Las simulaciones confirman que, para las flotas de titularidad pública, una transición más rápida no solo es superior desde el punto de vista medioambiental, sino también económicamente sólida a largo plazo debido a los significativos ahorros en OPEX. Las autoridades públicas deben predicar con el ejemplo, adoptando los plazos de electrificación más ambiciosos que sean factibles.

Esta investigación proporciona un marco analítico robusto para abordar las complejidades de la descarbonización del transporte urbano. Al comprender y abordar la interrelación entre las políticas, la tecnología y la economía, ciudades como Madrid pueden forjar un camino más eficiente, resiliente y exitoso hacia un futuro de movilidad sostenible.

EXECUTIVE SUMMARY

INTRODUCTION AND CONTEXT

The global imperative to mitigate climate change has placed the decarbonization of the transport sector at the forefront of environmental policy. In the European Union, where transport accounts for a significant portion of greenhouse gas emissions, ambitious targets have been set to achieve climate neutrality.

This study focuses on the critical role of urban public transport fleets in this transition, using Madrid, Spain, as a comprehensive case study. The city's extensive and complex public transport network, comprising of municipal buses (EMT), a large fleet of taxis and private hire vehicles (VTCs), and privately operated interurban coaches, presents an ideal environment to analyze the multifaceted challenges and opportunities of electrification.

While policies have traditionally focused on restricting polluting private vehicles, the high-utilization nature of public transport fleets offers a strategic multiplier effect; electrifying a single bus or taxi yields disproportionately large reductions in both greenhouse gases (CO2) and harmful local air pollutants (NOx, PM).

This report adopts a "tank-to-wheel" emissions boundary to isolate the direct impact of fleet technology choices from the broader carbon intensity of the national electricity grid, aligning with the standard methodology for city-level policy analysis.

OBJECTIVES OF THE STUDY

The primary objective of this work is to conduct an integrated, quantitative, and comparative analysis of the environmental and economic implications of electrifying Madrid's key public transport fleets. The study aims to move beyond high-level policy goals to provide detailed, data-driven simulations that can inform strategic decision-making. To achieve this, the research pursues five specific objectives:

i. **Model the Techno-Economic Evolution:** To simulate the changing composition of each fleet, contrasting policy-driven adoption pathways (for buses) with market-driven adoption based on Total Cost of Ownership (TCO) for private operators (taxis/VTCs).

ii. **Quantify the Environmental Impact:** To model the year-on-year reduction trajectory of CO2, NOx, and PM emissions for each fleet under various electrification scenarios between 2025 and 2045.

iii. **Assess the Impact on Energy and Infrastructure**: To calculate the resulting annual electricity demand and, crucially, the peak charging power required, thereby quantifying the potential strain on Madrid's electrical grid.

iv. **Determine the Financial Implications**: To conduct a basic financial analysis of the transition, tracking the evolution of both capital expenditures (CAPEX) and operational expenditures (OPEX) for fleet operators.

v. **Evaluate the Robustness of the Findings**: To test the sensitivity of the model's conclusions to changes in key economic variables, such as battery costs and fuel prices, and to explore hypothetical future scenarios.

METHODOLOGY

To navigate the complexity of the fleet transition process, this study employs an Agent-Based Modeling (ABM) framework implemented in MATLAB. This bottom-up computational approach simulates the discrete actions of thousands of individual agents (vehicles) over time, allowing for the observation of emergent, system-level patterns in fleet composition, emissions, and costs. The core of the methodology is its ability to model two distinct decision-making paradigms:

i. Policy-Driven Adoption: Simulates a transition pathway where fleet renewal adheres strictly to predefined government targets for BEV adoption, typical for publicly controlled fleets like EMT buses.

ii. Market-Driven Adoption: Simulates a free-market environment, primarily for the taxi and VTC fleet, where purchasing decisions are governed by the economic rationality of individual operators seeking to minimize their Total Cost of Ownership (TCO).

By running these simulations in parallel, the study creates a "digital sandbox" to test hypotheses, compare the efficacy of different policy levers, and, most importantly, quantify the potential gap between policy ambition and market reality.

KEY FINDINGS

The simulation results yield several insights into the dynamics of fleet decarbonization:

i. **The TCO is the Definitive Agent of Private Fleet Adoption:** For commercial operators like taxi and VTC drivers, the decision to electrify is overwhelmingly dictated by economic viability. The simulations show that unless a Battery Electric Vehicle (BEV) offers a clear TCO advantage over its internal combustion engine (ICE) counterpart, market adoption will significantly lag behind policy targets.

ii. **A Critical Mismatch Exists Between Policy and Market Dynamics:** Government plans are often designed around linear adoption targets, while the market responds non-linearly to economic tipping points. This creates a risk of two strategic failures: "Ambition Failure," where policy goals are missed because the economic case is not compelling, and "Preparation Failure," where a sudden improvement in BEV economics (a sharp drop in price) causes market adoption to massively outpace the planned rollout of charging infrastructure.

iii. **A Charging Infrastructure Deficit is a Primary Risk:** A hypothetical scenario involving the influx of low-cost BEVs demonstrated that a rapid, market-driven transition could create a severe charging infrastructure deficit, peaking at nearly 27 MW. This reveals that infrastructure planning must be proactive and anticipate market tipping points, rather than simply reacting to policy timelines.

iv. **The Economic Case for Electrification is Fragile:** A second hypothetical scenario, a "Battery Durability Crisis," showed that a single, unforeseen long-term cost (such as premature battery replacement) can completely invert the TCO calculation, making BEVs economically unviable and stalling, or even reversing, the transition. This highlights the importance of long-term technological reliability and operator confidence.

CONCLUSIONS AND STRATEGIC RECOMMENDATIONS

This study concludes that a successful and efficient transition to a zero-emission public transport system requires a fundamental shift in policymaking, moving from rigid mandates to a more dynamic, market-shaping approach.

MAIN CONCLUSIONS:

i. For private commercial fleets, achieving TCO parity is the most critical prerequisite for widespread BEV adoption.

ii. The linear, target-based nature of policymaking is often misaligned with the non-linear, TCO-driven behavior of the market, creating significant strategic risks.

iii. Proactive, and even "over-provisioned," infrastructure planning is essential to ensure resilience against rapid, market-led technology uptake.

iv. The long-term economic viability of electrification is sensitive to technological risks, and building operator confidence in the long-term reliability and cost of ownership is as crucial as addressing the initial purchase price.

STRATEGIC RECOMMENDATIONS:

Based on these conclusions, the following recommendations are proposed:

i. For Municipal and Regional Policymakers:

- Adopt TCO-Focused Policies: Shift from mandating adoption percentages to actively managing the TCO for operators through dynamic subsidies, competitive electricity pricing for commercial charging, and tax incentives that amplify the OPEX advantages of BEVs.
- Plan Infrastructure Proactively: Develop infrastructure rollout plans based on market stress-testing and "what-if" scenarios, aiming to build capacity *in advance* of projected market tipping points.

- De-Risk Long-Term Ownership: Implement policies that build operator confidence, such as government-backed extended warranty programs for commercial BEVs or support for "Battery-as-a-Service" (BaaS) models that separate vehicle and battery costs.

ii. **For Public Transport Authorities (EMT):**

- Accelerate Public Fleet Electrification: The simulations confirm that for publicly owned fleets, a faster transition is not only environmentally superior but also economically sound in the long term due to significant OPEX savings. Public authorities should lead by example by pursuing the most ambitious feasible electrification timelines.

This report provides a robust analytical framework for navigating the complexities of urban transport decarbonization. By understanding and addressing the interplay between policy, technology, and economics, cities like Madrid can forge a more efficient, resilient, and successful path toward a sustainable mobility future.

NOMENCLATURE

GENERAL MODEL

- $\boldsymbol{TCO_i}$: Total Cost of Ownership for a vehicle of technology *i*.
- $\boldsymbol{CAPEX_{net,i}}$: Net Capital Expenditure, calculated as the purchase price minus any subsidies.
- $\boldsymbol{OPEX_{annual,i}}$: Annual Operational Expenditure, including fuel, maintenance, and insurance.
- $\boldsymbol{OPEX_{BEV,initial}}$: Standard total annual operating cost for the BEV used in the base model.
- $\boldsymbol{OPEX_{BEV,new}}$: New total annual operating cost for the BEV in Hypothetical Scenario 2.
- $\boldsymbol{N_{years}}$: The projection period (in years) used for TCO calculations.
- $\boldsymbol{U_i}$: The economic "utility" or attractiveness of a vehicle of technology *i*.
- ***market_sensitivity***: A parameter that controls how strongly purchase decisions react to differences in TCO.

CUMULATIVE CALCULATIONS

- $\boldsymbol{E_{pollutant,cumulative}}$: The total cumulative emissions of a specific pollutant over the entire simulation period (2025-2045).
- $\boldsymbol{E_{pollutant}(y)}$: The total emissions of a pollutant in a single year *y*.
- $\boldsymbol{C_{total,cumulative}}$: The total cumulative cost of the fleet over the entire simulation period.
- $\boldsymbol{C_{total}(y)}$: The total cost of the fleet in a single year *y*.

ANNUAL CALCULATION DETAILS

- $\boldsymbol{E_{p,v}}$: Annual emissions of a specific pollutant *p* from an individual vehicle *v*.
- $\boldsymbol{EF_{p,v}}$: The emission factor (in g/km) for pollutant *p* and vehicle *v*.
- $\boldsymbol{D_v}$: The total annual distance traveled by vehicle *v*.
- $\boldsymbol{E_{i,pollutant}}$: The base emission rate for a pollutant from vehicle *i*.
- $\boldsymbol{d_i}$: The average daily distance driven by vehicle *i*.
- ***N(y)***: The total number of vehicles in the fleet in year *y*.
- $\boldsymbol{C_{capex,i}(y)}$: The capital expenditure for vehicle *i* in its year of purchase *y*.
- $\boldsymbol{C_{opex,i}(y)}$: The annual operating expenditure for vehicle *i* in year *y*.
- $\boldsymbol{Price_i(y)}$: The purchase price of vehicle *i* in year *y*.

- $\boldsymbol{Subsidy_i(y)}$: The government subsidy for vehicle *i* in year *y*.
- $\boldsymbol{I(\cdot)}$: An indicator function that is 1 if the condition is true and 0 otherwise.
- $\boldsymbol{C_{fuel,i}(y)}$: The annual cost of fuel or electricity for vehicle i.
- $\boldsymbol{C_{maint,i}(y)}$: The annual cost of maintenance and insurance for vehicle i.
- $\boldsymbol{d_{i,busy}}$ / $\boldsymbol{d_{i,empty}}$: Daily kilometers driven with passengers (busy) versus without (empty).
- $\boldsymbol{Cons_{i,...}}$: The vehicle's energy consumption rate (L/100km or kWh/100km) for a specific driving condition.
- $\boldsymbol{f_{season}}$: A seasonal adjustment factor for BEV/PHEV energy consumption to account for heating and cooling.
- $\boldsymbol{Cost_{i,routine}}$ / $\boldsymbol{Cost_{i,insurance}}$: The routine maintenance and insurance costs per kilometer.

INFRASTRUCTURE CALCULATION

- $\boldsymbol{P_{peak}(y)}$: The peak charging power (in MW) required by the fleet in year *y*.
- $\boldsymbol{E_{elec,total}(y)}$: The total annual electricity demand (in MWh) of the fleet.
- $\boldsymbol{T_{window}}$: The duration of the daily charging window (in hours).
- $\boldsymbol{f_{simul}}$: The simultaneity factor, representing the fraction of the fleet charging at the same time during peak hours.
- $\boldsymbol{\eta_{loss}}$: The energy loss factor during the charging process.

ACRONYMS

- **ABM**: Agent-Based Modeling
- **ASI**: Avoid-Shift-Improve
- **BEV**: Battery Electric Vehicle
- **CaaS**: Charging-as-a-Service
- **CAPEX**: Capital Expenditure
- **CMS**: Charge Management System
- **CNG**: Compressed Natural Gas
- **CO2**: Carbon Dioxide
- **CRTM**: Consorcio Regional de Transportes de Madrid
- **EMT**: Empresa Municipal de Transportes de Madrid
- **EU**: European Union
- **GHG**: Greenhouse Gas
- **GPC**: Global Protocol for Community-Scale Greenhouse Gas Emission Inventories
- **HEV**: Hybrid Electric Vehicle
- **ICE**: Internal Combustion Engine
- **IoT**: Internet of Things
- **NOx**: Nitrogen Oxides
- **OPEX**: Operational Expenditure
- **PHEV**: Plug-in Hybrid Electric Vehicle

- **PM**: Particulate Matter
- **SDG**: Sustainable Development Goals
- **TCO**: Total Cost of Ownership
- **V2G**: Vehicle-to-Grid
- **VTC**: Vehículos de Transporte con Conductor (Private Hire Vehicles)

TAXI & VTC SIMULATION

Main_simulation_taxi_vtc.m and the rest of the code for every simulation can be found in the in Annex Section of the report.

KEY SIMULATION CONTROL & SENSITIVITY PARAMETERS

- **start_year / end_year**: The beginning and end years for the simulation period.
- **scenarios_to_run**: An array specifying which policy scenarios to execute (1: Delayed, 2: Base, 3: Accelerated).
- **use_dynamic_adoption**: A boolean switch (true/false) to select between the market-driven (TCO-based) or policy-driven (target-based) adoption logic.
- **use_seasonal_effects**: A boolean switch to apply seasonal energy consumption adjustments for BEVs and PHEVs.
- **..._multiplier**: A set of sensitivity multipliers (battery_cost_reduction_multiplier) used to test the model's response to changes in economic assumptions.

KEY OPERATIONAL & ECONOMIC PARAMETERS

- **market_sensitivity**: A calibration parameter that determines how strongly the market reacts to differences in Total Cost of Ownership (TCO).
- **tco_projection_years**: The number of years of operational costs to include when calculating the TCO for a new vehicle purchase.
- **vehicle_lifespan_years / $\boldsymbol{L_{vehicle}}$:** The number of years a vehicle remains in service before being retired.
- **empty_taxi_ratio**: The proportion of a taxi's daily travel distance that is spent cruising without a passenger.
- **distance_Taxi_daily**: An array defining the average daily distance traveled by a taxi.
- **vehicle_costs_initial**: A matrix holding the initial (start year) economic data for each vehicle type, including purchase price, subsidies, fuel/energy prices, and maintenance costs.
- **cost_change_rates**: A matrix defining the year-over-year percentage change for each economic parameter in vehicle_costs_initial.
- **target_table_base**: A matrix defining the government's base-case annual targets for BEV and PHEV market share.

KEY CALCULATED VARIABLES

- **fleet**: The main data table representing all vehicles currently in the fleet, updated each year.
- **tco**: An array holding the calculated Total Cost of Ownership for BEV, PHEV, and ICE options in the current year.

- **market_shares**: The calculated purchase probability for each vehicle technology, derived from the tco values.
- **retired_idx**: A logical index identifying vehicles that have reached the end of their lifespan and need to be replaced.
- **annual_CO2, annual_NOx, annual_PM**: Variables that store the total calculated emissions for the entire fleet for the current year.
- **annual_cost**: The total fleet cost (CAPEX + OPEX) for the current year.
- **annual_energy_demand**: The total electricity (in MWh) consumed by all BEVs and PHEVs in the fleet for the current year.

EMT & INTERURBAN BUS SIMULATIONS

KEY PARAMETERS

- **EMTFleetS1**: The initial data matrix loaded for the EMT simulation, containing the starting fleet composition.
- **create_interurban_fleet()**: A function that programmatically generates the initial fleet for the interurban bus simulation.
- **early_retirement_rate_gnc**: (EMT Model) The percentage of the oldest CNG buses that are strategically retired early each year to accelerate modernization.
- **mandate_years_base**: (Interurban Model) An array defining the years in which new zero-emission vehicle mandates take effect.
- **zero_emission_mandate_pct**: (Interurban Model) The percentage of new vehicle purchases that must be zero-emission, corresponding to the mandate_years_base.

KEY CALCULATED VARIABLES

- **num_to_replace**: The total number of buses retired in the current year that need to be replaced.
- **num_zero_emission_mandated**: (Interurban Model) The number of new buses that must be BEVs to comply with the current year's mandate.
- **cheapest_conventional_fuel**: (Interurban Model) The result of a TCO comparison between Diesel and CNG, used to decide non-mandated replacements.
- **peak_power_demand_mw**: The calculated peak power (in MW) required to charge the electric portion of the bus fleet

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CHAPTER 1. INTRODUCTION

1.1 GLOBAL AND EUROPEAN CONTEXT: THE IMPERATIVE OF DECARBONIZATION

The decarbonization of the transport sector has become an imperative of global environmental policy, due to its disproportionate share of greenhouse gas (GHG) emissions. In the European Union, transport is responsible for roughly one quarter of total CO_2 output, with over 70% of that total attributed to road transport alone (European Environment Agency, 2024). In response, the EU has implemented a legally binding framework with its "Fit for 55" package that requires a 55% net GHG emissions reduction by 2030 from 1990 levels (European Commission, 2021). This near-term target is a necessary step towards the longer-term aim of a 90% decrease in transport-related emissions by 2050 and eventual climate neutrality (European Commission, 2019).

The imperative of these EU goals is highlighted by their explicit correlation with the Paris Agreement's goal of keeping global warming below 1.5°C above pre-industrial levels. Fulfilling this global promise is, however, a daunting task. An increasing body of work shows that a swift expansion and decarbonization of public transport is not only desirable but critical to this shift. Forecasts by prominent international organizations estimate that global public transport capacity needs to approximately double by 2030 in order to stay within a 1.5°C trajectory (Welle et al., 2023). A considerable burden is therefore placed on urban hubs to lead and introduce the transformative sustainable mobility innovations necessary to achieve this pivotal global milestone.

1.2 THE ROLE OF PUBLIC TRANSPORT IN URBAN SUSTAINABILITY

Although policy discussion tends to focus on private vehicle electrification, a more strategically effective approach is the decarbonization of public transport fleets. Because of their use case, with longer operating hours and much greater daily mileage, public service vehicles such as urban buses and taxis have a disproportionately large impact relative to private passenger vehicles (International Transport Forum, 2021). This intensity of operation implies that electrifying one public vehicle is the emissions equivalent of transforming many private ones, offering an obvious chance for expedited decarbonization.

The strategic significance of this shift is heightened by its ability to address two disparate environmental problems at once: global climate change and localized public health emergencies. In addition to reducing GHG emissions, fleet electrification explicitly reduces the emission of dangerous local air pollutants like nitrogen oxides (NO_x) and particulate matter (PM). This ancillary benefit is of paramount significance, as the World Health Organization has characterized traffic-related air pollution as a leading environmental health hazard, conclusively associating it with serious cardiovascular and respiratory diseases (World Health Organization, 2021). Thus, by removing tailpipe emissions, the electrification of high-mileage urban fleets becomes one of the most effective interventions currently available for simultaneously advancing climate objectives and improving urban public health.

1.3 CASE STUDY: MADRID

The strategic imperatives of public fleet decarbonization are felt especially keenly in Spain's principal urban hub, Madrid, which presents a fascinating case study. The city boasts a vast public transport ecosystem that consists of several distinct fleets: a municipal bus network (EMT) of more than 2,100 vehicles, a large number of which are already electric; a combined taxi and VTC (Spanish initials for Private Hire Vehicles) fleet of more than 20,000 vehicles; and several privately operated interurban buses linking the capital to its broader metropolitan area. The size and regulatory complexity of this network render it an ideal environment for examining a multi-pronged transition strategy.

The city's pre-existing environmental policies offer essential context for this transition. Traditionally, programs such as the Madrid Central low-emission zone and its replacement, Madrid 360, have emphasized demand-side management through the restriction of the circulation of older, more polluting private vehicles. As effective as these interventions have been, their very efficacy has drawn the emissions of high-intensity public fleets into sharper relief, making them the logical next decarbonization priority. In contrast to the dispersed ownership of private automobiles, these fleets constitute a more manageable policy target; their operation under public concession and strict regulatory regimes leads to predictable renewal cycles and makes them extremely responsive to municipal pressure, rendering them ideal candidates for an orderly, state-guided transition.

1.4 SCOPE AND STRUCTURE OF THE STUDY

This work will carry out an economic and environmental evaluation of the decarbonization of three of the most important public transport fleets in Madrid: taxis and VTCs, the EMT urban bus fleet, and the interurban coach fleet.

To match the analysis to the immediate sphere of influence of city and regional policymakers, this study adopts a tank-to-wheel emissions boundary. This boundary includes all emissions emitted during operation of the vehicle itself. It expressly omits well-to-tank emissions, which relate to the production and transport of fuel or the generation of electricity. This is the conventional methodological decision for city-level policy analysis because it enables the evaluation of direct fleet and technology decisions independent of the confounding variable of the carbon intensity of the national electricity grid, which is beyond municipal control.

The evaluation will be performed through a suite of agent-based simulation models built in MATLAB, where each fleet is represented based on its specific economic and operational conditions. In addition to the environmental effect, the research will calculate the overall annual costs of the transition and estimate the evolving need for charging infrastructure.

1.5 THE "AVOID-SHIFT-IMPROVE" FRAMEWORK: A HOLISTIC DECARBONIZATION PARADIGM

Urban transport decarbonization is a systematically intricate, multi-scale challenge that cannot be solved by a single technological solution. To structure policy and guide investment in a productive manner, a comprehensive conceptual framework is required. The globally accepted "Avoid-Shift-Improve" (ASI) approach bridges this gap, offering a powerful and coherent trajectory towards a sustainable transport future (BCG, 2024). It structures interventions into a rational sequence, ensuring efforts are systematically applied to achieve maximum impact and value for money. The structure includes three cumulative levers:

i. **Avoid**: The primary and first lever aims to cut the total demand for motorized travel. This means strategic interventions in urban planning and social organization to reduce trip length and frequency. The key strategies are to promote high-density, mixed-use urban growth where dwelling space, workplaces, and facilities are close to one another; reorienting street space from private motor vehicles toward active mobility like cycling and walking; and advocating remote and hybrid working patterns (BCG, 2024; U.S. Department of Energy, 2023). The potential for leverage from this level is great; it has been established through studies that one working-from-home day a week can reduce annual greenhouse gas emissions by an amount equivalent to the total output of a megacity like Greater London (BCG, 2024).

ii. **Shift**: The second lever addresses unavoidable journeys and aims to shift them from carbon-dependent modes to cleaner and more efficient modes. This is primarily by way of large investment in good-quality public transport systems, including buses and rail, and the creation of safe, connected, and attractive infrastructure for active transport modes like walking and cycling (U.S. Department of Energy, 2023; GIZ, Agora Verkehrswende, et al., 2023). Shared and public mobility promotion is essential to this level and rests on policies that induce a transition from private cars (World Bank, 2021).

iii. **Improve**: The final lever, "Improve," is focused on enhancing the energy and carbon efficiency of the vehicles that constitute the other motorized travel. This is where technological solutions, notably the transition from ICE vehicles to zero-emission vehicles like BEVs, come into play (BCG, 2024).

This report is primarily situated in the "Improve" axis of the ASI framework in that it mimics the technological substitution of car fleets. However, its findings are deeply connected to the other two levers. A successful "Shift" strategy, for instance, increases the appeal of public transport and enhances its use, thereby driving the environmental repercussions of electrifying the bus fleet.

Most fundamentally, the ASI framework reveals a logical sequence of intervention. The economic and infrastructural burdens of the "Improve" stage are significantly lessened by preceding success during the "Avoid" and "Shift" stages. The simulation models employed in this study presume that the fleet size is constant over the course of the analysis period, which is a condition of little success in demand reduction. The resulting cost estimates and infrastructural demand, therefore, must be viewed as a conservative, upper-bound estimate.

If Madrid can successfully decrease total vehicle-kilometers travelled through policies, the total size of fleets required to serve the city would decline, leading to less initial capital expenditure for electrification, a reduced load on the electricity grid, and a faster and cheaper path to meeting the city's decarbonization targets.

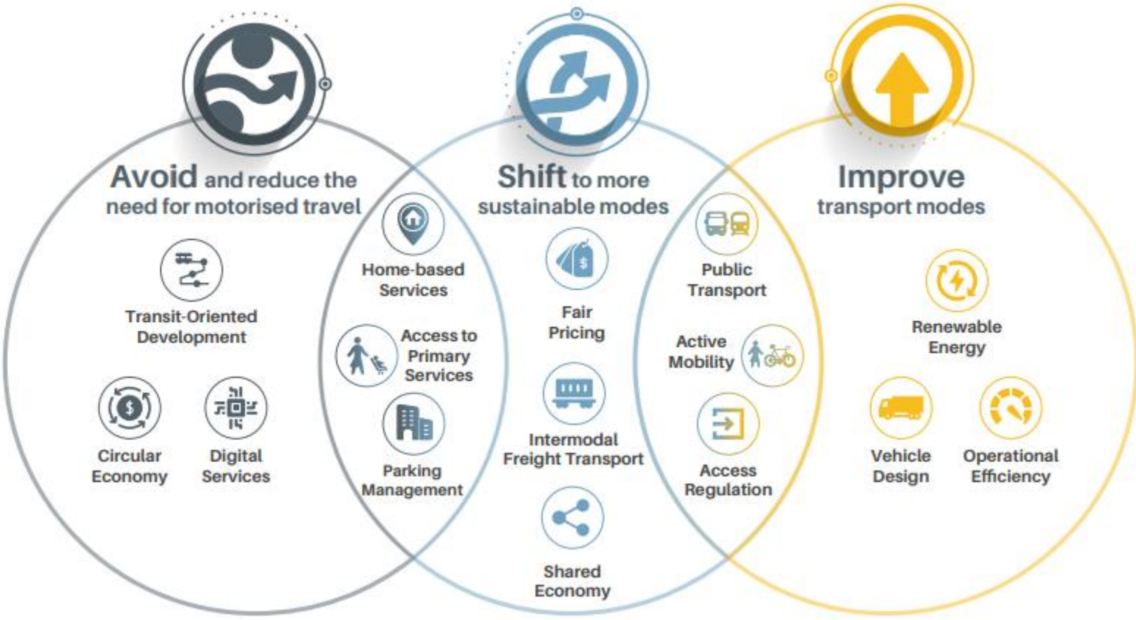


Figure 1: Avoid-Shift-Improve Framework (SLOCAT, 2025)

1.6 HIGH-UTILIZATION FLEETS: THE STRATEGIC DECARBONIZATION MULTIPLIER

While the electrification of all road transport is the goal, there needs to be a strategic, phased approach to have maximum effect with finite resources. In this context, high-utilization commercial fleets, such as taxis, ride-hailing vehicles (VTCs), urban and interurban buses, and last-mile delivery vans, are the most immediate and impactful priority for early decarbonization action. This is not a priority of convenience, but a strategic decision based on a clear environmental and economic justification.

Their disproportional environmental effect is the heart of the argument. Due to stringent operational schedules, with long hours and high daily mileages, a single commercial vehicle can produce emissions equivalent to those of numerous private vehicles, which remain stationary for most of the day. Consequently, electrifying one high-mileage taxi or bus has a "decarbonization multiplier" effect, with far greater greenhouse gas and local air pollutant savings per vehicle than electrifying one private passenger car.

This environmental imperative is matched by a similarly strong economic case. The economic viability of electrification is most assessed using a Total Cost of Ownership (TCO) model, which balances higher up-front capital expenditure (CAPEX) against lower operating expenditure (OPEX). For high-utilization fleets, this calculation favors electrification much more rapidly. The significant fuel and maintenance economies, which are achieved on a per-kilometer basis, quickly accumulate and offset the higher up-front purchase price of a BEV (McKinsey & Company, 2022; Rocky Mountain Institute (RMI), 2024). Studies consistently show that under moderate to high utilization levels, BEVs achieve cost parity with or are even lower in cost than their ICE counterparts, reaching TCO parity years ahead of privately owned vehicles (Figliozzi, 2013).

Furthermore, these fleets are a more accessible policy target. Compared to the dispersed and fragmented ownership of millions of private cars, public transport fleets are more likely to be centrally managed, operated under publicly concessioned contracts, and subject to predictable renewal cycles. This makes them highly responsive to regulatory levers like public procurement specifications (the EU Clean Vehicles Directive) and urban air quality legislation.

The strategic focus on these fleets also creates a virtuous "learning ecosystem" that accelerates the broader transition more quickly. As rational economic actors, fleet operators are early and sophisticated adopters of EV technology. In so doing, they must master the complexities of charging logistics, smart energy management, and BEV maintenance (GEP, 2025; McKinsey & Company, 2022). This concentration of demand stimulates investment in the supporting infrastructure that is necessary, such as high-capacity charging points and specialist repair garages, which then becomes available to the wider public. Meanwhile, the high profile of electric buses and taxis on city streets serves to make technology commonplace, providing confidence to the public and lowering behavioral obstacles such as range anxiety for private purchasers. In effect, focusing on high-utilization fleets first is a strategic stimulus, using the commercial sector to de-risk the technology and build the physical and social infrastructures for mass-market EV adoption.

1.7 THE METHODOLOGICAL IMPERATIVE: AGENT-BASED MODELING FOR POLICY ANALYSIS

Studying the nonlinear, dynamic, and complex process of a large-scale fleet transition, requires a highly sophisticated methodological approach. Agent-Based Modeling (ABM) is a high-performance computational framework that is especially well-suited to explore the intricate interaction between policy, technology, and economic behavior in urban systems, and this effort utilizes it.

ABM enables a "bottom-up" simulation approach to replicate a system by defining its constituent elements as autonomous "agents" with their own attribute characteristics and behavioral rules (Macal & North, 2010; Gilbert, 2008). For the purposes of this report, the agents are the constituent vehicles within the transport fleets. The model simulates the discrete behavior and interactions of these thousands of agents over time, say, aging, retirement, and replacement, to observe the "emergent" patterns at the system level, say, the fleet mix, overall emissions, and need for charging stations (Bonabeau, 2002).

This bottom-up approach stands in stark contrast to traditional "top-down," equation-based simulations, which are based on aggregate variables and averages. These models struggle to replicate heterogeneity of individual agents and complex feedback loops that occur within real-world systems (SmythOS, 2024; Bae & Moon, 2020). ABM is better suited to represent this diversity and complexity.

The greatest advantage of ABM in policy analysis is that it serves as a "digital sandbox" (SmythOS, 2024; Östman, et al., 2024). It allows policymakers and researchers to construct a replica of a system in a virtual space and test the potential effects of different policy interventions in-silico. By varying the rules governing agent action or the environment in which they operate, it is possible to explore "what-if" scenarios, identify potential unforeseen consequences, and compare the relative efficacy of different policy levers without undertaking the cost and often the irreversibility of real-world deployment (Bae & Moon, 2020).

The central research question of this report, comparing a policy-driven transition pathway with a market-driven one, is best suited to the capabilities of ABM. The method allows for the creation of two categories of behavioral rules for agents who make replacement decisions. In policy-driven situations, the decision by the agent is constrained by pre-specified adoption targets. In the market-driven situation, the agent acts as an economically rational agent, maximizing its decision through a calculation of TCO. By modeling under these alternative rule sets, this study can quantitatively investigate the emergent gap between market reality and policy intention.

This methodology elevates analysis beyond forecasting. The true strength of the ABM paradigm lies in its ability to signal why a given outcome is a consequence of the aggregate micro-level decision of thousands of independent agents. If a standard model forecasts a certain degree of BEV adoption, the causal process tends to be obscure. However, if the ABM developed for this research forecasts a lag in market adoption, its cause can be traced back to the agents' unattractive TCO calculations in specific years of simulation. This shifts the analysis from descriptive ("what is going to occur") to diagnostic ("why it is going to occur") and, ultimately, prescriptive ("how to remediate it"). It allows policy proposals to be targeted with surgical precision; for example, by identifying the exact TCO gap in a particular year and calculating the subsidy required to bridge the gap, transforming policy from a blunt instrument into an adaptive, intelligent tool for market shaping.

CHAPTER 2. STATE OF THE ART

2.1 GLOBAL TRENDS IN PUBLIC TRANSPORT ELECTRIFICATION

The worldwide shift to electric public transportation is marked by a highly uneven development, with China emerging as the undisputed leader, especially in the bus category. As of 2023, Chinese cities held more than 90% of the world's electric bus stock, a predominance fueled by aggressive national industrial policy and municipal ambition (IEA, 2023). The city of Shenzhen is a prime example of this state-led, rapid transformation. In 2017, it was the first large city in the world to completely electrify its 16,000-vehicle public bus fleet, an achievement followed by the total electrification of its 22,000 taxis a year later. This wholesale change, supported by substantial government subsidies, paid a twin dividend: dramatic improvement in urban air quality and considerable savings in operating costs from fuel and maintenance (World Bank, 2021).

Conversely, the European transition is on a more incremental but accelerating path. Starting from a lower base, electric buses accounted for a significant 14% of new city bus registrations in the EU in 2023 (UITP, 2022). Front-running urban hubs such as London and Paris illustrate the European paradigm. Transport for London (TfL) is pursuing a phased approach to a 100% zero-emission bus fleet by 2034, already running one of the largest such fleets in Europe (Transport for London, 2023). Paris, via its operator RATP, is likewise embarked on a large-scale fleet transition to deliver a 100% clean standard, embracing both electric and biogas technologies. Across the continent, these transitions are driven by a mix of regulatory pressure from proliferating low-emission zones and the increasingly attractive total cost of ownership for high-mileage BEV operators, illustrating a distinct, market- and regulation-driven route to decarbonization.

2.1.1 GLOBAL PROTOCOL FOR COMMUNITY-SCALE GREENHOUSE GAS EMISSION INVENTORIES

This protocol, developed by organizations like C40 Cities, Local Governments for Sustainability, and the World Resources Institute, is the most widely used standard for city-level greenhouse gas accounting.

The GPC solves the problem of what a city can and cannot control by dividing emissions into three distinct scopes:

i. **Scope 1**: These are direct emissions that happen within the city's geographic boundary. For transportation, this almost perfectly matches the "tank-to-wheel" definition, as it includes the combustion of fuel in vehicle engines.

ii. **Scope 2**: These are indirect emissions from the consumption of grid-supplied electricity or energy within the city. The emissions physically occur at the power plant, which is often outside the city and not under its direct control.

iii. **Scope 3**: This includes all other indirect emissions that occur outside the city boundary because of activities within the city. This covers the full "well-to-tank" lifecycle, including emissions from producing vehicles, extracting and refining fuel, and other supply chains.

The GPC framework is specifically designed to align emissions accounting with the direct sphere of influence of municipal policymakers. By focusing an analysis on Scope 1 emissions, a city can measure the direct impact of policies it controls, such as mandating electric taxis or transitioning the public bus fleet. The GPC establishes the analysis of Scope 1 emissions as a foundational and standard practice for city-level policy evaluation

(World Resources Institute, C40 & ICLEI, 2014).

2.2 *CHARGING INFRASTRUCTURE: THE CORE ENABLER AND KEY CHALLENGE*

The installation of adequate charging infrastructure is widely recognized as both the key enabler and the greatest bottleneck to fleet electrification. Unlike private cars, which can rely on a dispersed network of public and residential chargers, fleet operations require reliable, high-capacity, and strategically located charging solutions to minimize vehicle downtime. The main challenges include high initial investment costs, limited space availability in already dense urban depots, and the substantial load imposed on local power grids.

Two prevalent charging methods have become widespread for electric bus fleets, each with distinct operational and financial trade-offs:

i. **Overnight Depot Charging:** This method involves installing numerous lower-power (50–150 kW) chargers at the bus depot to recharge the entire fleet overnight during off-peak hours. It is generally less expensive in terms of hardware and causes less stress on the grid but requires buses to have large batteries capable of providing a full day’s service on a single charge.

ii. **Opportunity Charging (Pantographs):** This approach utilizes ultra-high-power chargers (300–600 kW) to provide rapid partial recharges to buses during their daily operations, typically at route termini or major stops. It allows buses to be equipped with smaller, lighter, and less costly batteries but necessitates significant investment in public-space infrastructure and may create high peak demand on the local electricity network.

2.2.1 *ADVANCED CHARGING MANAGEMENT AND VEHICLE-TO-GRID (V2G) SYSTEMS*

To mitigate grid impacts, smart charging and Vehicle-to-Grid (V2G) technology are being actively researched as innovative solutions. Smart charging times fleet vehicle charging sessions do not overlap with periods of peak electricity demand, conserving both energy cost and grid load. V2G technology extends this by providing parked vehicles as a source of electricity supply back into the grid, thereby offering grid stability services and generating an additional source of income for fleet operators.

The effective performance of big electric fleets is strongly dependent on sophisticated energy management practices beyond simple charging (Ampcontrol, 2025). The underlying strategy is one-way smart charging, or V1G, where charging rate and timing are dynamically controlled to align with low-rate periods of electricity and remain below the depot grid connection limit, thereby missing costly demand charges (Hive Power, 2021).

More transformative is bidirectional Vehicle-to-Grid (V2G), which allows a fleet not only to draw power from the grid but also to return stored energy back into it. This capability turns a transport fleet into a rolling battery energy storage system that can provide valuable ancillary services to the grid, such as frequency regulation, peak shaving, and absorbing excess renewable generation (International Renewable Energy Agency, 2019). Public transport buses are good candidates for V2G since they possess significant batteries, fixed timetables, and long overnight idle sojourn times. The application case has been pilot-tested at the large scale in examples like the "Bus2Grid" trial in London that leverages an electric bus fleet to develop a virtual power plant that can supply over 1 MW of electricity (Charged EVs, 2020).

Yet, mass-scale implementation of V2G is immensely constrained. The most important constraint is the effect of enhanced cycling on battery life, since every cycle of discharge leads to capacity loss that will never be recovered. Hence, the business case for V2G is a precarious one in which the revenue realized from grid services must be greater than the amortized cost of the accelerated battery degradation (Yilmaz & Krein, 2012). Furthermore, V2G's scaling is constrained by the capital expense associated with more costly bidirectional hardware and the lack of established regulatory procedures and grid connection codes formalized for bidirectional energy transfer.

2.2.2 SMART CHARGING AND GRID IMPACT

A crucial aspect of fleet electrification is the impact of smart charging strategies on the urban electrical distribution grid. While this research focuses on the "tank-to-wheel" perspective, a complementary analysis of the resulting strain on energy infrastructure is essential for a complete picture.

Modeling the effects of different charging protocols (like uncontrolled charging versus Time-of-Use tariffs) on a large urban grid reveals key issues related to power demand, component overloading, and voltage levels. The results show that while smart charging can certainly help mitigate grid stress from widespread EV adoption, it isn't a perfect solution. These strategies can create their own challenges, such as new, sharp demand peaks during what were previously off-peak hours (Huedo, 2023).

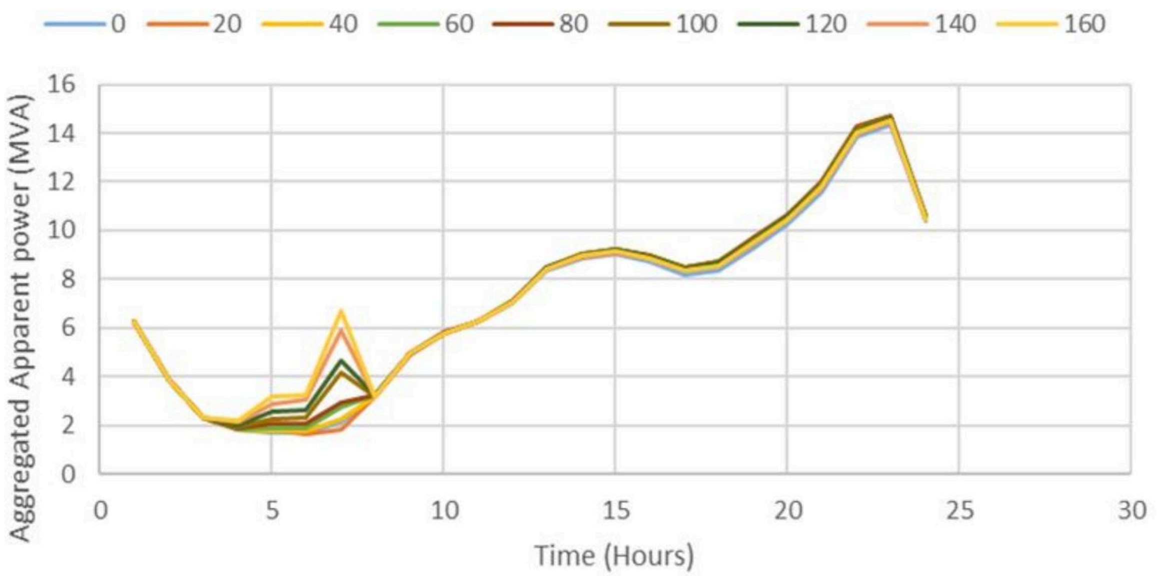


Figure 2: Aggregate Apparent Power as a function of time using a mixed strategy on weekdays (Huedo, 2023)

Figure 2 reveals two distinct demand peaks: a smaller one in the early morning around 7 AM and a much more pronounced peak in the late evening, culminating at approximately 10 PM. This pattern suggests that while smart charging can shift demand away from traditional daytime peaks, it may inadvertently create new, sharp peaks during evening hours as numerous vehicles begin charging simultaneously.

2.3 ECONOMIC FEASIBILITY AND TOTAL COST OF OWNERSHIP

The financial feasibility of converting a commercial fleet from internal combustion engine (ICE) vehicles to battery electric vehicles (BEVs) is predominantly evaluated using the Total Cost of Ownership (TCO) model. This approach, commonly employed in both academic and industry studies, provides a comprehensive perspective on all costs incurred throughout a vehicle's operational life, which is more informative than the purchase price alone. The TCO generally comprises two main components:

i. **Capital Expenditures (CAPEX):** The upfront purchase price of the vehicle and any necessary charging infrastructure. For commercial vehicles, BEVs currently have significantly higher CAPEX compared to diesel or compressed natural gas (CNG) vehicles.

ii. **Operational Expenditures (OPEX):** The ongoing costs of operating the vehicle, primarily energy (fuel/electricity) and maintenance. BEVs demonstrate clear advantages in this area. Electricity is typically less expensive per mile than diesel or petrol, and maintenance costs can be 40–60% lower due to the absence of oil changes, exhaust systems, complex engine components, and reduced brake wear from regenerative braking.

The critical economic consideration is identifying the TCO parity point, where the cumulative OPEX savings of a BEV fully offset its higher initial CAPEX. For most commercial vehicle segments, this parity is imminent or already achieved, especially for high-utilization vehicles such as taxis and buses. This economic tipping point strongly influences voluntary market adoption (Basma & Rodríguez, 2023).

2.4 *POLICY AND REGULATORY FRAMEWORKS*

Governments around the world have observed that market forces alone cannot drive the transition at the required speed and have therefore used a range of policy instruments to stimulate it. These are grouped under three broad categories:

i. **Financial Incentives:** These are aimed at reducing the CAPEX barrier for BEVs and include purchase incentives (Grants, tax credits) and operating benefits (exemption from road tolls or congestion charges).

ii. **Regulatory Needs:** These create an unbending decarbonization climate. The best examples are Low- and Zero-Emission Zones in inner city environments, restricting or banning entry for dirty vehicles, and fleet procurement rules. The most efficient of these in Europe is the Clean Vehicles Directive, mandating public authorities to have a minimum standard of clean and zero-emission buses and other fleet procurement in their public procurements (European Parliament and Council, 2019).

iii. **Investment in Infrastructure:** Government investment to enable the rollout of a robust public charging infrastructure, crucial to instill confidence in commercial operators and individual citizens alike.

2.5 *THE SPANISH CONTEXT: ADVANCES AND CHALLENGES*

Spain has established a strong national decarbonization plan with its Integrated National Energy and Climate Plan outlining ambitious GHG reduction and electric vehicle uptake objectives (Gobierno de España, 2021). Supported by the consumer and commercial sector is the Plan MOVES III, a significant subsidy program to reduce EV and charging point cost.

Certain Spanish cities are serving as pilot regions for public transportation electrification. Barcelona, run by TMB, has led the way, with full electrification of high-demand bus lines like the H16 (TMB, 2023). TMB's strategy is a blend of depot charging during the night and on-route opportunity charging using pantographs, being an integrated response to the infrastructure issue (TMB, 2023).

In Madrid, the city operator EMT also committed to a fully decarbonized bus fleet by 2033. It includes a ban on new diesel bus purchases, a significant increase in CNG and electric bus acquisitions, and a continuous process of converting major bus lines to full electrification. These local policies, driven by municipal sustainability goals and the EU Clean Vehicles Directive, are transforming the urban bus landscape. However, modernizing the more widespread taxi, VTC, and interurban private fleets remains a major challenge that depends on the interaction between TCO, national incentives, and local initiatives like the Madrid 360 low-emission zone.

2.6 DIGITALIZATION AND SMART FLEET MANAGEMENT: THE ROLE OF DATA IN OPTIMIZATION

The transition to electric fleets is not merely a replacement of hardware; it is intrinsically linked with a parallel transition towards digitalization. The technical challenges and unique character of BEVs, particularly regarding energy use and charging, necessitate the establishment of intelligent fleet management systems. These technologies leverage a portfolio of digital technologies, including the Internet of Things (IoT), telematics, cloud computing, and data analytics, to optimize all aspects of fleet operation, thereby enhancing efficiency, reducing costs, and overall economic justification for electrification (Arora, Parwez, & Narang, 2024).

The core element of a smart management system is a central software platform, typically called a Charge Management System (CMS) or Fleet Management Software, that consolidates in real-time information from vehicles, chargers, and external data sources to enable smart decision-making. The key functions are:

i. **Energy Management and Smart Charging**: This is perhaps the most critical function for an electric fleet. With reference to analysis of State-of-Charge (SOC) of vehicle, future route requirements, and prevailing electricity rates, the CMS can plan for charging the whole fleet. This makes "smart charging" possible where the vehicles get charged automatically during off-peak hours when electricity is cheapest in price, thus maintaining energy costs significantly low (bp pulse, 2024; Rosap, 2024). Besides, it manages the total power consumption of the depot so as not to overload the grid connection capacity, thereby avoiding costly demand charges and relieving stress on the local distribution network. It is practical, real-world application of the intelligent charging strategies modeled in theoretical research, such as the analysis of Time-of-Use tariffs on the Madrid grid (Huedo, 2023).

ii. **Route Optimization**: Telematics systems provide real-time GPS tracking of each vehicle. This data, combined with traffic, topography, weather, and current SOC of the vehicle, allows advanced algorithms to calculate and transmit the most energy-saving route for each trip. Dynamic route planning optimizes the operating range of the BEVs, conserves energy, and helps mitigate "range anxiety" for drivers and operators (SmarterFleet, 2024; Enhancing Urban Electric Vehicle (EV) Fleet Management Efficiency in Smart Cities, 2024).

iii. **Predictive Maintenance**: IoT sensors embedded within the vehicle continuously monitor the condition of critical parts, such as the battery, motor, and brake system. Through machine learning algorithms on this data stream, the management system can identify deviations and predict potential failures in advance. This shifts the maintenance paradigm from reactive to proactive, allowing planned repair that minimizes unplanned vehicle downtime and reduces long-term operating costs (Arora, Parwez, & Narang, 2024; FIC, 2024).

These are not optional add-ons but enablers essential to an effective electric fleet. Systematic savings in OPEX through lower-cost energy, better routes, and reduced maintenance directly enhances the TCO. The very parameter this study's market model has determined as the main driver of adoption. This constitutes a positive feedback loop: the initial decision to electrify necessitates digitalization, and the information that the digital infrastructure generates therewith subsequently provides the empirical grounds to de-risk and accelerate more electrification. To this extent, smart management is the information-generating engine that brings the theoretical economic advantage of BEVs into an actionable, operational reality.

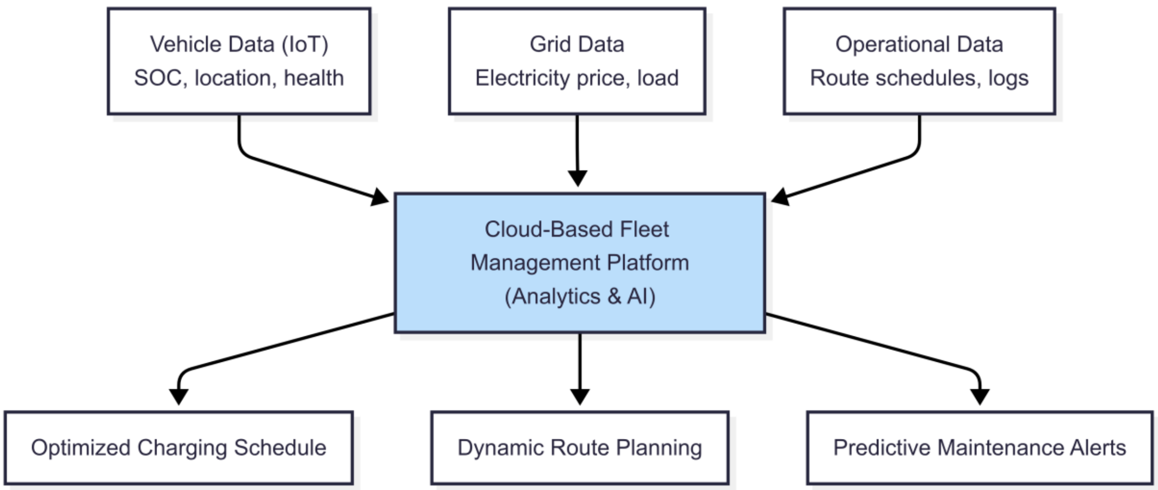


Figure 3: Data Flow in a Smart EV Fleet Management System

2.8 OVERCOMING CAPITAL BARRIERS: INNOVATIVE BUSINESS MODELS LIKE CHARGING-AS-A-SERVICE (CAAS)

Even though Total Cost of Ownership (TCO) is still the ultimate long-term economic driver for commercial electric fleet adoption, the biggest real-world roadblock typically precedes it: prohibitive initial capital cost (CAPEX). The significant sum of money to purchase and install charging equipment and any upgraded electricity infrastructure required can be overwhelming to most fleet owners, particularly small- and medium-sized enterprises (GEP, 2025; McKinsey & Company, 2022). To surmount this inherent "CAPEX barrier," the market devised new business models, primary among which is Charging-as-a-Service (CaaS).

CaaS is a business model designed for shifting the cost and operational burden of charging infrastructure away from the fleet operator to a specialized third-party provider (Vicente, et al., 2024; Terawatt Infrastructure, 2024). In a typical CaaS model, the service provider is responsible for the complete life cycle of the charging infrastructure: site planning, hardware procurement, installation, operation, and routine maintenance. The fleet operator pays a recurring, predictable subscription fee, usually per vehicle, per month, or per kilowatt-hour. This effectively transforms a massive, risky CAPEX into a tractable, sustainable operational expenditure (OPEX) (bp pulse, 2024; Yun & Dean, 2025).

The benefits of the CaaS model for fleet operators extend far beyond just finance:

i. **Financial Accessibility**: By eliminating the need for significant initial capital, CaaS makes fleet electrification affordable for a much greater number of operators who would otherwise be excluded from so doing due to the absence of the necessary capital. It releases the long-term TCO advantage by eradicating the initial investment hurdle (The Mobility House, 2023).

ii. **Operational De-risking**: Fleet operators have transportation and logistical know-how rather than necessarily electrical engineering or energy management expertise. CaaS allows them to shift the technical complexity and operational risk of operating a charging depot to a specialist provider. These providers usually offer service level agreements (SLAs) with uptime guarantees (99.9%), ensuring vehicles are charged and available for service, which is critical for business continuity (bp pulse, 2024; Terawatt Infrastructure, 2024).

iii. **Enhanced Scalability**: CaaS provides flexibility. An expanding fleet and the addition of other EVs enable the expansion of charging infrastructure without subjecting the company to another massive capital investment phase. Upgrading the operator's subscription allows the company to adapt to its evolving needs (Terawatt Infrastructure, 2024; Yun & Dean, 2025).

Feature	***Traditional Ownership Model***	***Charging-as-a-Service (CaaS) Model***
Upfront Cost	High (Full CAPEX for hardware & installation)	Low to None (Converted to OPEX)
Ongoing Cost	Variable (Electricity, maintenance, repairs)	Predictable (Fixed subscription fee)
Operational Burden	High (Operator manages design, permits, O&M)	Low (Provider manages entire lifecycle)
Technology Risk	High (Operator bears risk of hardware obsolescence)	Low (Provider bears technology risk)
Scalability	Difficult (Requires new CAPEX for expansion)	Easy (Subscription adjusts to fleet size)

Table 1: Comparison of Charging Infrastructure Ownership Models

The emergence of CaaS is more than just a financing innovation; it represents a maturation of the EV ecosystem. By creating a professionalized service layer for charging, CaaS providers introduce economies of scale, standardized processes, and specialized expertise that individual operators would struggle to replicate. They absorb the technology risk and provide the operational reliability that commercial fleet managers demand. This builds confidence and removes key non-financial barriers, thereby acting as a powerful catalyst for accelerating the adoption of electric fleets.

2.9 THE HUMAN FACTOR: BEHAVIORAL ECONOMICS IN COMMERCIAL FLEET ADOPTION

While quantitative models using TCO provide a strong analytical framework for detecting the economic forces behind fleet electrification, these models assume a perfectly rational economic actor when making decisions. Actual decision-making is much more complex, involving all sorts of cognitive biases and psychological factors. Behavioral economics is a useful discipline to examine non-monetary drivers and barriers (or inhibitors), adding a welcome level of sophistication to commercial fleet adoption analysis (Tattini, et al., 2015).

Even when the TCO calculation is in their interest, commercial operators experience various behaviorally rooted barriers to change:

i. **Risk Aversion and Status Quo Bias**: Vehicle reliability and availability are uppermost in the minds of fleet managers operating in a risk-averse culture. They may be more comfortable with the known operational characteristics of ICE vehicles, a technology to which they have been accustomed to for decades. The known risks of an unknown and novel technology, such as battery longevity, maintenance complexity, or charger reliability, may induce them to resist change, even if a strictly logical TCO calculation determines that a transition is best (McKinsey & Company, 2018; Egbue & Long, 2012).

ii. **Range Anxiety**: This is a widely documented psychological barrier within the retail sector, but one that also affects commercial operators. Even when the daily range of a BEV far exceeds the usual length of the fleet's normal route, managers may become fixated upon outlier scenarios or unusual days when the range will prove insufficient. Range anxiety was able to induce them to heavily discount the viability of BEVs (Figliozzi, 2013).

iii. **Dynamic Development of Attitudes**: The motivators to take the decision to own an EV are variable; they undergo a transformative shift with experiential exposure. A pioneering longitudinal investigation of corporate fleet users revealed a striking dynamic. Before first use, "environmental concern" was the dominant personal motivator of intention to use a BEV. But after three to six months of experience, environmental concern's effect vanished. It was replaced with more experiential, immediate drivers. "Enjoyment" of the driving experience (for example, smoothness, speed) became a robust positive driver, while "perceived risks" (for example, dealing with charging problems) became a robust negative driver only through long-term use, suggesting that initial support systems may mask for long-term issues (Roemer, et al., 2022).

This research provides a note of caution to the deliverables of this report's market-oriented model. Ideal is when the model concludes that it is a TCO-only decision. It will be slower than the model predicts due to the resistance of these behavioral barriers. There needs to be a two-pronged transition plan. First, it must address the economics by creating a competitive TCO.

Second, and no less important, it must address psychology by de-risking the technology in use and improving the user experience. That means policy extending beyond financial incentives to include strategies like overall "try-before-you-buy" propositions for fleet managers, government-sponsored long-term battery warranties to share longer-term risk and encouraging business models like CaaS that transfer technology risk away from the customer and on to the provider. Through ignoring the human factor, one can find oneself confronted with a growing policy-market outcome divergence even as underlying economics appear to be desirable.

2.10 THE POLICY-MARKET DICHOTOMY: RECONCILING REGULATION WITH ECONOMIC REALITY

Decarbonizing transport is motivated by two distinct, and sometimes conflicting, drivers: the "top-down" driver of public policy and the "bottom-up" driver of market dynamics. The main analytical goal of this report is to look at the tension and potential misfit between these two drivers. It is critical to understand this duality for constructing effective, efficient, and resilient transition plans.

Policy pressure is characterized by government action to accelerate the transition, often in response to international or national climate commitments. These interventions typically consist of regulative pressures (bans on selling ICE cars by a certain date, zero-emission vehicle targets for manufacturers), financial mechanisms (subsidies, carbon pricing), and norm-setting and low-emission areas (Center for American Progress, 2019; Gillingham & Munk-Nielsen, 2019). These policies are usually drafted to follow a pre-determined, linear course toward a declared objective.

The market pull for privately-owned fleets such as taxis and VTCs, in contrast, is influenced by the non-linear, dynamic forces of economic self-interest, spearheaded by the TCO. This is not an organized or orderly process. It is also subject to the volatility of fuel and electricity prices, the pace of technological evolution (the falling costs of batteries), access to infrastructure, and those behavioral drivers mentioned earlier (Hau, 2021; World Bank, 2020). The market does not operate on a fixed timetable; it responds to tipping points in the economy.

The greatest policy challenge is that these two forces do not necessarily work in parallel. This asynchrony can create two forms of strategic failure, and both are considered by this research's simulations:

i. **Ambition Failure**: Where policy sets high adoption targets that are not supported by an economic argument for the market actor that is as strong. If the TCO of a BEV remains significantly greater than an ICE alternative, operators, acting in their own economic self-interest, will resist the shift. The result is policy goals are unreached, emissions are excessive, and the government is forced to either offer monumental, non-sustainable subsidies or abandon its goals. The base-case assumption on the taxi/VTC fleet in this report is a stark illustration of this danger.

ii. **Preparatory Failure**: This is the opposite issue, where technological progress or market disruption (a sudden drop in BEV prices) causes the TCO to become radically competitive much sooner than policy makers had anticipated. The market, responding to such a compelling economic stimulus, would in turn adopt BEVs at a rate multiple times that of planned deployment of charging points. This results in a scenario whereby the transition has been brought to a standstill not due to a lack of demand, but due to a critical infrastructure deficit, resulting in pandemonium among operators and losing confidence in the transition. This low-cost Chinese BEV hypothetical scenario in this report embodies this same risk.

This dichotomy suggests that the optimal policy reaction is not one that seeks to dominate the market with hard mandates but one which seeks to shape the market's economic landscape. The policymaker's function should be reoriented from that of a "commander" into that of a "market architect." The objective is to utilize dynamic, intelligent policy instruments, such as TCO-pegged subsidies that gradually phase out by themselves, incentives for circular economy models such as SLBs, and de-risking tools such as CaaS, to make the most environmentally friendly choice also the most rational and profitable choice for the individual economic agent. This report, through the direct simulation of the TCO-affected behavior of the market agent combined with policy-affected scenarios, provides precisely the sort of analytical tool needed to develop such sophisticated, market-differentiating policies (ITF, 2021).

CHAPTER 3: OBJECTIVES OF THE STUDY

3.1 GENERAL OBJECTIVE

The primary aim of this report is to offer an integrated, quantitative, and comparative analysis of the environmental and economic implications resulting from the electrification of the central public transport fleets in Madrid: taxis and VTCs, city buses operated by EMT, and interurban coaches. The goal is to move beyond general policy intentions and deliver detailed, data-based estimations that can facilitate strategic decision-making. In a world where cities are hubs for both climate issues and solutions, solid analytical capabilities are necessary to tackle the multifaceted transition towards sustainable urban mobility. This research, therefore, is not merely an academic exercise but also a contribution to the field of evidence-based policymaking, presenting a dynamic simulation model to test hypotheses, explore scenarios, and identify optimal paths toward decarbonizing the city's public transportation system (Wilensky and Rand, 2015).

3.2 SPECIFIC OBJECTIVES

To achieve the general objective, this study will pursue five specific, interconnected research goals:

i. To Quantify the Environmental Impact and Trajectory of Fleet Electrification
ii. To Model the Techno-Economic Evolution of the Fleets Under Different Adoption
iii. To Assess the Consequent Impact on Energy Consumption and Infrastructure
iv. To Determine the Comprehensive Financial Implications of the Transition
v. To Evaluate the Robustness and Scalability of Findings

3.2.1 QUANTIFICATION OF THE ENVIRONMENTAL IMPACT AND TRAJECTORY OF FLEET ELECTRIFICATION

This study will go beyond a simple before-and-after snapshot to model the year-by-year reduction trajectory of key atmospheric pollutants from 2025 to 2045. The analysis will focus on three primary pollutants, selected for their distinct impact:

i. **Carbon Dioxide (CO2):** The principal greenhouse gas responsible for climate change. Tracking its reduction is essential for evaluating the contribution of the transport sector to national and international climate targets.

ii. **Nitrogen Oxides (NOx):** A group of gases that are major contributors to urban smog, acid rain, and the formation of fine particulate matter. They are particularly associated with diesel engines and have severe impacts on respiratory health.

iii. **Particulate Matter (PM):** Ultrafine particles with high lung penetration potential, which result in cardiovascular and respiratory disease. Road transport remains a significant source of PM in urban areas (European Environment Agency, 2023).
These particles vary in size, composition, and origin. For regulatory and health purposes, they are categorized based on their diameter (United States Environmental Protection Agency, 2023). The two main categories of concern are:

- **PM_{10}:** These are inhalable particles with a diameter of 10 micrometers or less. To put this into perspective, the average human hair is about 70 micrometers in diameter. PM_{10} includes dust, pollen, and mold spores. Due to their size, they can be inhaled and can penetrate the upper respiratory tract and lungs.

- **$PM_{2.5}$:** Known as fine particulate matter, these particles have a diameter of 2.5 micrometers or less. $PM_{2.5}$ is a sub-category of PM_{10}. These fine particles are primarily formed from combustion processes, including vehicle exhaust, power plants, and industrial emissions. Because of their extremely small size, they can bypass the body's natural defenses and penetrate deep into the lungs and even enter the bloodstream. This makes $PM_{2.5}$ particularly hazardous to human health, as it is linked to a range of cardiovascular and respiratory diseases.

A combination of overall PM is used in this report, not specifically adhering to one or the other, as both are harmful pollutants.

Quantifying each of these three pollutants separately for each fleet and across each scenario, this goal aims to provide a detailed description of the environmental effects, distinguishing between global climate action and enhancing local air quality.

3.2.2 MODELLING OF THE TECHNO-ECONOMIC EVOLUTION OF THE FLEETS UNDER DIFFERENT ADOPTION

A core objective is to simulate how the composition of each fleet evolves over time. This requires a sophisticated approach that recognizes that different fleets are driven by different motivations. The model will analyze this evolution through two distinct lenses:

i. **Policy-Driven Adoption (Buses):** For the EMT and interurban bus fleets, the model will simulate a transition pathway based on predefined regulatory targets, reflecting the strategic, long-term planning of public authorities.

ii. **Market-Driven Adoption (Taxis & VTCs):** For the taxi and VTC market, a more advanced Total Cost of Ownership (TCO) model will be utilized. This technique, rigorously tested in economics research, simulates individual owners' buying behavior in reaction to fluctuating economic drivers like vehicle purchase prices, subsidies, fuel and electricity prices, and repairs (ICCT, 2019). This allows the model to generate a true S-curve of technology adoption and identify the probable gap between policy intention and market reality. This two-tiered method will allow the study to analyze the complex interplay between technological progress (batteries getting cheaper (International Energy Agency, 2024)), regulatory push, and economic action.

3.2.3 *Assessing the Impact on Energy Consumption and Infrastructure*

The transition from fossil fuels to electricity fundamentally shifts the energy demand of the transport sector. This objective aims to quantify this shift by calculating the total annual electricity demand (in GWh/year) required by the electric vehicles in each fleet. More importantly, the analysis will estimate the peak charging power (in MW) that the grid must be prepared to supply. According to the International Energy Agency, managing the grid impact of large-scale EV charging is one of the most critical challenges for a successful transition (International Energy Agency, 2024). This objective will therefore provide a quantitative assessment of the strain placed on Madrid's electrical infrastructure, identifying potential bottlenecks and informing of the necessary scale and timeline for the deployment of public and depot-based charging solutions.

3.2.4 *Determining the Comprehensive Financial Implications of the Transition*

Electrification involves a significant reallocation of capital, shifting costs from operational expenditures (fuel) to capital expenditures (vehicles and infrastructure). This objective is to conduct a thorough financial analysis of this shift from the perspective of both fleet operators and public entities. The simulation will track the total annual cost of each fleet, comprising:

i. **Capital Expenditures (CAPEX):** The cost of purchasing new vehicles each year, factoring in declining prices for BEVs and the gradual phasing out of government subsidies.

ii. **Operational Expenditures (OPEX):** The aggregated annual cost of fuel, electricity, and maintenance for the entire fleet. By modelling these costs over a 20-year horizon, the study will identify the initial investment peaks required for the transition and determine the point at which long-term operational savings begin to offset the high upfront capital outlay, providing crucial insights into the business case for electrification.

3.2.5 *Evaluate the Robustness and Scalability of Findings*

In an attempt to ensure conclusions are not simply the product of a rigid set of assumptions, one of the primary objectives is to develop a model with internal flexibility. This will be achieved by means of a sensitivity analysis, whereby the principal economic variables (the fuel price change rate, electricity prices, and battery cost) can be adjusted. By examining how simulation outputs change with these adjustments, this objective aims to find out to what extent the conclusions are robust and set up a framework of whose implications can notionally be extended to other municipalities, even if the numbers involved are specific to Madrid.

3.3 ALIGNMENT WITH THE UNITED NATIONS SUSTAINABLE DEVELOPMENT GOALS

The project objectives are directly and substantively connected to several of the UN's 2030 Sustainable Development Goals (SDGs) and form part of a broad agenda for international sustainability (United Nations, 2015):

i. **SDG 11:** Sustainable Cities and Communities. This is the target SDG addressed by the project. By modelling ways to reduce pollution and increase the efficiency of urban mobility systems.

ii. **SDG 13:** Climate Action. The primary environmental goal of this study is to quantify the reduction in CO_2 emissions, clearly contributing to SDG 13. The transport sector is one of the main sectors to intervene in to reach the objectives of the Paris Agreement, and this project simulates concrete measures to incorporate measures on climate change into municipal policy and planning.

iii. **SDG 3:** Good Health and Well-being. The local air pollution reduction of NOx and PM, which contribute to various noncommunicable diseases (European Environment Agency, 2023).

iv. **SDG 7:** Affordable and Clean Energy. The project assesses the large-scale shift of energy demand into electricity.

v. **SDG 9:** Industry, Innovation, and Infrastructure. Electric mobility requires a significant expansion of new sustainable infrastructure, including charging stations and grid upgrades.

Figure 4: Sustainable Development Goals

Specifically, the study uses a detailed simulation model to quantify the impacts of different transition scenarios, identifying key challenges and strategic pathways for success, guided by three motivations.

3.3.1 IMPROVE PUBLIC HEALTH AND URBAN LIVABILITY

This goal, which falls within SDG 3 (Good Health & Well-being) and SDG 11 (Sustainable Cities), is to quantify the local air quality and urban environment impacts of direct transport electrification

The study achieves this goal by simulating the elimination of local air pollutants of damage; Nitrogen Oxides (NOx) and Particulate Matter (PM) at the tailpipe by battery electric vehicles (BEVs). Quantitative proof of a "Public Health Dividend," that ambitious electrification scenarios deliver the highest and most urgent health gains in urban air quality, is given by the analysis. This material health gain constitutes a strong political argument for transition, supporting ambitious long-term climate objectives. In addition, the study verifies that charging infrastructure needs can be a driver for smart city transformation, opening the doors to more effective, sustainable, and equitable public spaces and, hence, to overall urban quality of life.

3.3.2 ANALYZE INFRASTRUCTURE, INNOVATION, AND ENERGY CHALLENGES

In synergy with SDG 9 (Industry, Innovation & Infrastructure) and SDG 7 (Affordable & Clean Energy), this objective is to quantify the systemic engineering and economic hurdles of the transition.

The report achieves this by quantifying the incredible new demand for power and charging points. A key finding is the threat of an "Infrastructure Deficit," whereby a large-scale, market-driven take-up of BEVs, triggered by cost tipping point, may swamp predicted levels of infrastructure supply. This highlights a systemic risk of "Preparation Failure" if planning remains responsive to policy timetables rather than proactive to market drivers.

The examination also reveals the weakness of the economic case for electrification. A "Battery Durability Crisis" worst-case scenario demonstrates how unexpected long-term technological risks, such as premature battery failure, can destroy the Total Cost of Ownership (TCO) advantage of BEVs and switch the market to fossil fuels. This points out that consumer confidence in long-term technological durability is just as critical as the upfront economic viability. Finally, the research examines how added energy demand necessitates new solution management like smart charging and Vehicle-to-Grid (V2G) technology in a bid to stabilize the grid and stay affordable.

3.3.3 EVALUATE PROGRESS TOWARD CLIMATE ACTION

This aim, centered on SDG 13 (Climate Action), is to evaluate the effectiveness of decarbonization activities in reducing greenhouse gas emissions and identify barriers to climate target attainment.

The study accomplishes this objective by simulating Carbon Dioxide (CO2) emissions across scenarios. Given that policy-driven scenarios have a clear path to deep cuts in emissions, the most relevant observation comes from comparing these intentions to a market-driven reality. The study finds an important "Policy-Market Chasm": a wide difference between the pace of adoption required by climate policy and the slower pace of adoption enabled by the market's TCO estimations.

This leads to the possibility of "Ambition Failure," in which good things on climate policy unexpectedly fail because there are no economic mechanisms to induce market change. The simulation illustrates that under a purely market-driven alternative, CO2 emissions can still go up for many years before finally declining because there is not a compelling business case for operators to transition to BEVs at the necessary speed. This finding indicates that there will be no climate goals met unless policies are framed so that the sustainable alternative is made the financially viable alternative for market participants.

CHAPTER 4: SIMULATION METHODOLOGY

4.1 OVERALL MODELLING FRAMEWORK

To analyze the complex, dynamic process of a large-scale fleet transition, this study employs an Agent-Based Modelling (ABM) approach. ABM is a computational modelling paradigm that simulates the actions and interactions of autonomous agents (in this case, individual vehicles) to observe the emergent, system-level behavior (Bonabeau, 2002). This bottom-up methodology is especially well-suited for transportation analysis, as it allows for the capture of heterogeneity within a fleet and the modelling of discrete events like individual vehicle retirement and replacement, providing a more granular and realistic simulation than traditional top-down models.

To analyze the fleet's evolution, this study utilizes a simulation framework developed in the MATLAB (R2024b) environment. The model operates on a year-by-year basis, simulating a timeline from 2025 through 2045.

All simulations were executed on a 2019 MacBook Pro equipped with a 2.6 GHz 6-Core Intel Core i7 processor. The specific runtimes for each scenario are detailed in Table 2.

Fleet Model	***Scenario***	***Processor***	***Total Execution Time (seconds)***	***Avg. Time per Year (seconds)***
Taxi & VTC	Policy - Driven	Intel Core i7	40.3	2.01
Taxi & VTC	Market - Driven	Intel Core i7	42.1	2.10
EMT Bus	Complete Simulation	Intel Core i7	2.6	0.13
Interurban Bus	Complete Simulation	Intel Core i7	2.7	0.13

Table 2: Simulation duration in MATLAB

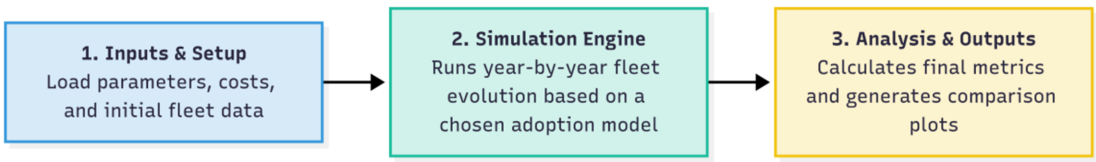


Figure 5: Modelling Framework I

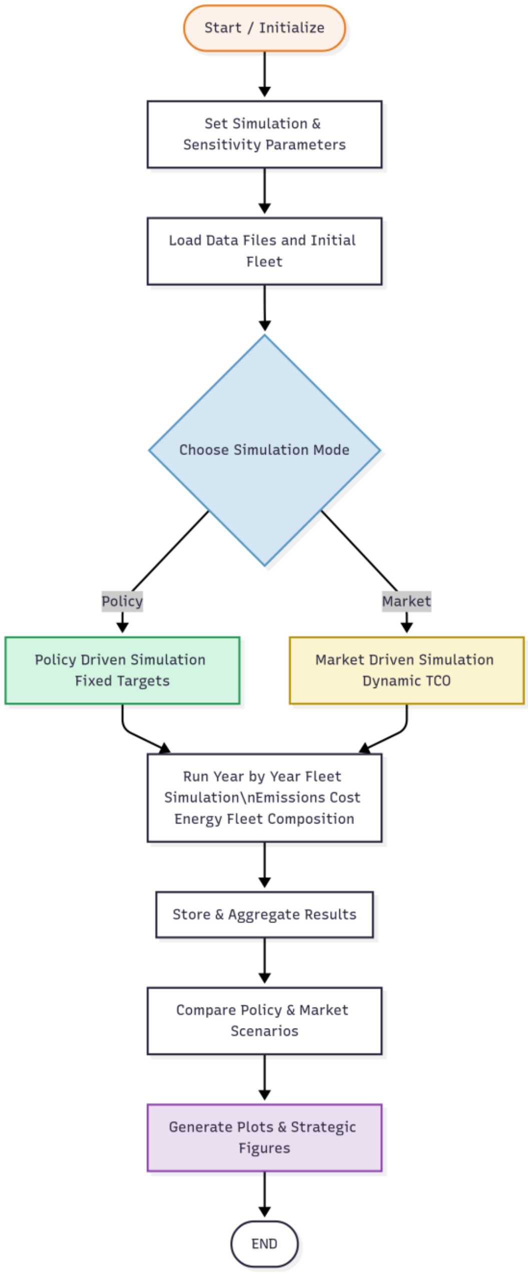


Figure 6: Modelling Framework II

4.2 MODEL 1: SIMULATION OF THE TAXI AND VTC FLEET

This model simulates the behavior of the privately owned taxi and VTC fleet in Madrid, where economic incentives are the primary driver of change.

The model is a forecasting tool designed to predict how a vehicle fleet, such as taxis and ride-sharing services, will evolve over 20 years from 2025 to 2045. The primary purpose of the model is to compare two potential futures: one where fleet renewal is dictated by government policy and another where it's driven by real-world economics.

The model operates as a year-by-year simulation. In each simulated year, it retires old vehicles and replaces them with new ones. The core of the model lies in its two distinct modes for deciding which types of new vehicles (BEV, PHEV, or ICE) are purchased:

i. **Policy-Driven Mode**: This mode assumes strict adherence to a pre-defined schedule of electrification targets, regardless of cost.
ii. **Market-Driven Mode**: This mode simulates a free market where purchasing decisions are based on the Total Cost of Ownership (TCO), reflecting the most economically attractive option.

By simulating both modes, the model generates data on fleet composition, total annual emissions, energy demand, and fleet-wide costs for each scenario. The final step is to process this data and create strategic figures that visually compare the outcomes, highlighting potential gaps between policy ambitions and market realities.

4.2.1 ADOPTION LOGIC: POLICY-DRIVEN SCENARIO

This scenario simulates a future where vehicle adoption is dictated by pre-defined government targets, ignoring the real-world costs for the consumer.

Here’s how it works for each year of the simulation:

i. **Check for Retirements**: The simulation first identifies all vehicles that have reached the end of their operational lifespan and removes them from the fleet.
ii. **Look Up Policy Targets**: It then consults the established targets of the current year to find the government-mandated market share for electric vehicles.
iii. **Replace Retired Vehicles**: For each vehicle that was retired, a new one is added by generating a random number between 0 and 1:
   - If the number is less than the BEV share, the new vehicle is a BEV.
   - If the number is greater than the BEV share but less than the combined BEV and PHEV share, the new vehicle is a PHEV.
   - If the number is greater than the combined share, the new vehicle is a conventional ICE car.

This process ensures the fleet's composition evolves to precisely match the policy goals, year by year.

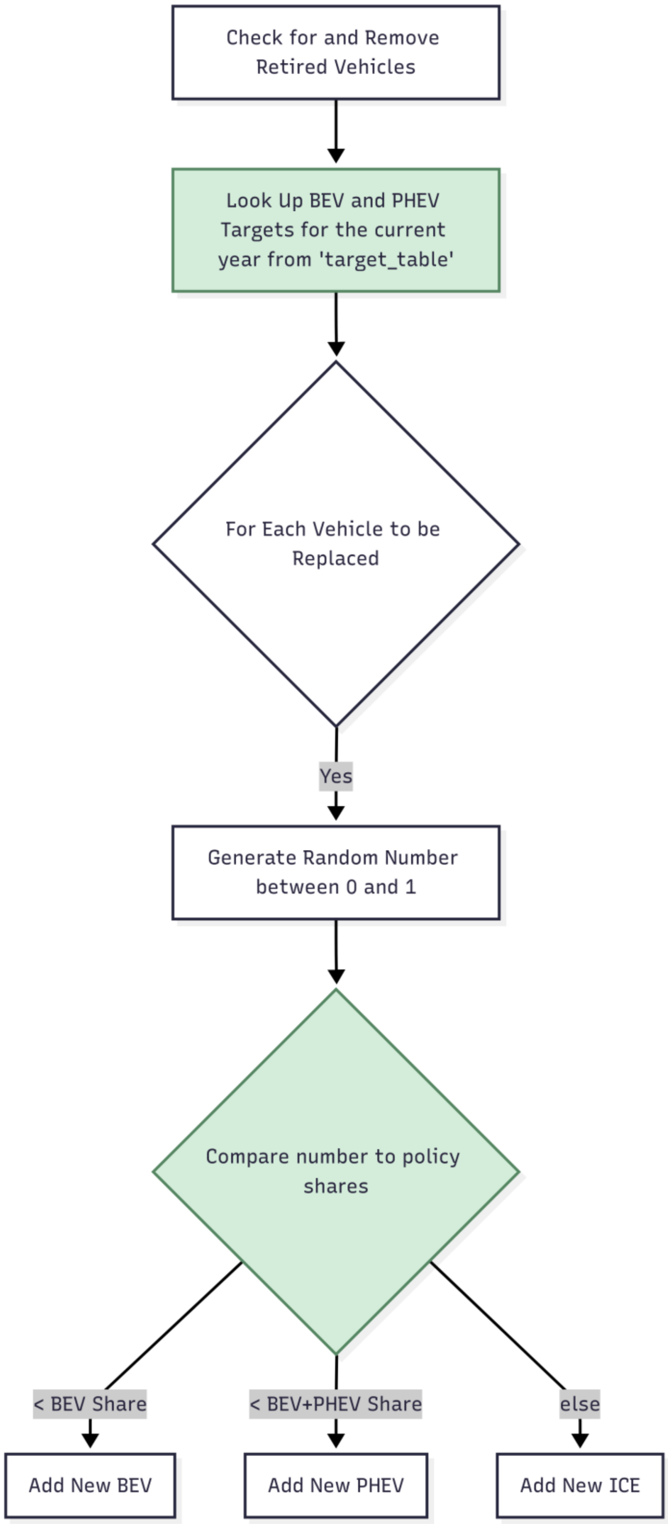


Figure 7: Policy-Driven Fleet Renewal Modelling for Taxis / VTCs

4.2.2 ADOPTION LOGIC: MARKET-DRIVEN SCENARIO

The decision to replace a retired vehicle with a new BEV, PHEV, or conventional ICE vehicle is determined by a market-driven model based on the Total Cost of Ownership (TCO). The TCO for each available vehicle technology i is calculated for a projected operational period of 5 years, although parameters like this one can easily be changed. The formula is defined as:

$$TCO_i = CAPEX_{net,i} + (OPEX_{annual,i} \times N_{years}) \tag{1}$$

All terms of the equation can be found in the "Definitions" section at the end of the report:

i. TCO_i is the projected Total Cost of Ownership for a vehicle of technology i.

ii. $CAPEX_{net,i}$ represents the net capital expenditure. This is calculated as the initial purchase price minus any applicable government subsidies.

iii. $OPEX_{annual,i}$ is the estimated annual operational expenditure, calculated from the sum of annual energy/fuel costs and total maintenance and insurance costs.

iv. N_{years} is the TCO projection period, set to 5 years.

The calculated TCO values are then converted into probabilities of purchase using a discrete choice model, a standard methodology for modelling decision-making (Train, 2009). The utility of each option (U_i) is assumed to be inversely proportional to its cost, controlled by a sensitivity parameter.

$$U_i = e^{-(\text{market\_sensitivity} \times TCO_i)} \tag{2}$$

The market share, or probability of choosing each technology, is then the normalized utility of that option. This dynamic logic allows the model to generate a realistic adoption S-curve that responds to the evolving economic landscape. As shown in Figure 8 the adoption model used in this study represents the cumulative rate of adoption, which starts slowly, accelerates rapidly, and then tapers off as it approaches market saturation.

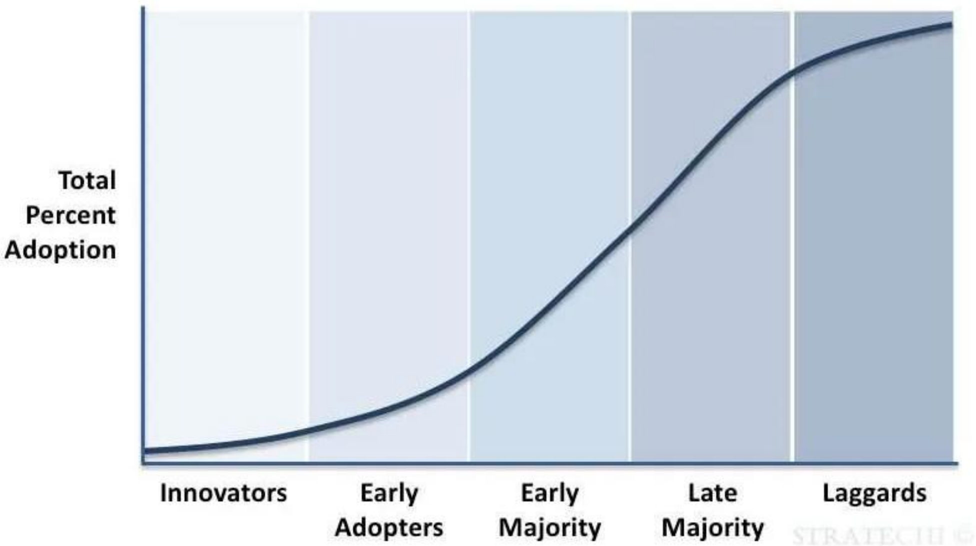


Figure 8: Adoption S-Curve (McKinsey and Partners)

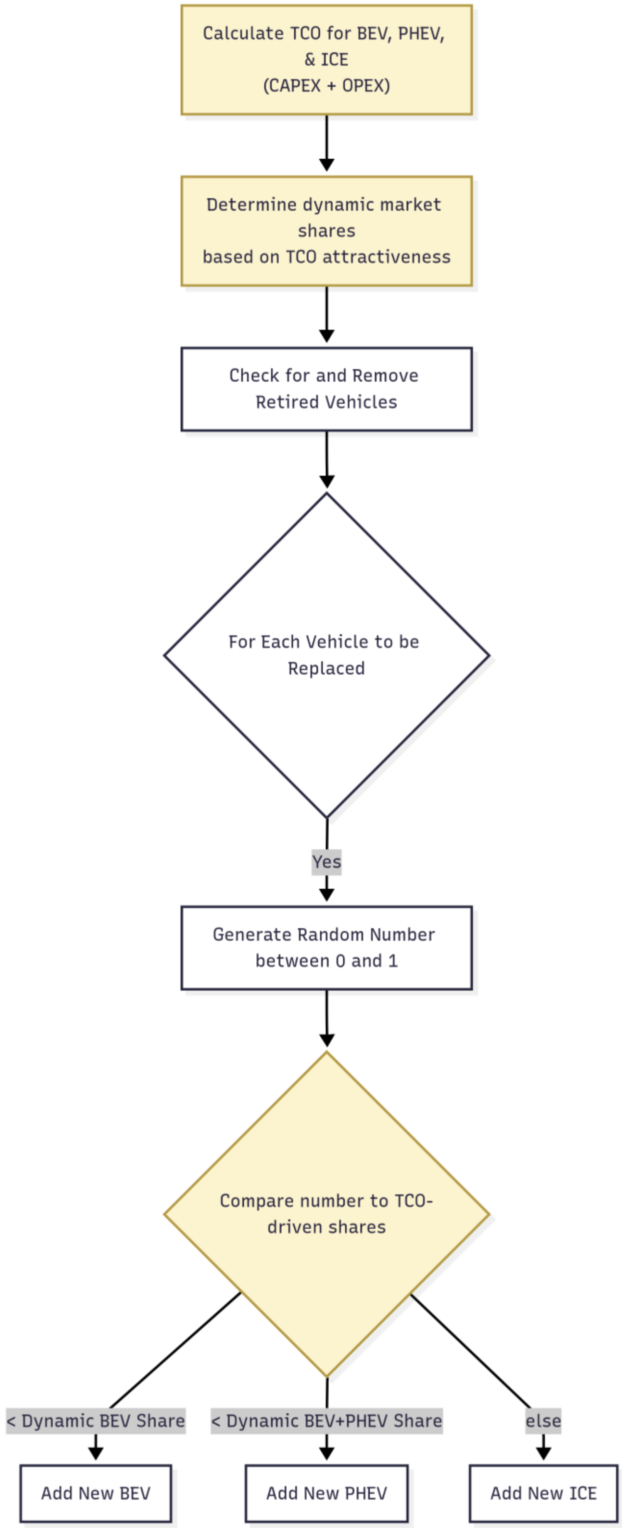


Figure 9: Market-Driven Fleet Renewal Modelling for Taxis / VTCs

4.3 POLICY-DRIVEN DEMAND PROJECTIONS AS A BENCHMARK

One of the key analysis techniques, particularly for the VTC and taxi fleet, is the use of the Policy-Driven simulation as a planned capacity baseline estimate for infrastructure. The expectation here is that whatever government adoption target is adopted would be accompanied by an accompanying plan for infrastructure rollout. Therefore, the electricity demand according to the Policy-Driven scenarios can be converted into the planned supply of charging power. By comparing the actual demand predicted by the more realistic Market-Driven model against the above standard, we can quantify the possible infrastructure shortfall or surplus during the simulation interval, gaining a useful insight into the alignment of policy intentions and marketplace facts.

4.4 MODEL 2: SIMULATION OF THE EMT URBAN BUS FLEET

It simulates (or models) the annual updating of the fleet of buses by mimicking a policy-based probabilistic process. It is meant to create the shape of the fleet over time to meet specific electrification goals. The EMT is owned by the Madrid City Council and runs the public bus network and the different bus services. Because of the public exposure of EMT buses, there is a less complex model employed with the cases being purely based on the adoption goals.

i. For each year of the simulation, the model first calculates all buses that must be retired. This is done through two conditions: periodic end-of-life retirement and a strategic premature retirement of some of the oldest, least efficient CNG buses to encourage the accelerated fleet modernization.

ii. Once it is established how many buses need to be replaced, the model then looks at the official BEV adoption target for that specific year. This is a percentage that dictates how many new car sales must be electric.

iii. Finally, for each retired bus, one is replaced by adding a new one, selected randomly by drawing a number between 0 and 1. If the drawn number is less than the desired BEV, a new BEV is added to the fleet. Otherwise, a new CNG bus is added. This random approach ensures that the proportion of new buses purchased throughout the year aligns with the city's policy goals, guiding the city toward incremental, year-by-year fleet replacement.

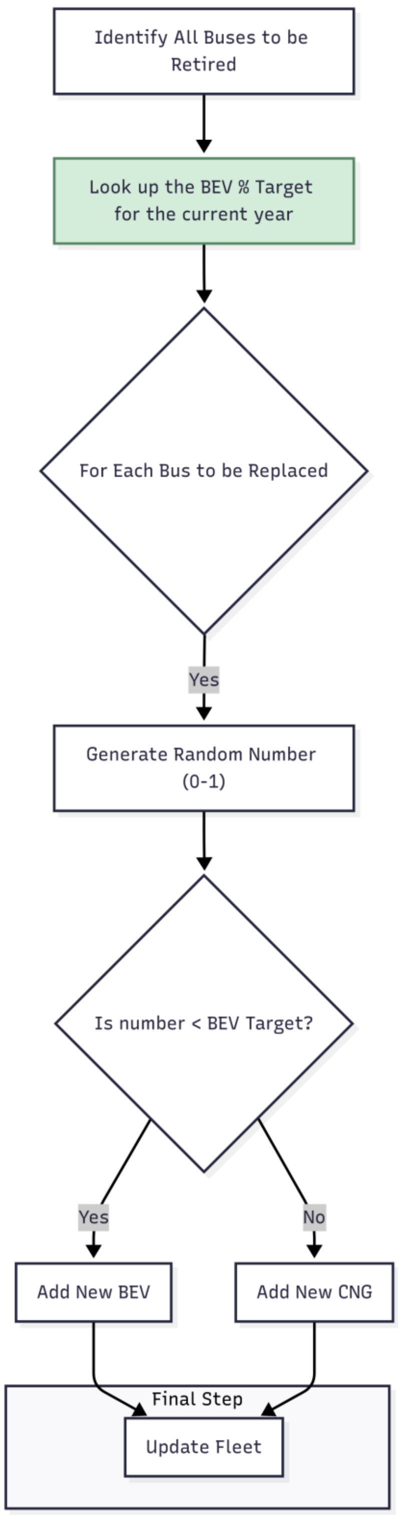


Figure 10: Fleet Renewal Modelling for EMT

4.5 MODEL 3: SIMULATION OF THE INTERURBAN BUS FLEET

The model mimics the year-to-year evolution of the inter-urban bus stock in Madrid. Each year of the simulation, it removes the old buses and adds new ones. It selects the new bus technology in a hybrid manner that combines regulatory strictures with economic choice.

i. Age the Fleet and Retire Old Buses: In the model, at the start of each simulated year, it is first determined which buses have reached the end of their working life. The age of each bus is calculated and if it has exceeded the vehicle lifespan it has been set, then it is removed from the fleet. The number of buses retired determines the number of new buses that must be purchased.

ii. Comply with Zero-Emission Needs: The priority of the model for new bus purchase is to comply. Based on a pre-established timeline (depending on the scenario), a specified proportion of all new buses must be zero-emission.

iii. Choose Cheapest for Rest of the Buses on TCO: Once the mandate has been attained, if there are still buses to be replaced, it makes a purely economic choice for the rest. It calculates the Total Cost of Ownership (TCO) of the available conventional technologies (Diesel vs. CNG) and purchases the cheapest on TCO.

iv. Rejuvenate All Expenses for Next Year: It simulates a dynamic market by assuming that costs evolve over time. As it progresses to the next simulation year, it renews all economic parameters with yearly change rates. This simulates a dynamic market where BEV purchasing prices can go down, while diesel fuel prices can rise over time.

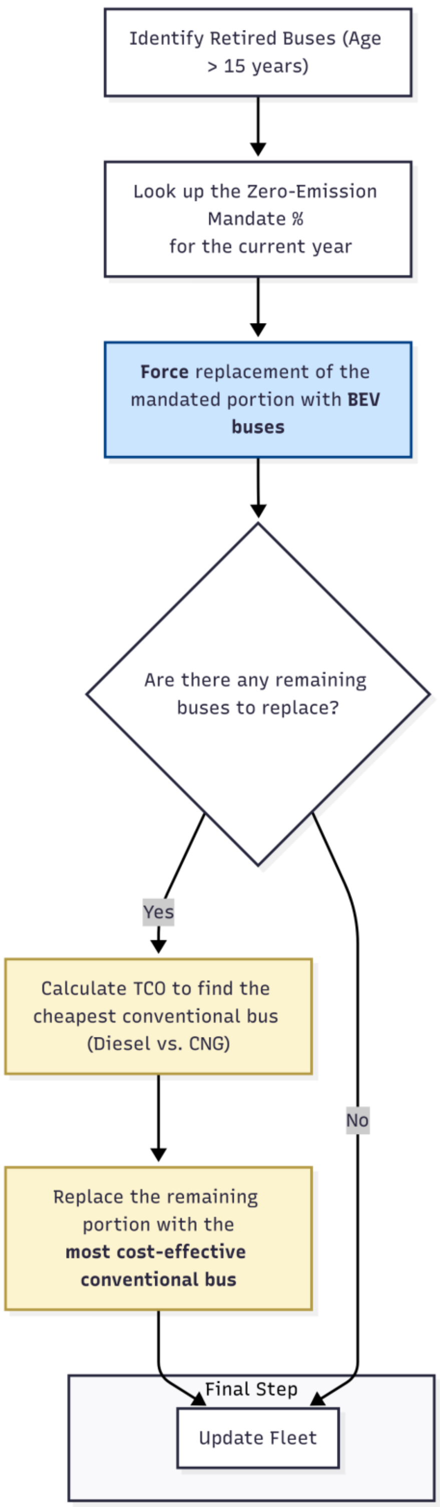


Figure 11: Fleet Renewal Modelling for Interurban Bus Fleet

4.5.1 GREEN FLEET MANDATES: DRIVING MADRID'S BUS NETWORK TOWARDS ZERO EMISSIONS

The Community of Madrid, through the Consorcio Regional de Transportes de Madrid (CRTM), imposes stringent demands on the private companies operating the green interurban buses. These demands specify the progressive updating of the fleet with the priority being assigned to low and, more recently, zero-emission vehicles. This is an essential component of regional and national transport decarbonization, air quality enhancement, and compliance with the demands of both the Spanish Climate Change and Energy Transition Law and European Union directives. The mandates are not implemented as a simple, one-size-fits-all percentage dictate for all fleets simultaneously. Instead, they are enforceable legal conditions contained within the public service concession contracts. The key points of this regulatory process are as follows.

i. Contractual Requirements: Whenever a concession contract is renewed or tendered, the CRTM includes specific clauses within it that compel the operator to renew a portion of its fleet. The clauses specify the kind of low, or zero-emission technology to be installed in the new vehicles.

ii. Progressive Renewal: It is a mechanism that ensures a gradual but consistent and legally enforceable change. The operators are required to buy and operate buses that meet these environmental specifications to win and maintain their contracts. This includes not just the buses themselves, but the necessary depot facilities / electric charging points.

4.6 EMISSIONS MODEL: JUSTIFICATION AND LIMITATIONS

4.6.1 METHODOLOGY FOR EMISSIONS CALCULATION

The simulation calculates total emissions as the sum of emissions from each vehicle. The annual emission for vehicle v is determined by the formula:

$$E_{p,v} = EF_{p,v} \times D_v \tag{3}$$

Where $EF_{p,v}$ is the specific emission factor (in g/km) and D_v is the total annual distance traveled.

4.6.2 THE COPERT MODEL AS A VALIDATION BENCHMARK

The emission factors (EF) used in this study are based on and validated against the **COPERT model**, the standard European methodology for calculating road transport emissions developed by the European Environment Agency (European Environment Agency, 2023).

4.6.3 LIMITATIONS OF THE IMPLEMENTED EMISSIONS MODEL

The application of this methodology has three main limitations:

i. **Generalization of Factors:** The model uses average emission factors for broad vehicle categories, not accounting for variations between specific models of the same class.
ii. **Impact of Driving Behavior:** The emission factors per kilometer are static and do not vary dynamically with traffic conditions or driving style.
iii. **Vehicle Aging:** The simulation does not model the potential degradation of emission control systems over a vehicle's lifespan.

CHAPTER 5: DATA AND PARAMETER JUSTIFICATION

5.1 INTRODUCTION

The credibility of a simulation model is generally dependent on the realism and quality of input data. A systematic and clear description of the key operating, economic, and environmental parameters used for constructing three various fleet models in this study is given in this chapter.

5.2 TAXI AND VTC FLEET PARAMETERS

The model for the taxi and VTC fleet, being market-driven, relies on a detailed set of parameters that influence the economic decisions of individual operators.

5.2.1 OPERATIONAL PARAMETERS FOR THE TAXI & VTC MODEL

Parameter	Value and Units	Justification and Source
Vehicle Lifespan	11 years	*This reflects the high-intensity usage of commercial service vehicles, which are typically subject to stricter age limits and faster renewal cycles than private cars. The value is a defensible average based on studies of taxi fleet operations in Madrid. (Ayuntamiento de Madrid, 2021)*
Average Daily Distance	220 km	*(Ayuntamiento de Madrid, 2017) reflects a median of 208 km. It is widely accepted that the exact value falls in between 189-250km per day.*
Empty Cruising Ratio	54.4%	*(Ayuntamiento de Madrid, 2017) reflects a median empty rate of 54.6%.*
TCO Projection Period	5 years	*A 5-year horizon is a common timeframe used in business case analyses for commercial vehicle procurement, representing a balance between long-term savings and short-term capital planning realities for small operators.*
Market Sensitivity	0.0002	*This is a calibration parameter that defines how strongly operators react to TCO differences. A low value represents a market with high inertia, where choices are less sensitive to small cost variations.*
Seasonal Consumption Increase	+25% (Winter), +15% (Summer)	*These multipliers account for the increased energy consumption of BEVs and PHEVs for cabin heating in winter and air conditioning in summer, a well-documented real-world factor (Desreveaux et al., 2020).*

Table 3: Operational Parameters for the Taxi & VTC Model

5.2.2 ECONOMIC PARAMETERS FOR THE TAXI & VTC MODEL (YEAR 2025)

The data shown below is extracted from the "Plan Moves III". *Movilidad Eficiente y Sostenible*, or Efficient and Sustainable Mobility is the cornerstone of the plan to promote the deployment of electric vehicles and the building of charging points. It is a national scheme of incentives and subsidies to accelerate the transition from fossil fuels in transport.

The program is financed and coordinated at the national government level by the Ministry of the Ecological Transition and the Demographic Challenge (Ministerio para la Transición Ecológica y el Reto Demográfico) and regulated by the IDAE (Instituto para la Diversificación y Ahorro de la Energía). The money is allocated and managed by each Autonomous Community of Spain separately (IDAE, 2024).

Vehicle Technology	***Purchase Price (€)***	***Subsidy (€)***	***Maintenance & Insurance (€/km)***	***Justification and Source***
BEV	45,000	7,000	0.0135	*Representative price for a suitable BEV. Subsidy aligns with Spain's "Plan MOVES III".*
PHEV	33,000	4,500	0.0292	*Acknowledges a lower purchase price than BEVs but higher maintenance due to dual-powertrain complexity. Subsidy aligns with "Plan MOVES III".*
HEV	35,000	2,000	0.0190	*Positioned between PHEVs and conventional ICEs in cost and complexity. Subsidy aligns with "Plan MOVES III".*
GNC / GLP	22,000 - 23,000	1,000	0.0390	*Lower purchase price reflects mature technology. Maintenance is higher due to specialized fuel systems.*
Euro 7 ICE	26,000	0	0.0440	*Baseline for the newest ICE vehicles, which receive no subsidies.*
Euro 6 ICE	30,000	0	0.0220	*Represents slightly older but still prevalent models in the used market or late-stage new sales.*
Euro 5 ICE	30,000	0	0.0220	*Represents the oldest class of vehicles being replaced in the simulation.*

Table 4: Economic Parameters for the Taxi & VTC Model (Year 2025)

5.2.3 ANNUAL ECONOMIC CHANGE RATES FOR THE TAXI & VTC MODEL

The rates model key market trends: decreasing costs for EV technologies, the phasing out of subsidies, and a steady increase in fossil fuel and electricity prices. These assumptions are aligned with long-term industry forecasts.

Vehicle Technology	Purchase Price	Subsidy	Battery Cost	Fuel/Energy Price	Maintenance Cost
BEV	-2.0%	-5.0%	-4.0%	+1.0% (Elec.)	-1.0%
PHEV	-1.0%	-7.0%	-3.0%	+1.5% (Fuel) / +1.0% (Elec.)	+0.5%
ICE (All types)	+0.5% to +1.0%	-10.0% or N/A	N/A	+1.0% to +1.5%	+1.0%

Table 5: Annual Economic Change Rates for the Taxi & VTC Model

5.2.4 TANK-TO-WHEEL EMISSION FACTORS FOR THE TAXI & VTC MODEL

The below table was extracted from key European opean sources, including COPERT (Computer Programme to calculate Emissions from Road Transport). The official methodology of the European Environment Agency (EEA) for calculating road transport emissions. Provides detailed emission factors for all vehicle types, Euro standards, and driving conditions (EMEP/EEA, 2023).

Vehicle Technology	Euro Standard	CO_2 (g/km)	Nox (g/km)	PM (g/km)	Justification and Source
BEV	N/A	0	0	0	*Zero tailpipe emissions by definition.*
PHEV (Petrol)	Euro 6	37	0.010	0.0003	*Low CO_2 reflects mixed electric/petrol use. NOx/PM align with Euro 6 petrol limits.*
HEV (Petrol)	Euro 6	100	0.100	0.0015	*Representative values for a modern hybrid vehicle under real-world driving.*
GNC / GLP	Euro 6	178 - 200	0.056 - 0.088	0.0011 - 0.0013	*Gaseous fuels have lower CO_2 than petrol but are still significant sources of NOx.*
E7 (Petrol)	Euro 6	150	0.100	0.0014	*Standard emission factors for a modern gasoline vehicle.*

Vehicle Technology	Euro Standard	CO_2 (g/km)	Nox (g/km)	PM (g/km)	Justification and Source
E7 (Diesel)	Euro 6	150	0.100	0.0014	*Standard emission factors for a modern diesel vehicle with DPF and SCR systems.*
E6 (Diesel)	Euro 5	173	0.168	0.0015	*Higher NOx emissions, representative of the less stringent Euro 5 standard for diesel.*
E5 (Diesel)	Euro 4	200	0.200	0.0018	*Higher emissions across all categories, representative of older diesel technology.*

Table 6: Tank-to-Wheel Emission Factors for the Taxi & VTC Model

5.3 EMT URBAN BUS FLEET PARAMETERS

The EMT bus fleet model is parameterized based on the specific operational and economic realities of a large, municipally owned public transport authority.

5.3.1 OPERATIONAL PARAMETERS FOR THE EMT BUS MODEL

Parameter	*Value and Units*	*Justification and Source*
Initial Fleet Composition	2,108 buses (85% CNG, 15% BEV)	*Based on the official fleet registry published by EMT Madrid as of May 31, 2024. (EMT Madrid, 2024)*
Vehicle Lifespan	15 years	*Standard operational lifespan for urban buses in Europe, designed for durability and intensive use. (UITP, 2022)*
Average Daily Distance	126 km	*Fleet-wide average derived from total annual kilometers reported in EMT's public activity reports. (EMT Madrid, 2023)*
Early Retirement Rate (CNG)	10% / year	*Simulates a proactive policy to accelerate the phase-out of emitting vehicles, representing an ambitious but feasible target for a public authority.*

Table 7: Operational Parameters for the EMT Bus Model (Source: EMT)

5.3.2 ECONOMIC AND ENVIRONMENTAL PARAMETERS FOR THE EMT BUS MODEL

Parameter	Value and Units	Justification and Source
BEV Purchase Price	€650,000	*Realistic market price for a new 12-meter electric city bus in 2025 (Szumska et al., 2022)*
CNG Purchase Price	€350,000	*Representative price for a new Euro VI CNG bus. (Szumska et al., 2022)*
Electricity Price	€0.09 / kWh	*Assumes a large municipal operator can negotiate favorable bulk electricity rates for scheduled, high-volume overnight charging at its depots. (International Energy Agency, 2025)*
BEV Consumption (Urban)	130 kWh / 100 km	*Representative real-world energy consumption for an electric bus in stop-and-go urban conditions. (Szumska et al., 2022)*
CNG Consumption (Urban)	40 kg / 100 km	*A standard consumption value for a 12-meter CNG bus in dense urban traffic. (Röck et al., 2020)*
BEV Emissions (CO_2, NOx, PM)	0, 0, 0 g/km	*Zero tailpipe emissions by definition. (Röck et al., 2020)*
CNG Emissions (CO_2, NOx, PM)	1100, 2.0, 0.05 g/km	*Emission factors derived from the average fuel consumption and carbon content of CNG in modern Euro VI bus engines. (Röck et al., 2020)*

Table 8: Economic and Environmental Parameters for the EMT Bus Model

5.4 INTERURBAN BUS FLEET PARAMETERS

The parameters for the interurban fleet model are chosen to reflect the distinct operational characteristics of long-haul coach services.

5.4.1 OPERATIONAL AND ENVIRONMENTAL PARAMETERS FOR THE INTERURBAN BUS MODEL

Parameter	Value and Units	Justification and Source
Initial Fleet Composition	Fleet of 2114 buses: (80% Diesel, 15% CNG, 5% BEV/Hybrid)	*Total number of 2114 (CRTM,2025). A synthetic composition was generated based on the average composition of in-use coach fleets across Europe.*
Average Daily Distance	300 km	*Higher mileage representative of interurban routes with longer distances between municipalities.*

Parameter	**Value and Units**	**Justification and Source**
BEV Consumption (Extra-Urban)	150 kWh / 100 km	*Assumes higher energy consumption for electric coaches on highways due to a lack of regenerative braking and increased aerodynamic drag.*
Diesel Consumption (Suburban)	35 L / 100 km	*A standard consumption value for a modern diesel coach in mixed driving conditions.*
Diesel Emissions (CO_2, NOx, PM)	1300, 2.5, 0.08 g/km	*Representative factors for a modern Euro VI coach, consistent with heavy-duty vehicle data.*
CNG Emissions (CO_2, NOx, PM)	1100, 2.0, 0.05 g/km	*Assumed to be consistent with urban CNG buses for modelling purposes. (Röck et al., 2020)*

Table 9: Operational and Environmental Parameters for the Interurban Bus Model

5.5 ADDITIONAL MODEL ASSUMPTIONS

In addition to the specific parameters of every fleet, the simulation model relies upon a series of underlying assumptions that define the scope and boundary of the analysis.

One of the principal assumptions is that the aggregate fleet size of each of the three fleets simulated (taxis and VTCs, EMT buses, and interurban buses) remains constant throughout the 2025-2045 simulation period. In the case of the taxi and VTC fleet, this assumption follows from the supposition that an established and mature city such as Madrid is not expected to experience exponential growth in aggregate mobility demand. Research on mobility in mature European urban cities shows that while modal shifts are bound to occur, net growth in the aggregate travel demand is bound to stabilize as populations and urbanization mature (Jones, 2014). It is therefore assumed that the number of licenses and vehicles in use will continue to be managed to meet reasonably stable demand, so the main variable of changing the technological mix of the fleet, not its absolute size, is.

An analogous assumption is made with respect to a constant fleet size of the interurban and urban bus fleets. Public transport fleet's fleet size is intrinsically linked to route planning, frequency of service, and transport authority budget. With an extremely advanced and extensive network like that of the Consorcio Regional de Transportes de Madrid, fleet change is typically propelled by optimization of operations for efficiency rather than by extensive network growth to cover new urban areas. The passenger demand is mature and the focus of the model is thus correctly placed on the technological improvement of the existing fleet to meet sustainability targets, rather than its quantitative increase.

Furthermore, the model incorporates seasonal efficiency adjustments for electric vehicles to account for the energy demands of cabin heating and cooling. This is a critical real-world factor, as empirical data from urban bus fleets clearly shows that fuel consumption varies significantly with daily temperatures and by season (Bravo Bernal, 2023).

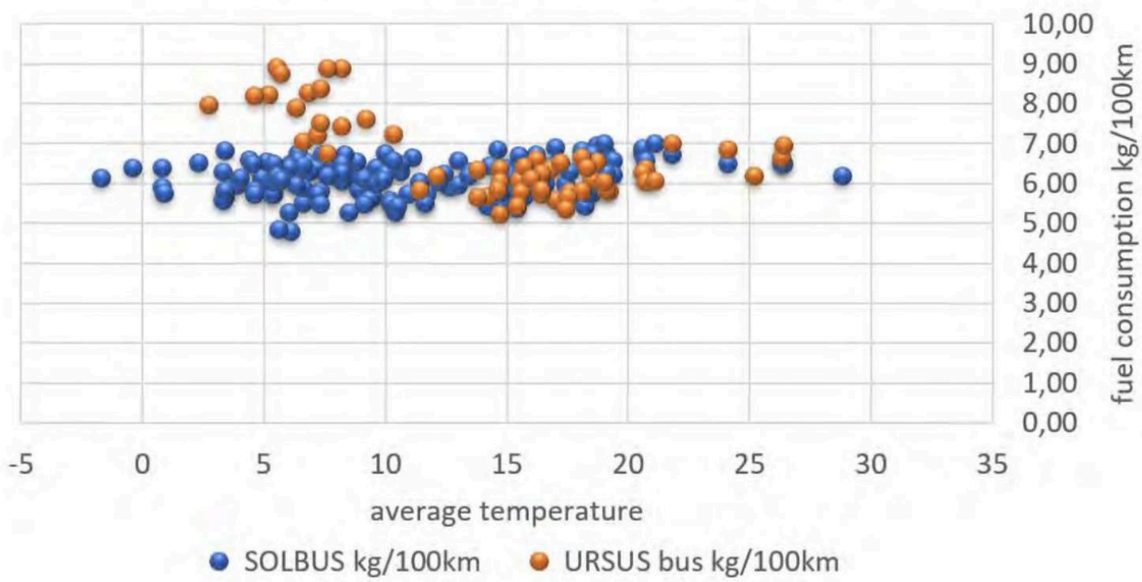


Figure 12: Fuel Consumption and Daily Temperature (Bravo, 2023)

Chapter 6. Results

6.1 GENERAL APPROACH

This chapter presents the quantitative outcomes generated by the three agent-based simulation models. Outputs are divided by fleet and show the forecasted evolution of the structure of each fleet, its carbon footprint, its economic spending, and its charging infrastructure demand for each of the three defined scenarios: Delayed, Base, and Accelerated.

One critical analytical method for the VTC and taxi fleet is using Policy-Driven simulation as a basis for anticipated infrastructure capacity. The assumption here is that any adoption target by a government would come with a plan for deploying infrastructure. Therefore, the anticipated electricity demand for the Policy-Driven scenarios can be thought of as planned supply of charging power. By comparing the estimated demand projection from the more precise Market-Driven model against this reference point, we can quantify the relative infrastructure shortage or surplus over the period of simulation and gain a valuable insight into the consistency between policy targets and market realities.

All the outcomes in this chapter were calculated by utilizing identical formulas but scaled to their model parameters. For example, the Taxi / VTC model considers 300 days of operation, whereas the bus simulations consider 365 days. This is just a sample case; however, as was also pointed out in the preceding chapter, parameters vary with regard to the model. Furthermore, all the calculations are available in the attached code (see Annex).

It should be emphasized that the simulations will be performed on the platform MATLAB, and all the parameters will be adjusted to the values assumed in the previous chapter.

6.2 RESULTS FOR THE TAXI / VTC SIMULATION

6.2.1 CUMULATIVE IMPACT

Figure 13 displays the total projected CO2 emissions in thousands of tons from Madrid's taxi and VTC fleet over the entire simulation period of 2025 to 2045. The chart compares the environmental impact of four different fleet renewal scenarios.

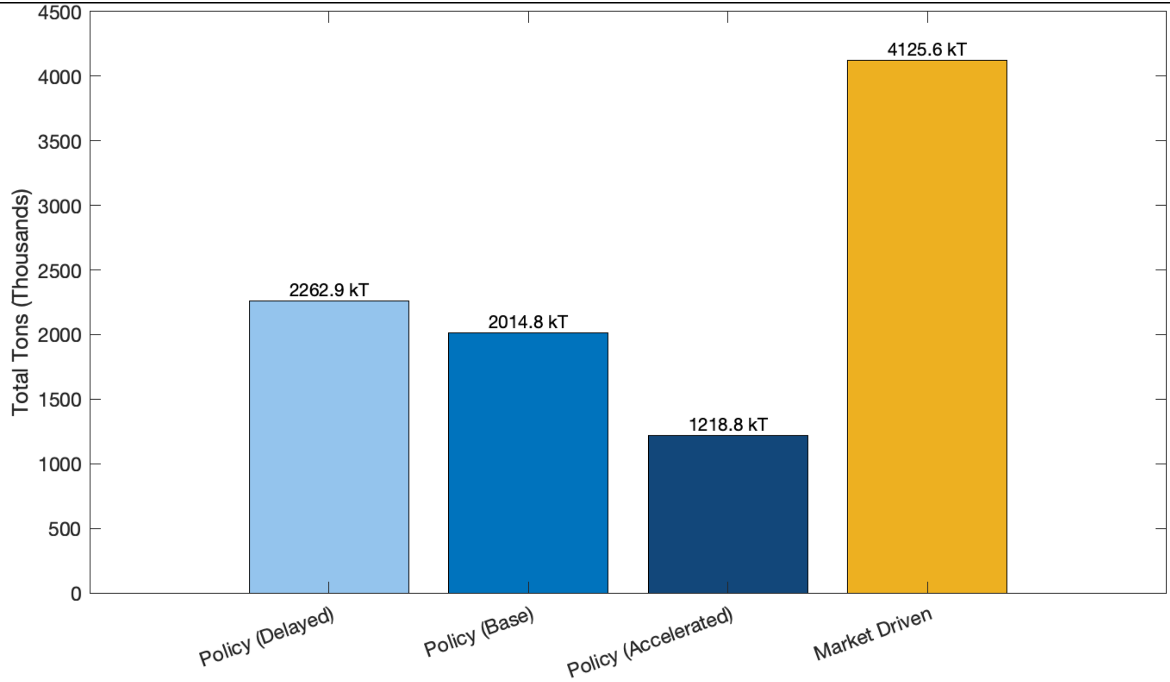


Figure 13: Total Cumulative CO2 Emissions (Taxi / VTC Model)

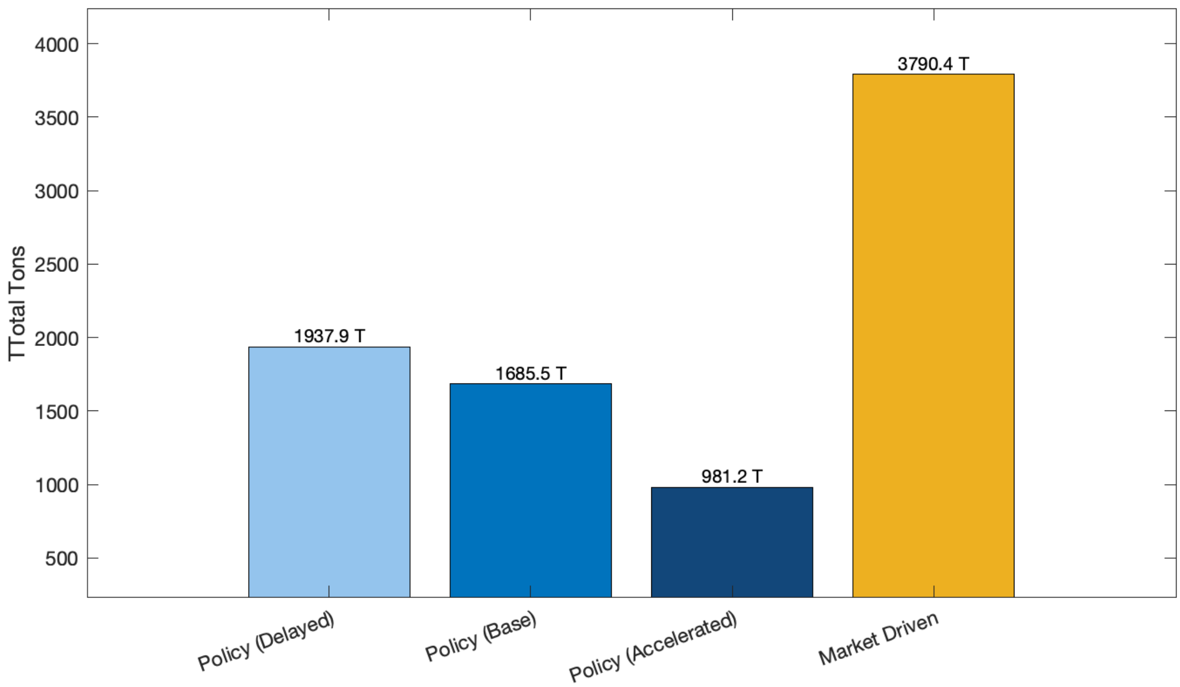


Figure 14: Total Cumulative NOx Emissions (Taxi / VTC Model)

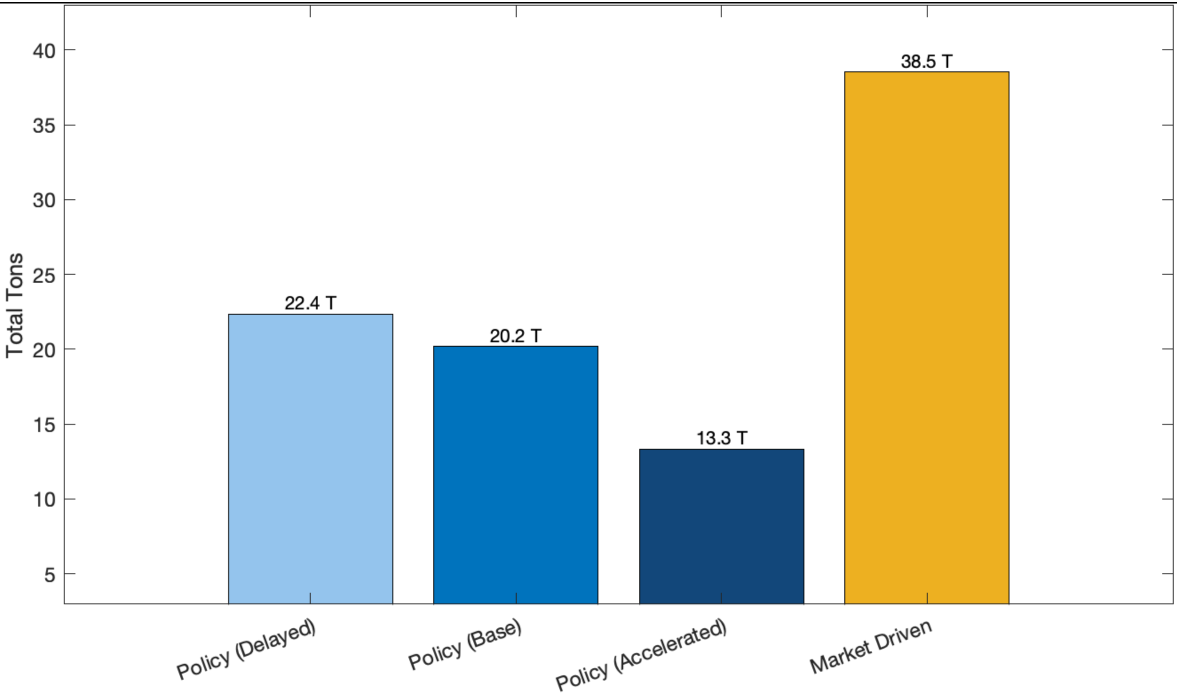


Figure 15: Total Cumulative PM Emissions (Taxi / VTC Model)

Having compared Figure 14 and Figure 15 to Figure 13, it is clear that the absolute quantities of pollutants differ significantly (thousands of tons for CO2 versus tons for NOx and PM), the relative outcomes of the scenarios remain identical. This indicates that policies designed to accelerate the adoption of electric vehicles for climate change purposes (reducing CO2) yield powerful co-benefits by simultaneously and proportionally reducing pollutants that harm local air quality and public health (NOx and PM). The uniform results across these different environmental metrics strengthen the overall argument for proactive and ambitious policy intervention in the transport sector.

The next formula expresses total cumulative emissions:

$$E_{pollutant,\text{cumulative}} = \sum_{y=2025}^{2045} E_{pollutant}(y) \tag{4}$$

Where $E_{pollutant}(y)$ is the total annual emission for a given pollutant (CO_2, NO_x, or PM) in year y.

As reported earlier, all definitions can be found at the end of the report.

Figure 16 shows that the total cumulative cost of all scenarios is similar, with the Market Driven scenario having the lowest total costs.

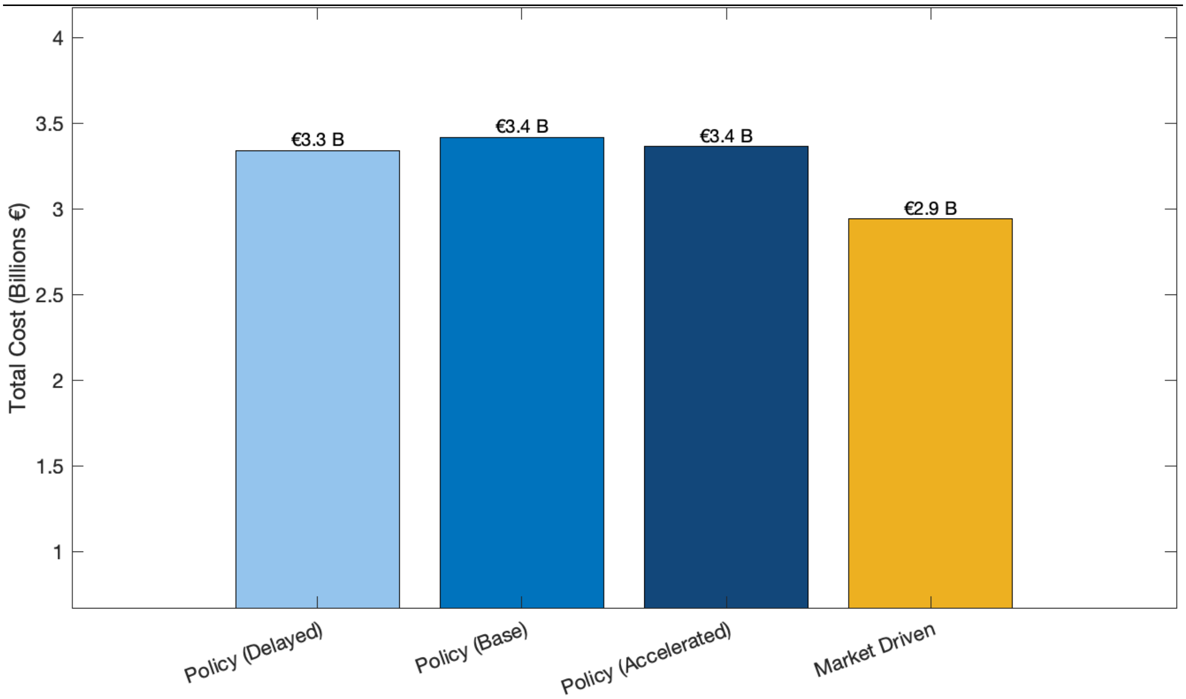


Figure 16: Total Cumulative Fleet Cost (Taxi / VTC Model)

This formula expresses the cumulative fleet cost:

$$C_{total,\text{cumulative}} = \sum_{y=2025}^{2045} C_{total}(y) \tag{5}$$

6.2.2 *POLICY – DRIVEN SCENARIOS*

The scenario shown in Figure 17 represents a gradual, government-mandated transition away from traditional cars. The stacked areas illustrate how the fleet's composition changes over time:

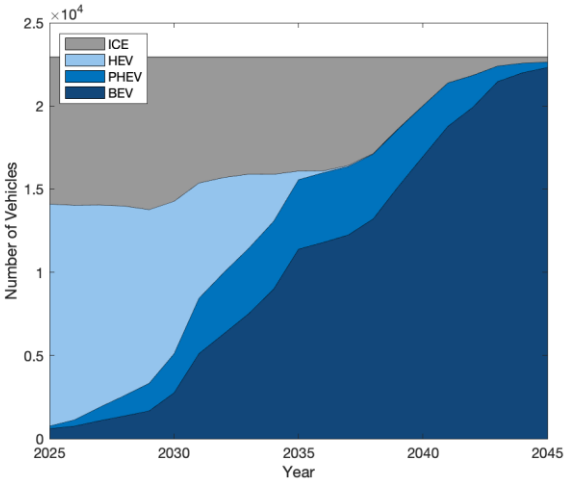
ICE (Internal Combustion Engine): The gray zone at the top represents gasoline and diesel vehicles. It starts as the largest sector but steadily decreases over the 20-year period. Nevertheless, under this lagging policy, there are plenty of ICE vehicles that remain in the fleet in 2045.

HEV (Hybrid): The light blue area shows that hybrids play an important role in the transition initially, but their numbers begin to decline after about 2032 as more advanced electric options become prevalent.

PHEV (Plug-in Hybrid) & BEV (Battery Electric): The dark and light blue areas show steady growth. BEVs, in particular, start from almost zero and increase to become the largest single vehicle type in the fleet by the end of the simulation horizon.

Figure 18 depicts a faster transition. By 2045, electric vehicles (BEV, PHEV, HEV) dominate the fleet, with very few ICE vehicles remaining.

Figure 19 illustrates the most aggressive transition, where ICE vehicles are almost entirely phased out well before 2045, replaced by a fleet composed almost exclusively of electric variants.



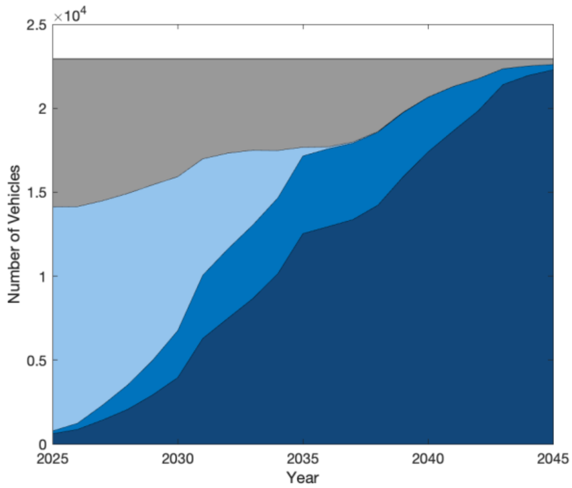


Figure 17 (left): Taxi / VTC Fleet Composition (Policy - Delayed)

Figure 18 (right): Taxi / VTC Fleet Composition (Policy - Base)

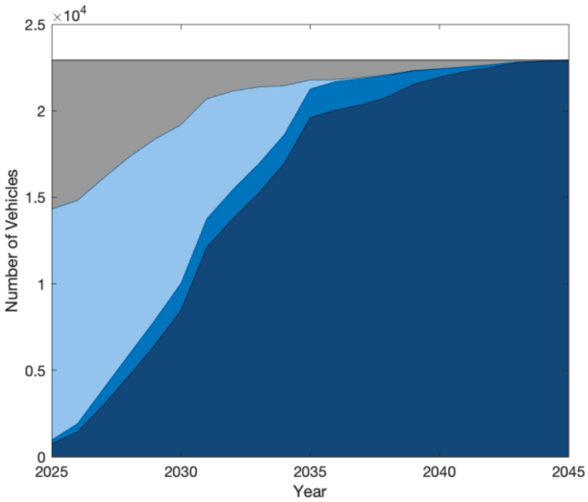


Figure 19: Taxi / VTC Fleet Composition (Policy - Accelerated)

Figure 20 illustrates the projected year-by-year carbon dioxide emissions from Madrid's taxi and VTC fleet between 2025 and 2045. The y-axis represents annual emissions, with a scale in the thousands of tons. The graph compares three different policy-driven scenarios for vehicle electrification:

i. **Delayed (dashed line):** This scenario shows the slowest reduction in CO2 emissions over the period, representing the least ambitious policy.

ii. **Base (solid line):** This line represents the baseline policy and shows a moderately paced decline in emissions.

iii. **Accelerated (dotted line):** This scenario results in the most rapid and significant decrease in CO2 emissions, achieving near-zero levels well before 2045.

Figure 20, Figure 21 and Figure 22 clearly demonstrate that the speed of policy implementation has a direct and substantial impact on the fleet's annual carbon footprint. All three policy-driven approaches lead to a significant long-term reduction in emissions, but the accelerated strategy provides the fastest and deepest cuts, highlighting its superior effectiveness in achieving climate goals.

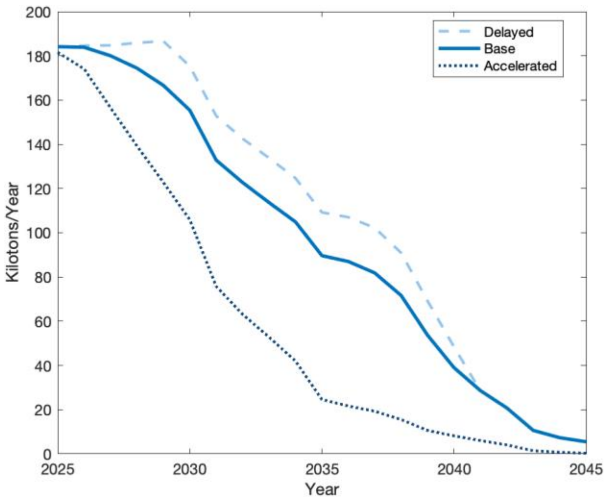
Figures 20, 21 and 22 show a descent on emissions in different velocities, caused by a lag of electrification goals in the policy-oriented simulation.

They are expressed by the following formula:

$$E_{pollutant}(y)[\text{tons}] = \frac{300}{10^6} \sum_{i=1}^{N(y)} (E_{i,pollutant} \times d_i) \tag{6}$$

Where $E_{i,pollutant}$ is the base emission rate of the pollutant for vehicle i in grams/km for CO_2, NO_x and PM.

The formula includes the necessary conversion factor. di is the average daily distance driven by vehicle i in km. The factor of 300 represents the number of operational days per year (this parameter changes for bus simulations). The factor of 10^6 converts grams to tons.



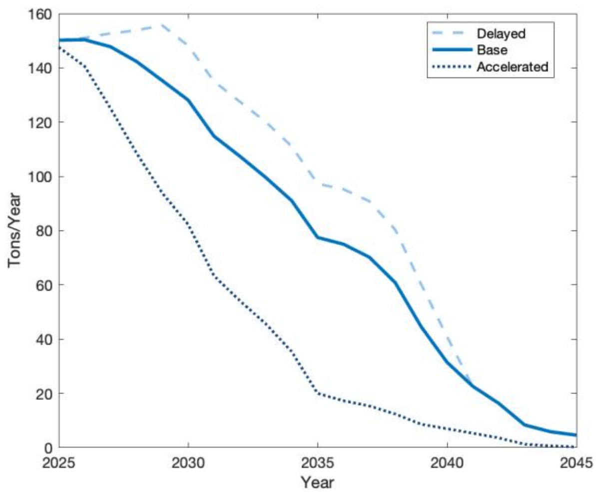


Figure 20 (left): Annual CO2 Emissions for Taxi / VTC Model (Policy Projections)

Figure 21 (right): Annual NOx Emissions for Taxi / VTC Model (Policy Projections)

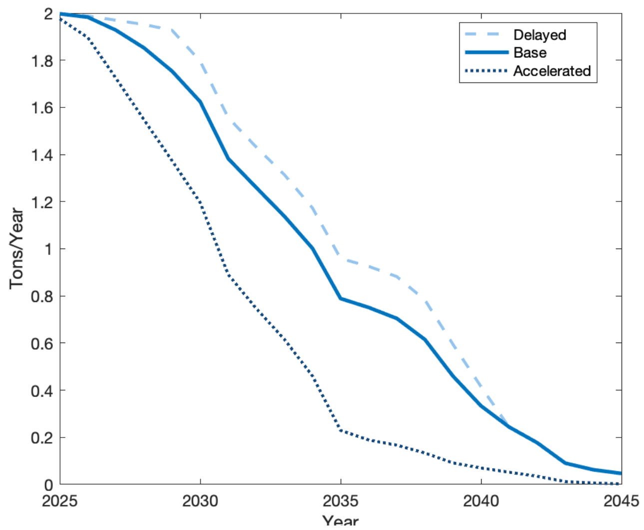


Figure 22: Annual PM Emissions for Taxi / VTC Model (Policy Projections)

As represented in Figure 23, the cost fluctuates significantly over the years, showing several peaks around 2031 and 2041 and troughs around 2035. Fluctuation is caused by vehicle renewals.

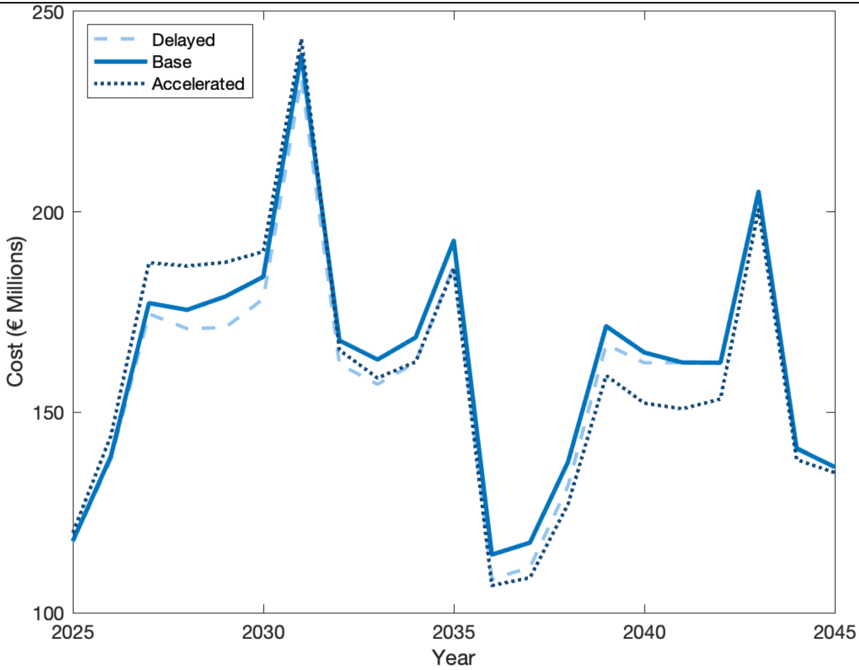


Figure 23: Total Annual Fleet Cost for Taxi / VTC Model (Policy Projections)

Total cost: Given by the following formula

$$C_{total}(y) = \sum_{i=1}^{N(y)} [C_{capex,i}(y) + C_{opex,i}(y)] \tag{7}$$

i. **Net Capital Expenditure (CAPEX):** The purchase cost of new vehicles applied only in their year of registration.

$$C_{capex,i}(y) = (\text{Price}_i(y) - \text{Subsidy}_i(y)) \times \mathbb{I}(\text{purchase\_year}_i = y) \tag{8}$$

Where II(·) is the indicator function (it is 1 if the condition is true, and 0 otherwise)

ii. **Operating Expenditure (OPEX):** The sum of annual fuel and maintenance costs.

$$C_{opex,i}(y) = (C_{fuel,i}(y) + C_{maint,i}(y)) \tag{9}$$

Fuel Cost is calculated based on distance driven, consumption rates for different driving cycles, and energy prices.

$$C_{fuel,i}(y) = 300 \times \left(\frac{d_{i,busy}\mathrm{Cons}_{i,busy,fuel} + d_{i,empty}\mathrm{Cons}_{i,empty,fuel}}{100} \cdot \mathrm{Price}_{i,fuel}(y) + \frac{d_{i,busy}\mathrm{Cons}_{i,busy,elec} + d_{i,empty}\mathrm{Cons}_{i,empty,elec}}{100} \cdot \mathrm{Price}_{i,elec}(y) \cdot f_{season} \right) \quad (10)$$

The entire formula is multiplied by 300 to scale the cost from daily to annual (based on 300 operational days for the Taxi / VTC simulation).

The first term within the main brackets calculates the cost of fossil fuels (such as gasoline and diesel). For a pure BEV, this term is zero.

The second term calculates the cost of electricity. For a conventional ICE vehicle, this term is zero. For a PHEV, both terms are used.

$d_{i,busy}$ and $d_{i,empty}$ are the daily kilometers driven while occupied and searching, respectively.

C_{ons} represents the vehicle's consumption rate (in L/100km or kWh/100km), which is why the term is divided by 100.

f_{season} is the annual consumption adjustment factor that only applies to electricity consumption to model the effects of heating and air conditioning.

Maintenance costs are explained by the following formula:

$$C_{maint,i}(y) = (300 \times d_i) \times (\mathrm{Cost}_{i,routine} + \mathrm{Cost}_{i,insurance}) \quad (11)$$

As shown in the figure below, all scenarios show a continuous increase in power demand over the period. The Accelerated scenario requires the most rapid and highest increase in power demand. The Delayed scenario has the slowest growth, and the Base scenario falls in between. By 2045, all three scenarios converge towards a high-power demand of over 90 MW.

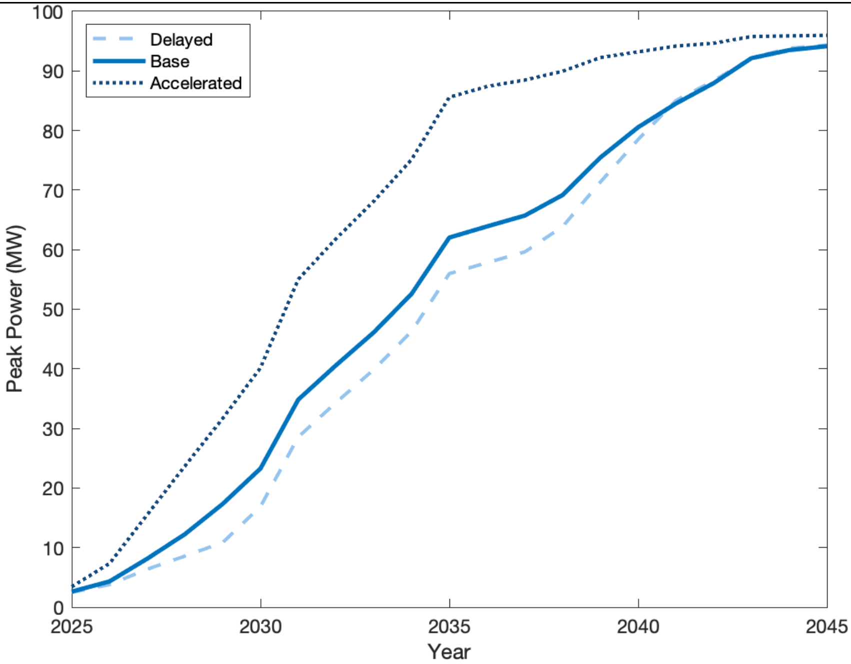


Figure 24: Charging Power Demand for Taxi / VTC Model (Policy Projections)

The results shown in Figure 24 have been calculated in the following way:

$$P_{peak}(y) = \frac{E_{elec,total}(y)}{300 \cdot T_{window}} \cdot \frac{f_{simul}}{1 - \eta_{loss}} \tag{12}$$

$E_{elec,total}(y)$ is the total annual electricity demand from all BEVs and PHEVs in Megawatt-hours (MWh).

T_{window} is the daily charging window in hours.

f_{simul} is the simultaneity factor, representing the fraction of EVs charging at the same time during the peak.

η_{loss} is the charging loss factor. The factor of 300 converts annual energy demand to average daily demand.

6.2.3 MARKET – DRIVEN SCENARIO

Figure 25 shows the changing composition of the vehicle fleet over time in a market driven simulation. The fleet is divided into Internal Combustion Engine (ICE), Hybrid (HEV), Plug-in Hybrid (PHEV), and Battery Electric (BEV) vehicles. It illustrates a slow transition, where

ICE vehicles remain the dominant type throughout the period, though their share gradually decreases as electric and hybrid vehicles are slowly adopted.

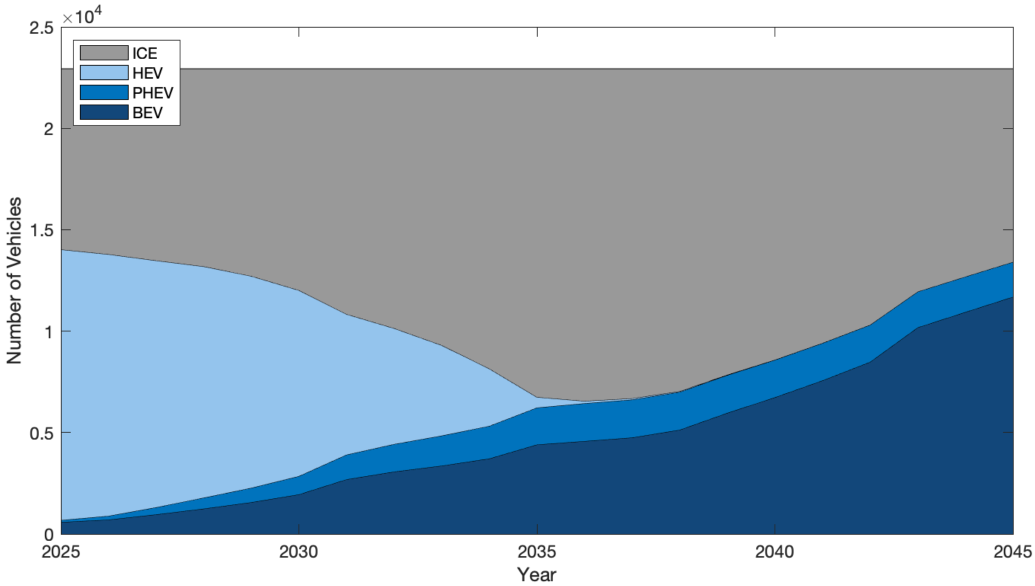


Figure 25: Taxi / VTC Fleet Composition (Market Projections)

Figure 26 displays the total annual CO_2 emissions in tons per year. The emissions trend shows an initial increase, which means that ICE vehicles dominate the fleet, peaking around the year 2038, before starting a decline. This phenomenon is caused due to economically favorable tendencies to ICE vehicles in this initial period.

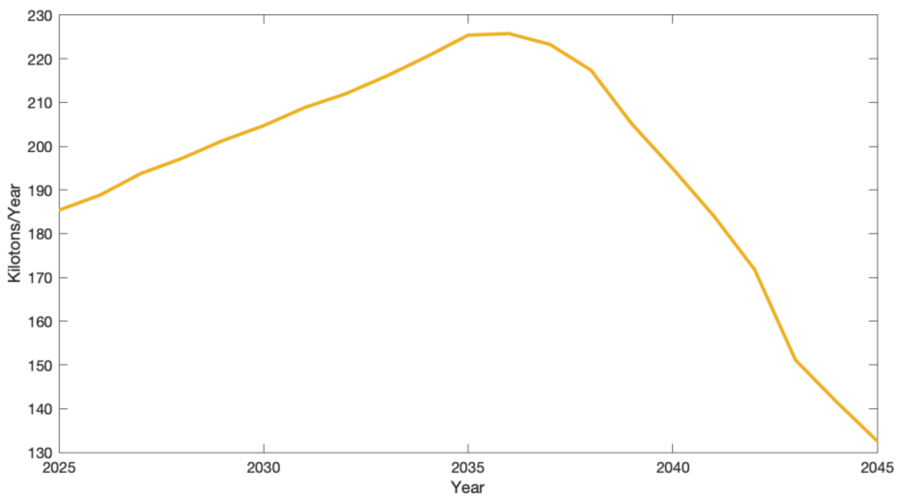


Figure 26: Annual CO2 Emissions for Taxi / VTC Model (Market Projections)

Figure 27 projects the peak yearly power demand in Megawatts (MW) needed for charging the electric vehicles in the fleet. The demand shows a steady and accelerating upward trend, starting near zero in 2025 and rising to over 50 MW by 2045, directly corresponding to the increasing number of electric vehicles.

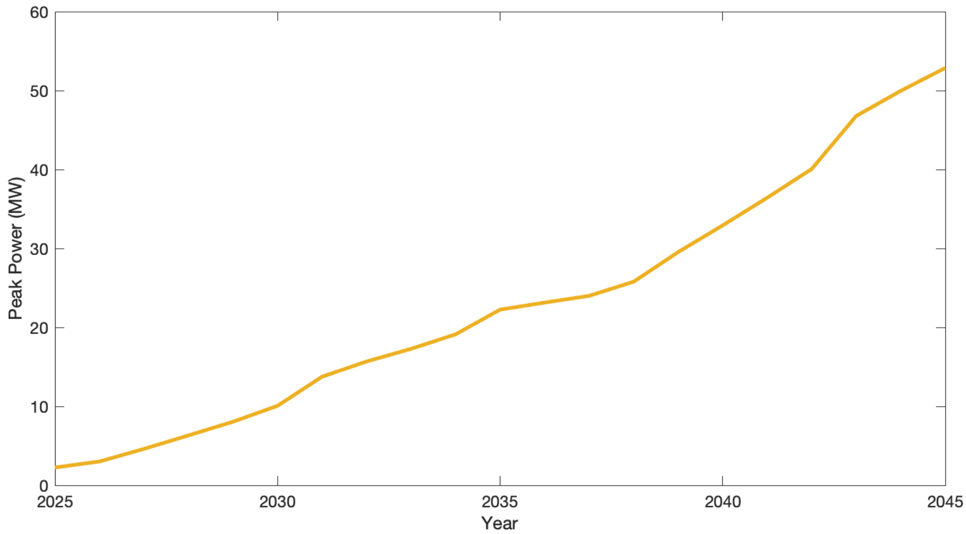


Figure 27: Charging Power Demand for Taxi / VTC Model (Market Projections)

This line chart illustrated in Figure 28 shows the total annual cost of the fleet in millions of Euros. The cost shows significant volatility over the years, with several peaks around 2028 and 2042 and troughs around 2035 reflect vehicle purchase and replacement cycles.

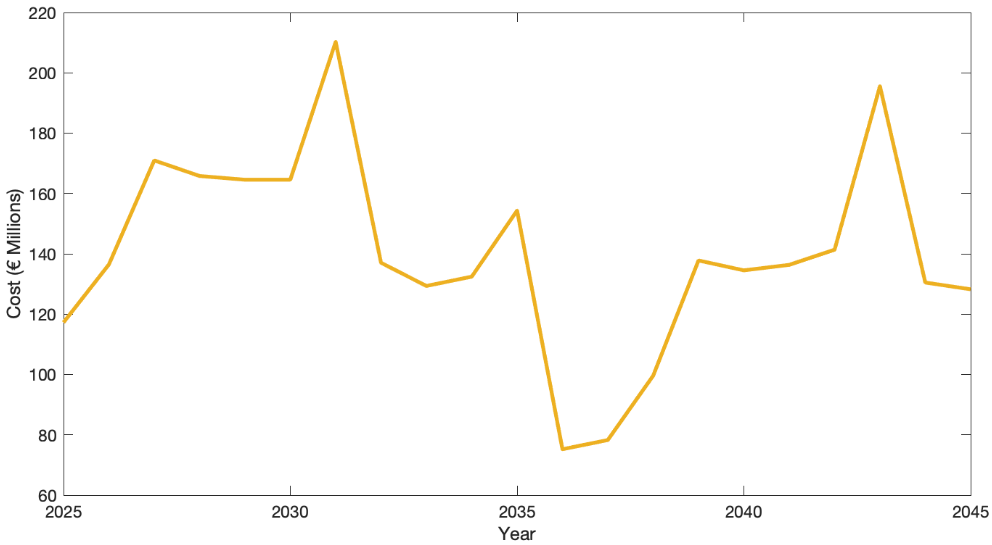


Figure 28: Total Annual Fleet Cost for Taxi / VTC Model (Market Projections)

6.2.4 GOVERNMENT PLAN VS. MARKET REALITY

In Figure 29, we can see a significant and growing gap between the government's ambitions and the market's reality. The market is projected to adopt BEVs at a much slower rate than any of the government's policy scenarios.

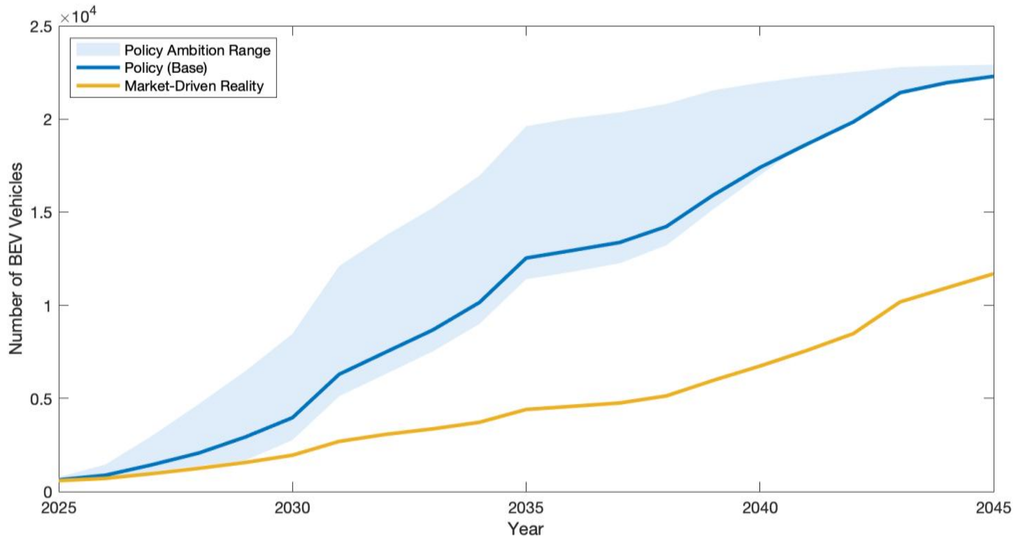


Figure 29: BEV Adoption Policy Ambition vs Market Reality

In Figure 30, it is shown that the planned charging infrastructure supply, even under the least ambitious Delayed Plan, is always sufficient to meet the projected market demand. There is no predicted infrastructure deficit.

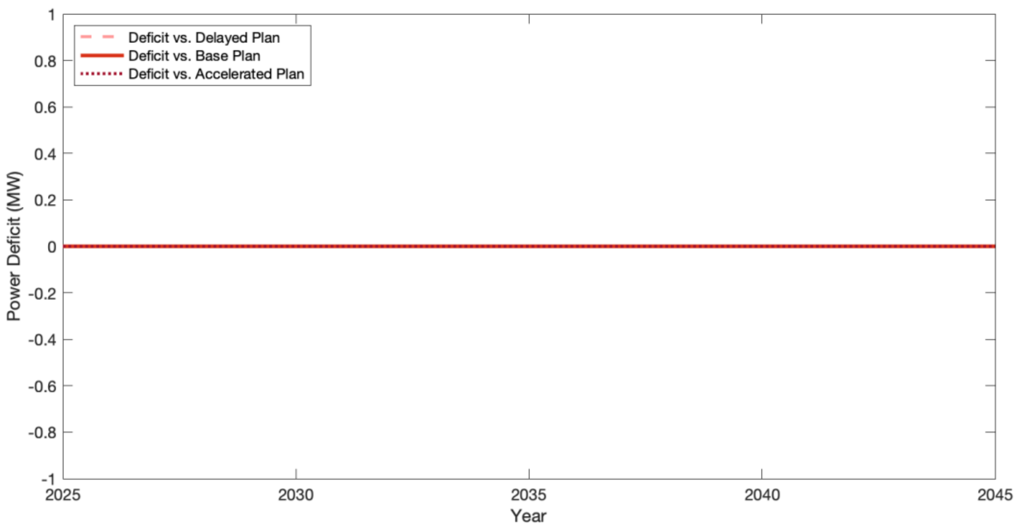


Figure 30: Infrastructure Deficit (Market Demand vs Planned Supply)

6.3 RESULTS FOR THE EMT SIMULATION

In this section, the results of the EMT simulation will be shown. It is essential to understand that there is no TCO decision being done in this model, as explained in Chapter 4.

6.3.1 CUMULATIVE IMPACT

As expected, Figure 31, Figure 32 and Figure 33 show the total amount of emissions, for each of the four scenarios. The Delayed scenario corresponds to the highest emissions, then Base, and finally the Accelerated scenario results in the lowest.

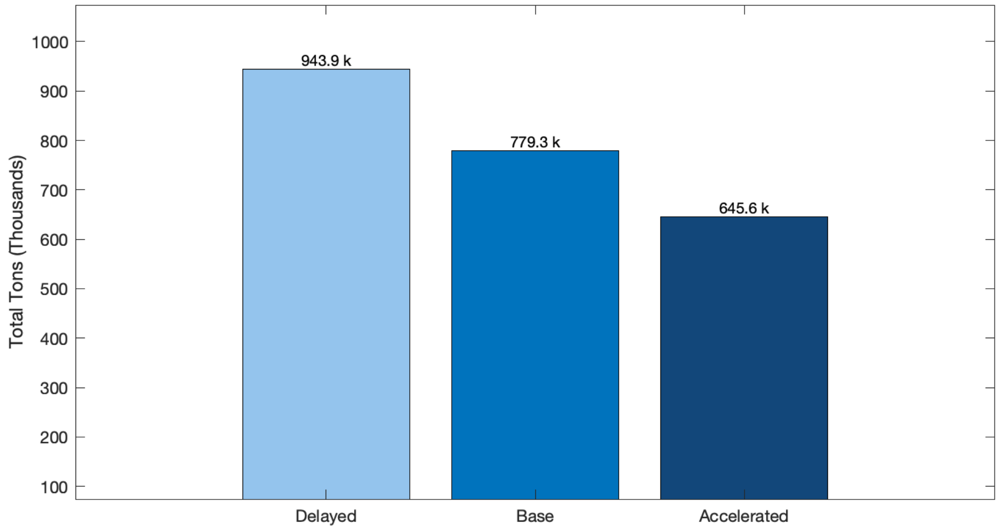


Figure 31: Total Cumulative CO2 Emissions (EMT Model)

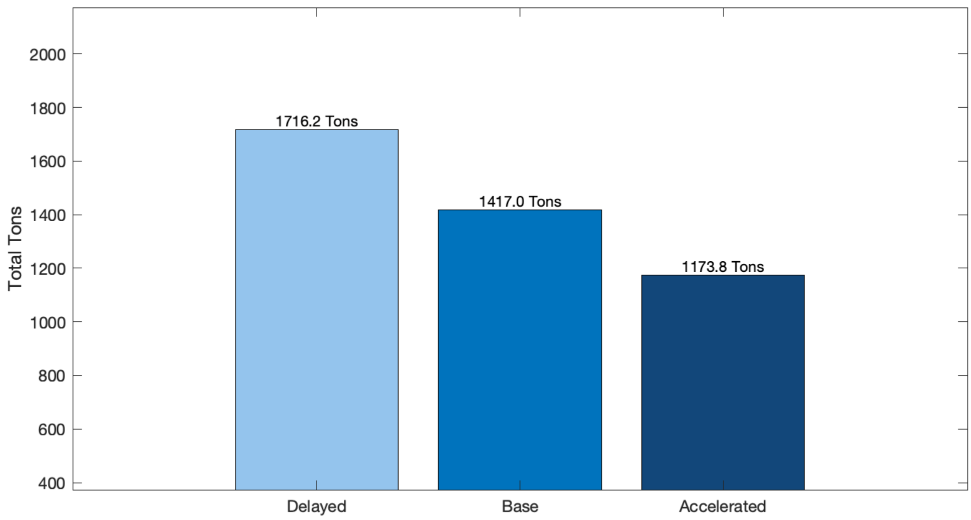


Figure 32: Total Cumulative NOx Emissions (EMT Model)

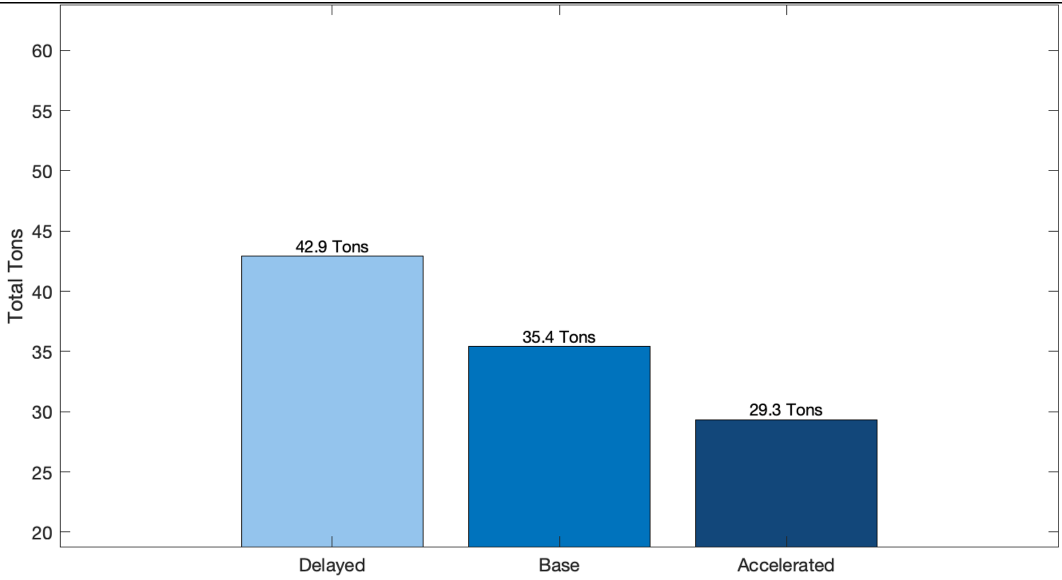


Figure 33: Total Cumulative PM Emissions (EMT Model)

Unlike the emissions plots, Figure 34 describes that the total costs across the three scenarios are very similar, all hovering around €2.5 billion. The Delayed scenario is marginally the most expensive, and the Accelerated scenario is the least expensive, but the difference is minimal.

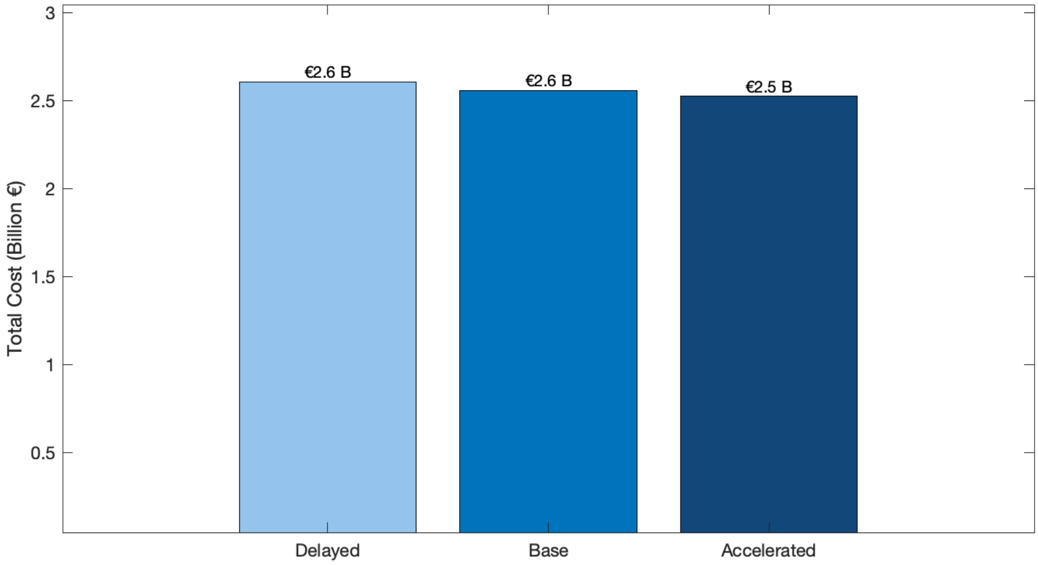


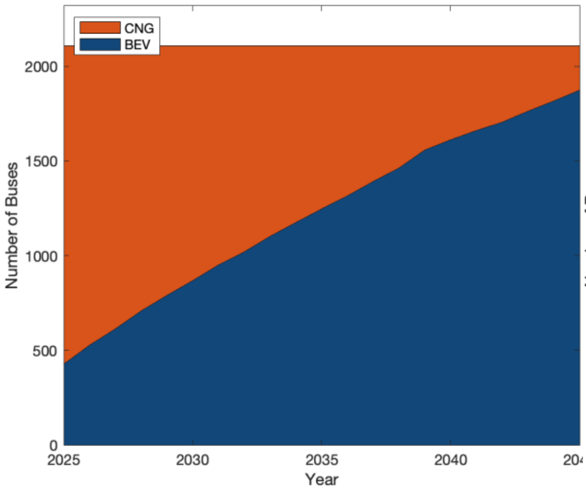
Figure 34: Total Cumulative Fleet Cost (EMT Model)

6.3.2 YEARLY PROJECTIONS

Figure 35, Figure 36 and Figure 37 represent the fleet composition throughout the simulation years. All three figures start with +2000 buses, and around 20% of them are BEV.

Figure 35 shows the Delayed scenario, where it appears that by year 2045, there is still a small stretch of the fleet which is not electric.

On the other hand, Figure 36 and Figure 37 reflect tighter environmental policies, which end up in a final higher number or BEV buses by the end of the simulation, reaching 100% in Figure 37.



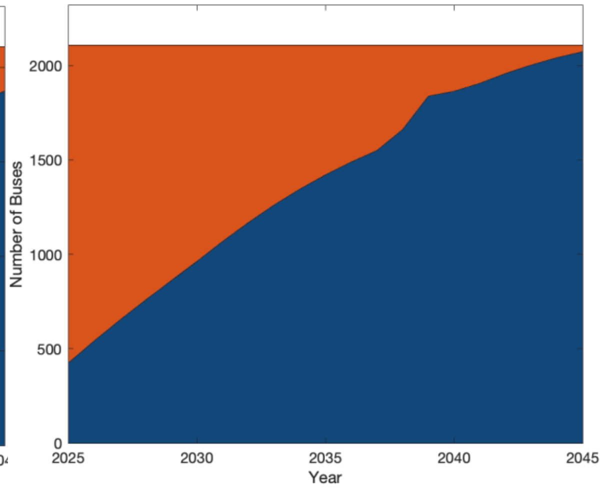


Figure 35 (left): EMT Fleet Composition (Policy - Delayed)

Figure 36 (right): EMT Fleet Composition (Policy - Base)

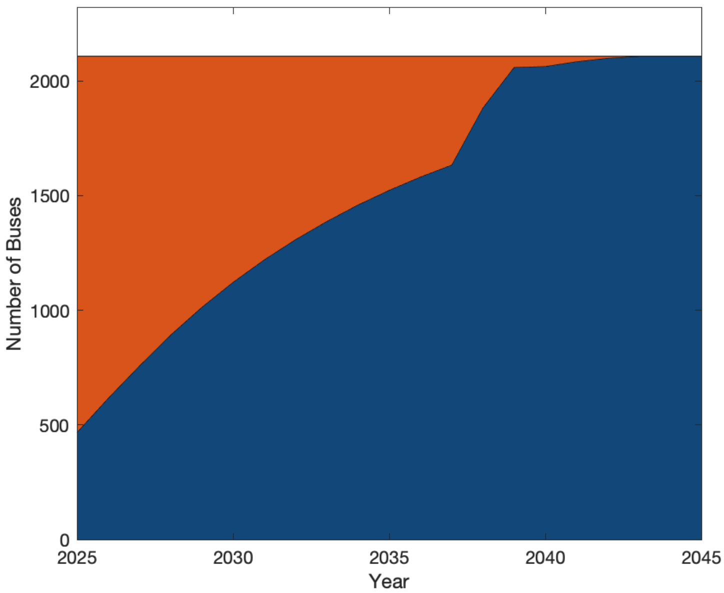
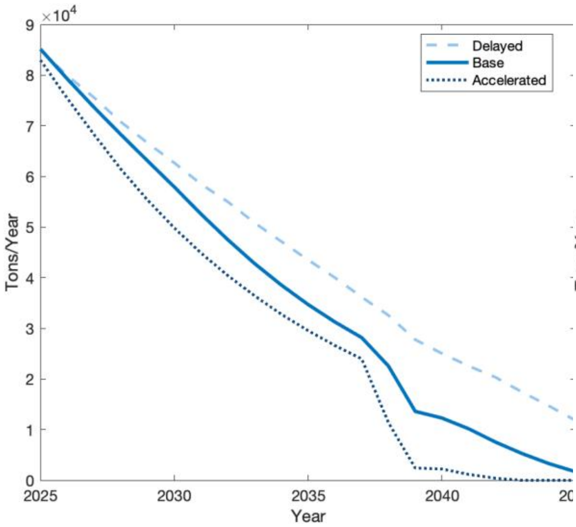


Figure 37: EMT Fleet Composition (Policy – Accelerated)

As described in Figure 38, Figure 39 and Figure 40, these follow the same patterns as the taxi / vtc, modelling characterized by a decrease in overall emissions and tighter policies result in fewer environmental pollutants caused by circulation in a shorter time span.



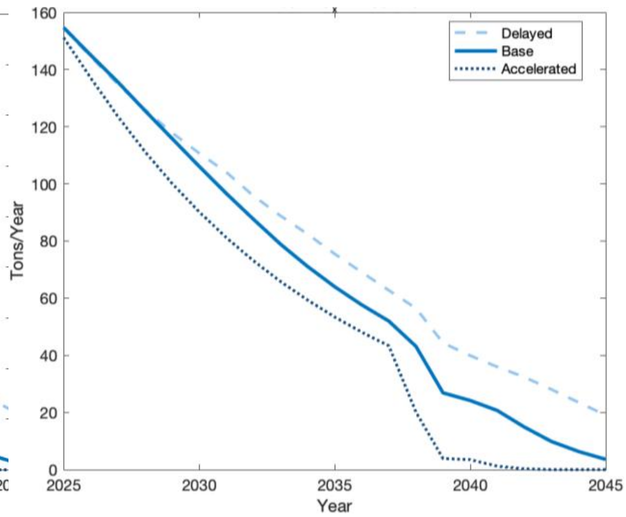


Figure 38: Annual CO2 Emissions for EMT Model (Policy Projections)

Figure 39: Annual NOx Emissions for EMT Model (Policy Projections)

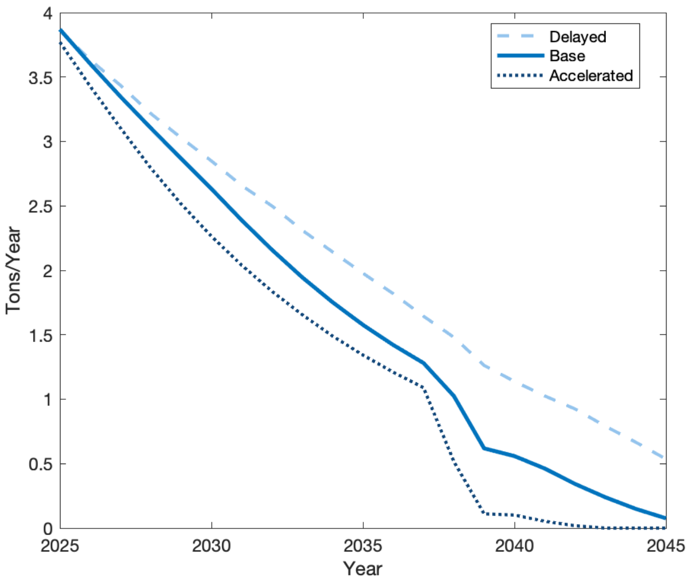


Figure 40: Annual PM Emissions for EMT Model (Policy Projections)

Figure 41, Figure 42 and Figure 43 represent expected policy-driven results in adoption rates, costs and charging power demand for each scenario.

No comparison is made with market behavior as it is not modelled due to the state-owned nature of the EMT.

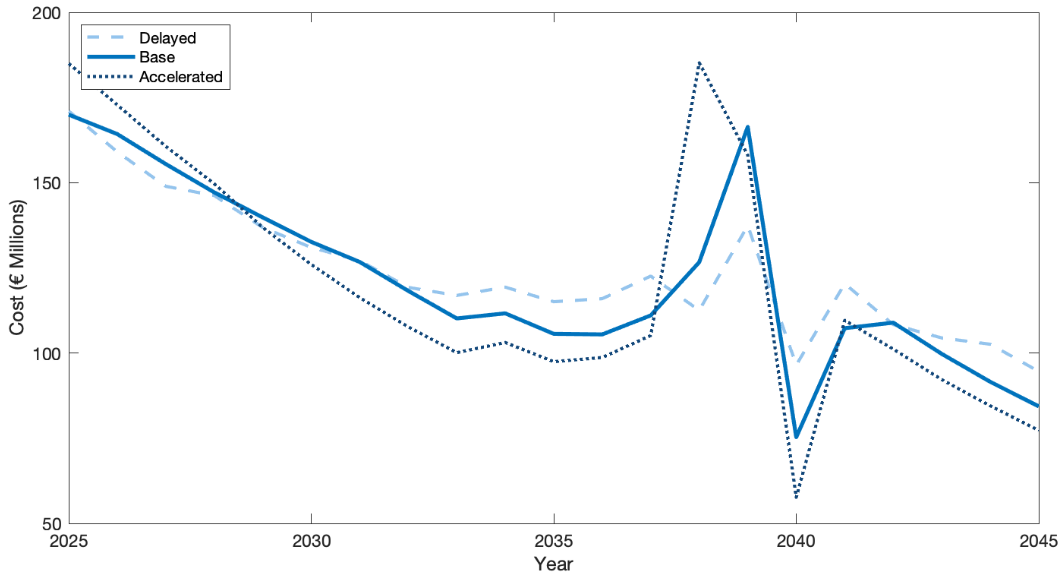


Figure 41: Total Annual Fleet Cost for EMT Model (Policy Projections)

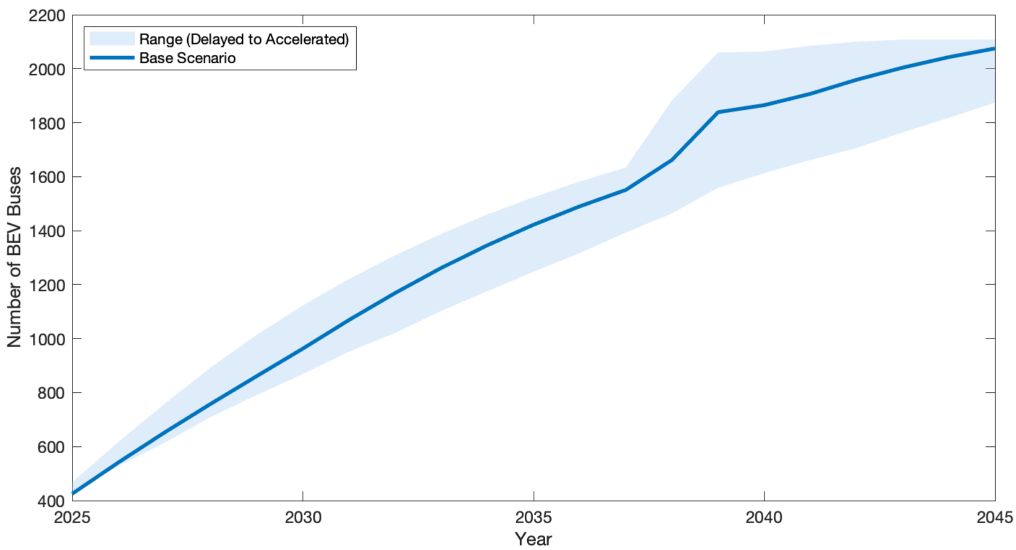


Figure 42: BEV Adoption Across Scenarios (EMT)

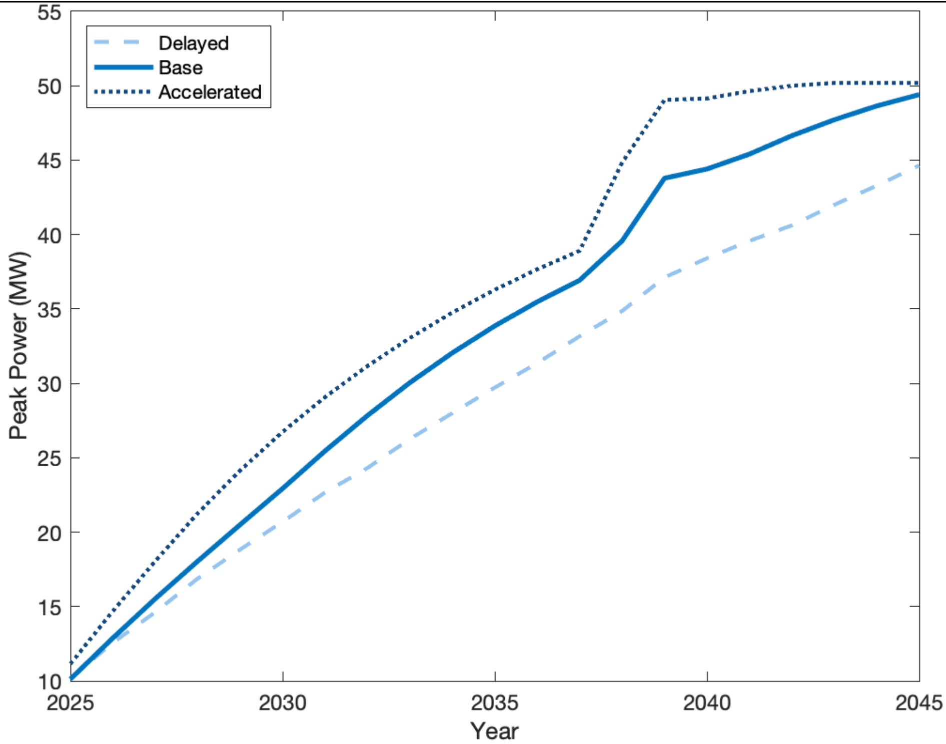


Figure 43: Charging Power Demand for EMT Model (Policy Projections)

6.3 RESULTS FOR THE INTERURBAN SIMULATION

As explained in Chapter 4, interurban bus simulations are executed within a market-driven decision making, with some government-forced renewal mandates.

6.3.1 CUMULATIVE IMPACT

It is important to understand why there is such a drastic difference between the cumulative costs derived from both bus simulations (EMT & Interurban, Figures 34 and 47 respectively) if the number of buses in both fleets is very similar, with the EMT operating 2,108 buses and the interurban fleet comprising 2,114.

The significant difference in the total cumulative cost stems almost entirely from their different operational roles, which dramatically impacts their lifetime running costs.

The primary reason for the higher cumulative cost of the interurban bus fleet is its vastly greater daily mileage. According to the model's parameters, an interurban bus travels an average of 300 km per day, whereas an EMT urban bus travels only 126 km per day. This means each interurban bus covers more than double the distance of its urban counterpart every single day.

This operational difference creates a massive divergence in the cumulative operational expenditures (OPEX) over the 20-year simulation period. The higher mileage directly translates into substantially greater lifetime costs for fuel and maintenance, which are calculated on a per-kilometer basis in the simulation. Although the initial purchase prices (CAPEX) for the vehicles are comparable, the relentless accumulation of these higher daily operational costs is what accounts for the nearly €1.5 to €2 billion difference shown in Figure 34 and Figure 47 the total cost of the fleets.

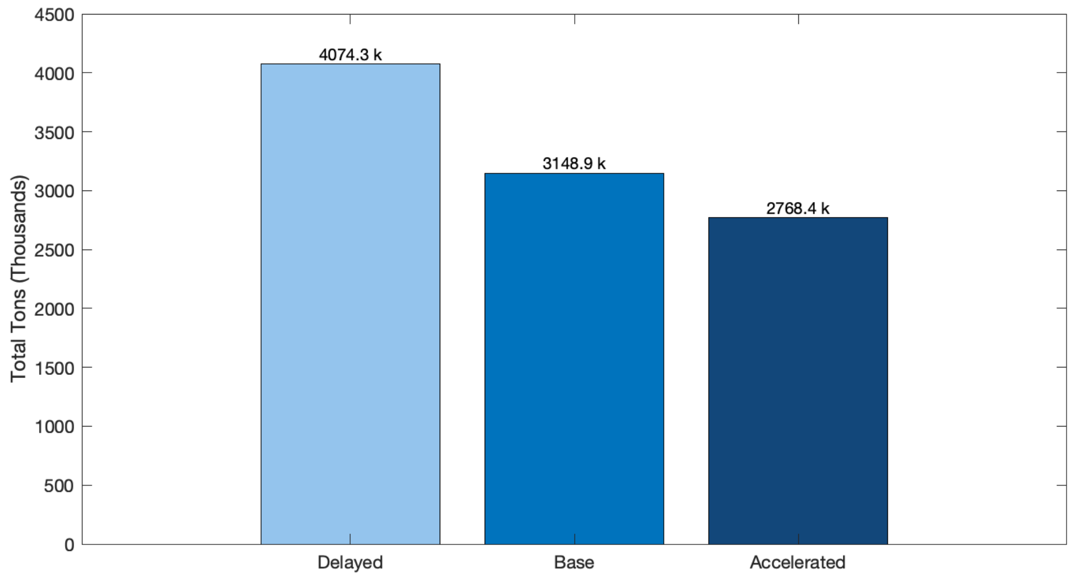


Figure 44: Total Cumulative CO2 Emissions (Interurban Bus Model)

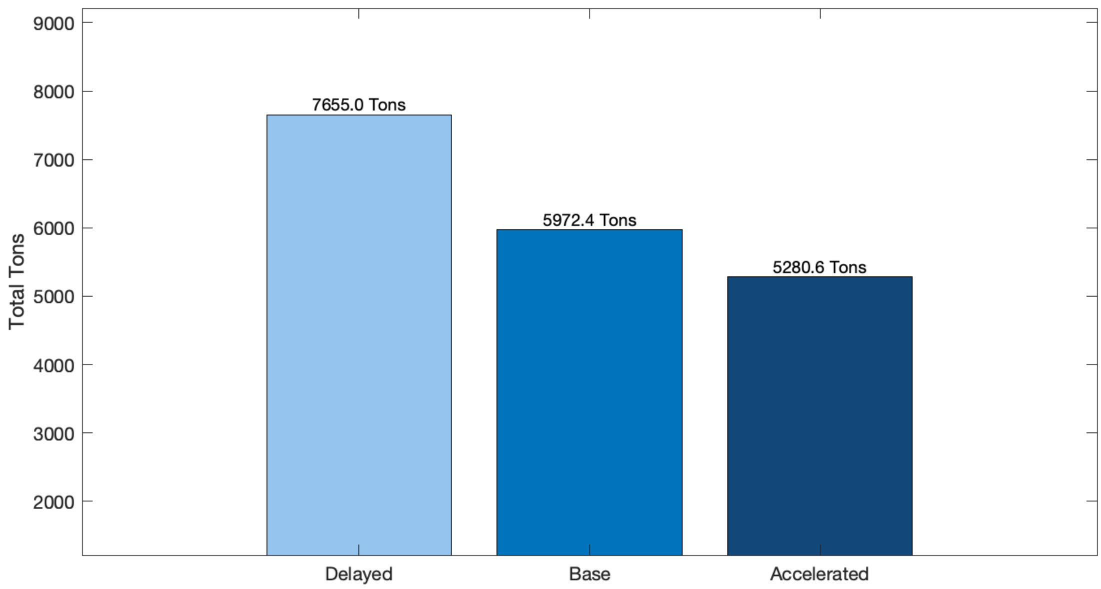


Figure 45: Total Cumulative NOx Emissions (Interurban Bus Model)

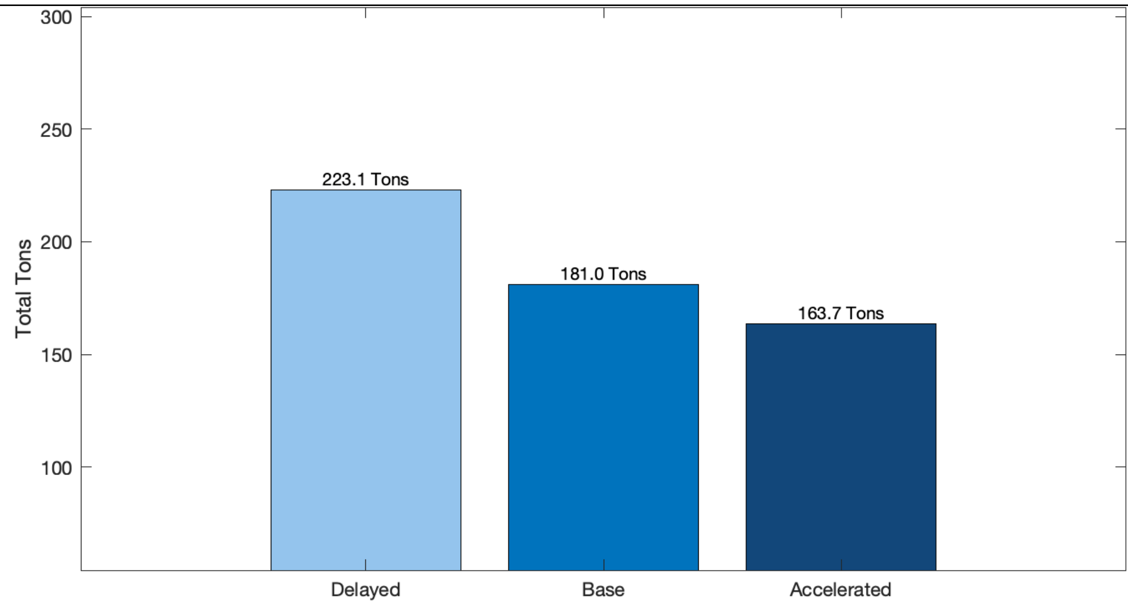


Figure 46: Total Cumulative PM Emissions (Interurban Bus Model)

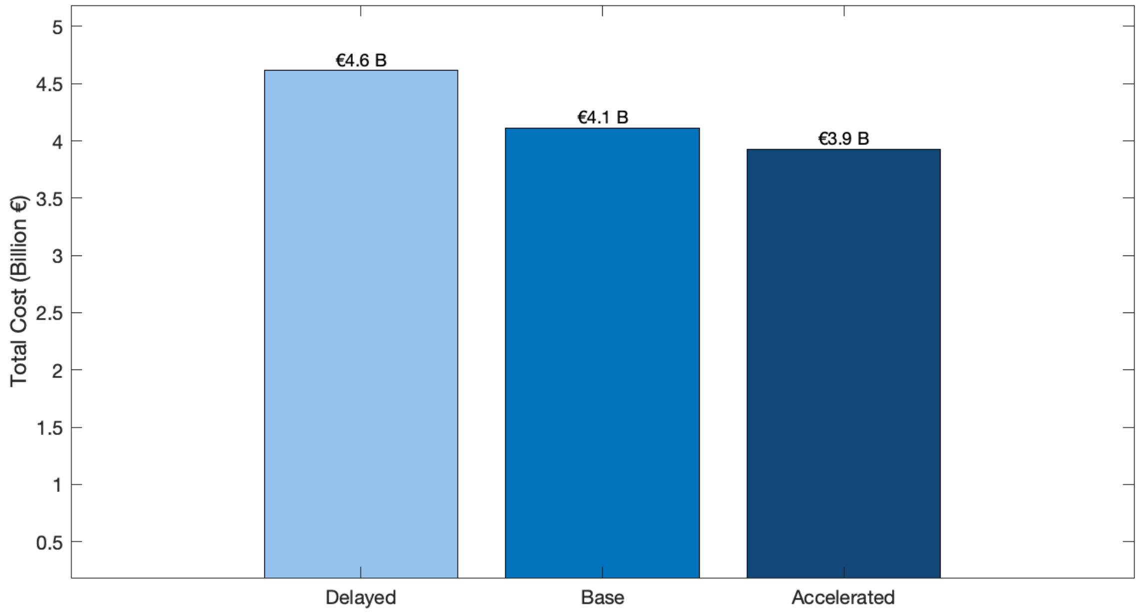
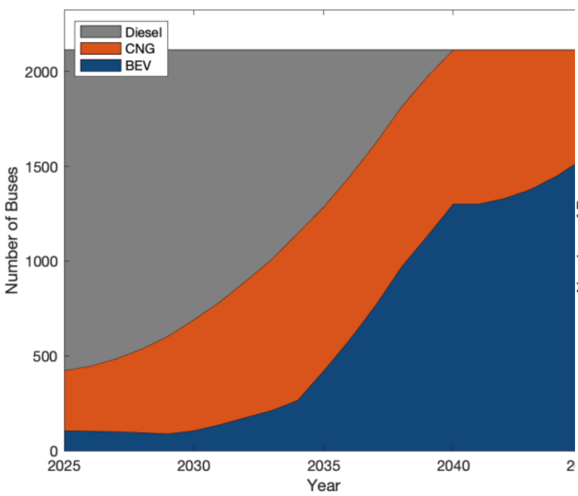


Figure 47: Total Cumulative Costs (Interurban Bus Model)

6.3.2 MARKET – DRIVEN SCENARIOS WITH GOVERNMENT-MANDATED RENEWALS

Figures 48 – 56 show the same patterns as the EMT graphs. The Delayed scenario (dashed line) is consistently the most expensive and most pollutant, while the Accelerated scenario (dotted line) is the least expensive, and least pollutant.

Furthermore, the increasing BEV adoption dynamic throughout the simulation, and the necessity for additional charging power is also apparent in the graphs.



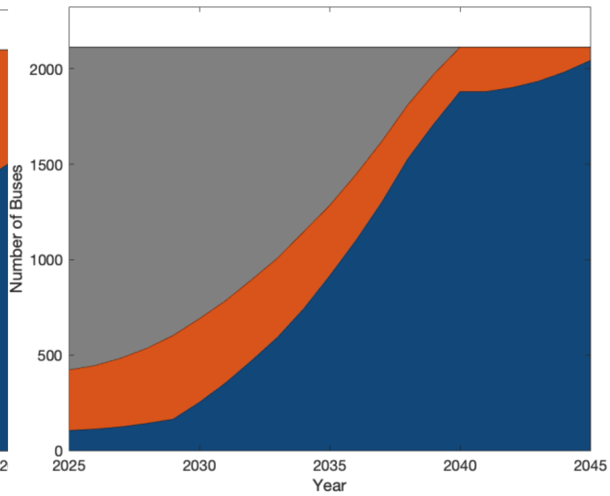


Figure 48 (left): Interurban Bus Fleet Composition (Policy - Delayed)

Figure 49 (right): Interurban Bus Fleet Composition (Policy - Base)

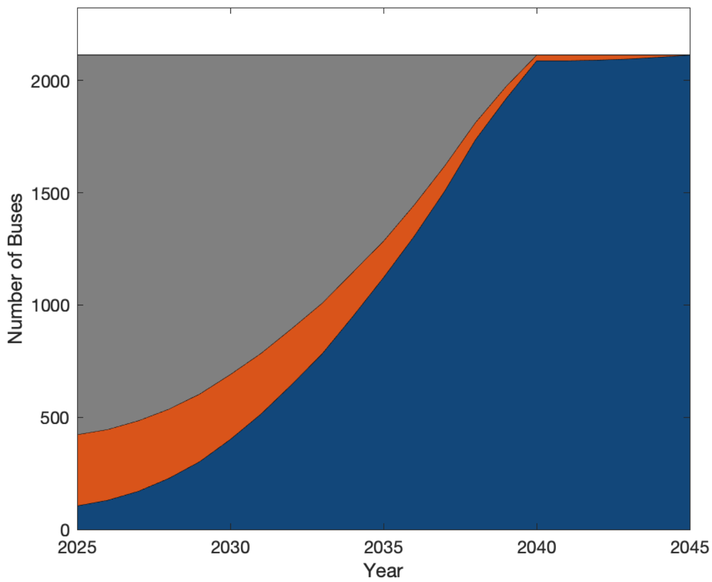
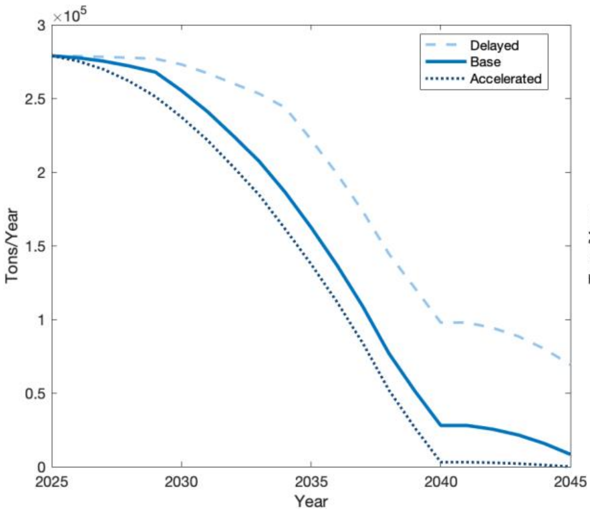


Figure 50: Interurban Bus Fleet Composition (Policy - Accelerated)

Unlike the EMT, the Interurban fleet is composed of diesel buses as well as CNG and BEV. This is because interurban routes cover much longer distances between municipalities, where the long-range and rapid refueling capabilities of diesel are still necessary. The required charging infrastructure for a fully electric long-distance fleet is not yet as developed as it is within the dense urban core where the EMT operates.



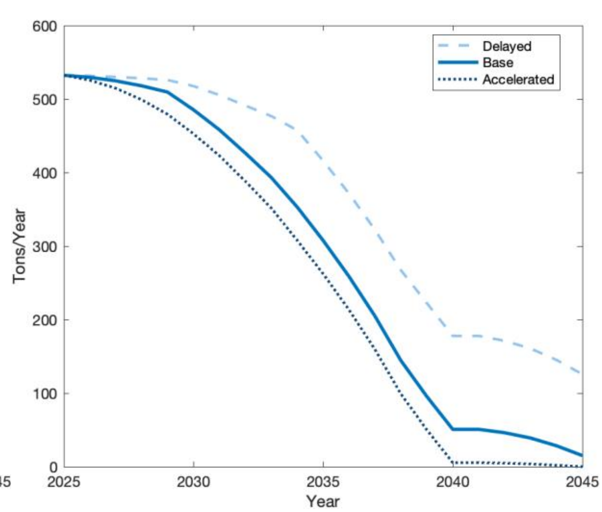


Figure 51 (left): Annual CO2 Emissions for Interurban Bus Model Across Scenarios

Figure 52 (right): Annual NOx Emissions for Interurban Bus Model Across Scenarios

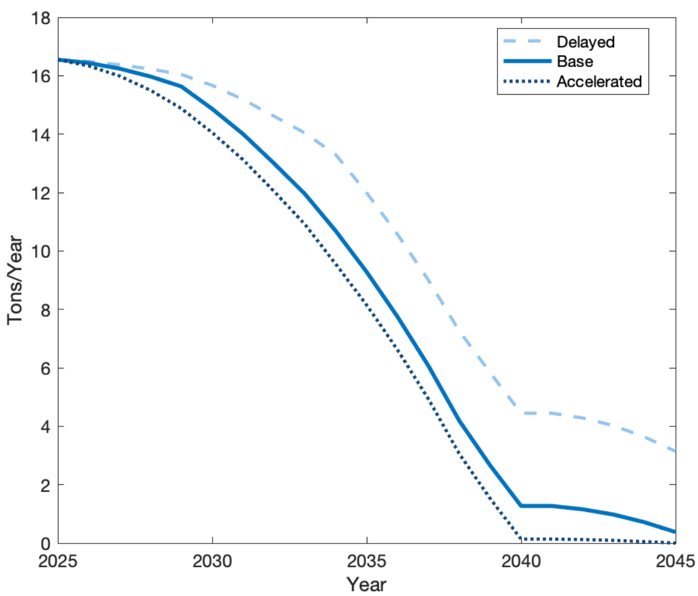


Figure 53: Annual PM Emissions for Interurban Bus Model Across Scenarios

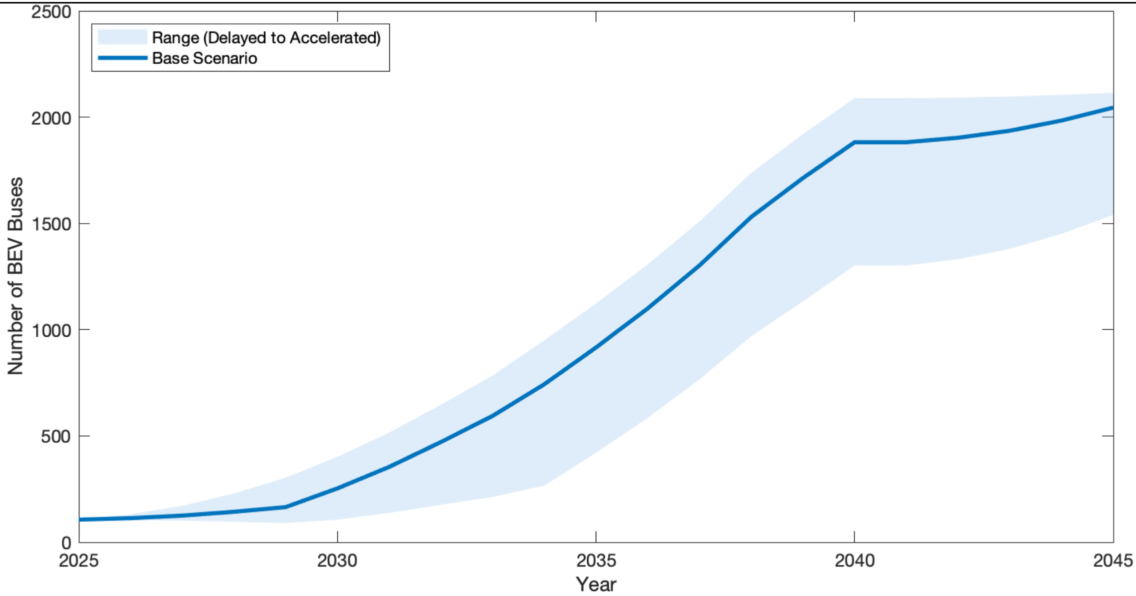


Figure 54: BEV Adoption Across Scenarios (Interurban)

As shown in Figure 55 and other cost evolution figures, the Delayed scenario is consistently the most expensive after the initial peak. The Accelerated scenario is generally the least expensive, particularly in the later years, suggesting that a faster transition leads to lower long-term annual costs.

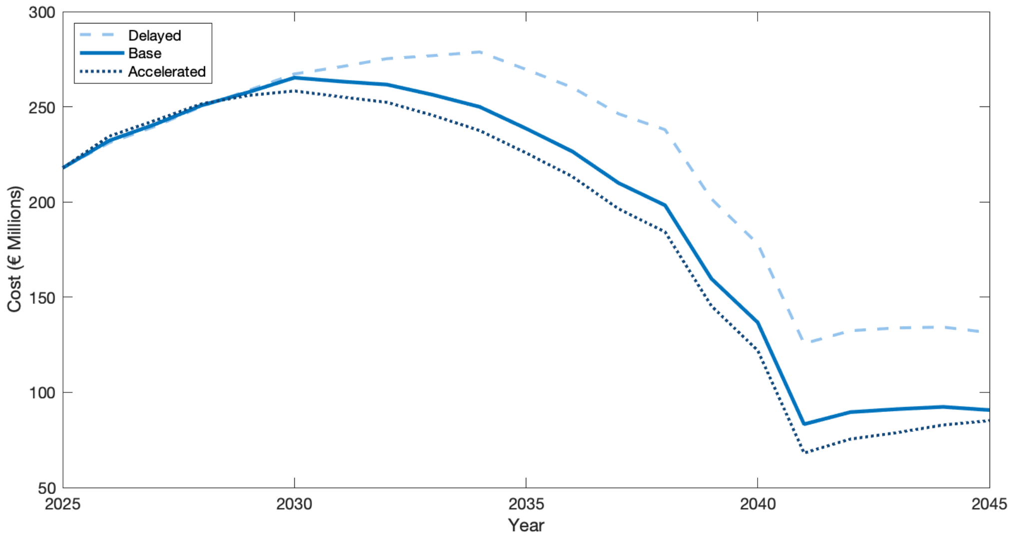


Figure 55: Total Annual Fleet Cost for Interurban Bus Model Across Scenarios

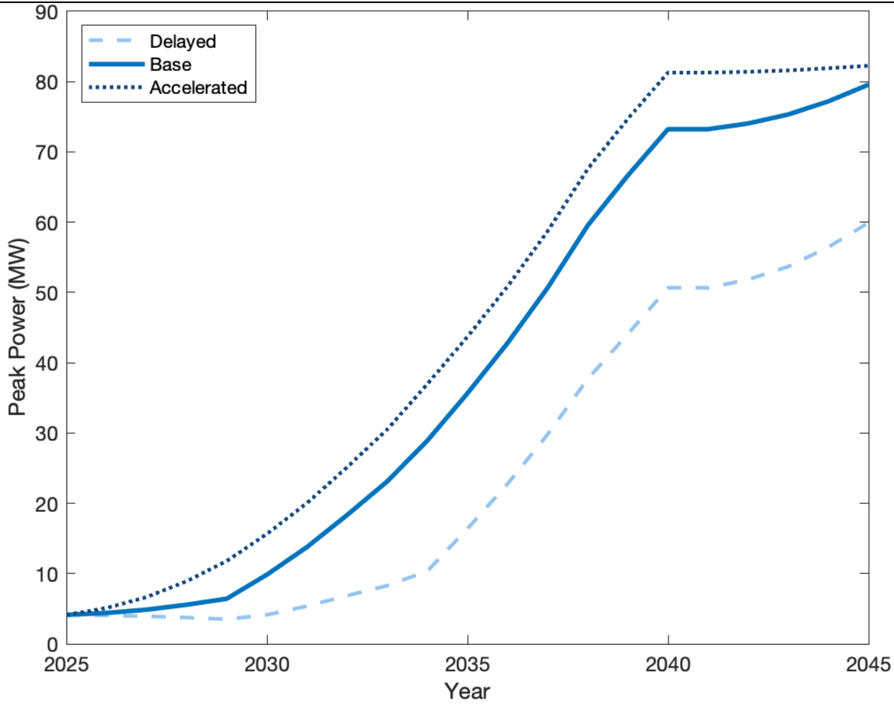


Figure 56: Charging Power Demand for Interurban Bus Model Across Scenarios

CHAPTER 7: DISCUSSION OF RESULTS

7.1 ANALYSIS OF FLEET ELECTRIFICATION SCENARIOS: A SYNTHESIS OF KEY FINDINGS

The objective of this chapter is to discuss the base results and use them as a benchmark for running potential scenarios that may provide valuable insights to round up a conclusion.

For this analysis, the Taxi/VTC fleet simulation was selected as the primary case study to represent the broader dynamics of vehicle fleet electrification in Madrid. This decision is based on the comprehensive nature of the Taxi/VTC model, which uniquely allows for a direct and insightful comparison between policy-driven ambitions and market-driven realities. The bus fleet models, while accurate for their specific segments, represent dynamics that are conceptually nested within the more encompassing framework of the Taxi/VTC simulation.

7.1.1 THE TAXI/VTC MODEL

Captures the full spectrum of decision-making: This model is singularly comprehensive as it simulates two distinct decision-making paradigms:

i. A Policy-Following Framework, where fleet renewal adheres to predefined government targets.
ii. A Market-Driven Framework, where purchasing decisions are governed purely by the economic rationality of Total Cost of Ownership (TCO).

By running these frameworks in parallel, the Taxi/VTC model generates the most critical strategic insight of this study: the quantitative tension between policy goals and market behavior, exemplified by the infrastructure deficit analysis.

7.1.2 THE BUS MODELS

Represent subsets of this core dynamic: While the bus simulations are important, their reasoning is not unique and is already represented within the Taxi/VTC analysis, making their inclusion redundant for a strategic overview:

i. The EMT Urban Bus Model operates as a pure policy-following model. Its renewal logic is dictated by a fixed target schedule, making its behavior conceptually analogous to the government plan scenarios within the Taxi/VTC simulation. Presenting its results would confirm that policy mandates drive outcomes but would not introduce a new analytical dimension.
ii. The Inter-urban Bus Model operates as a policy-dominant hybrid model. The primary driver for BEV adoption is the regulatory mandate. The TCO calculation is a secondary factor, used only to decide between conventional fuel types (Diesel vs. CNG) for non-mandated replacements. Therefore, its narrative arc is also largely

shaped by the policy schedule, making it similar in principle to the other policy-driven scenarios.

The key results of the base simulation are distributed in three categories:

i. Environmental Impact
ii. Economic Implications
iii. Recharge Infrastructure

7.1.1 ENVIRONMENTAL IMPACT ANALYSIS

A primary finding across all modeled fleets is that policy-driven electrification is a highly effective strategy for reducing harmful emissions. The rate and magnitude of the reduction in CO_2, NO_x, and PM emissions are directly proportional to the aggressiveness of the policy implementation.

For both the EMT and Inter-urban bus fleets, the Accelerated scenario always exhibits the lowest overall emissions throughout the simulation. This is due to the rapid phase-out of internal combustion engine (ICE) vehicles (CNG and Diesel) for Battery Electric Vehicles (BEVs), which produce no tailpipe emissions. The private vehicle fleet study reveals a significant ambition gap between policy aims and market-led outcomes. While all policy scenarios show a steady reduction in emissions, the Market-Driven scenario shows the improvement to be much slower. Interestingly, annual CO_2 emissions under the market scenario are projected to increase and peak near the end of the time horizon of the simulation (approx. 2038) before the reductions begin. This means that without strong policy intervention, emissions from fleet growth and the gradual replacement of the existing ICE fleet will initially outweigh the benefits of BEV adoption.

7.1.2 ECONOMIC AND COST IMPLICATIONS (TANK TO WHEEL)

For both the Inter-urban and EMT fleets, the total fleet costs across the Delayed, Base, and Accelerated scenarios are remarkably close. In fact, for the Inter-urban fleet, the Accelerated scenario is the most cost-effective over a 20-year period. This indicates that while the initial capital expenditure (CAPEX) of BEVs is higher, the lower operational expenditures (OPEX), primarily from fuel and maintenance savings, recover this initial outlay over the life of the vehicle.

The private vehicle fleet shows the Market-Driven scenario as having the lowest cumulative cost. This is because consumers delay the purchase of newer, more expensive BEV technology. The policy scenarios, which stimulate or mandate faster uptake, must therefore have greater overall costs. All fleets' annual cost profiles exhibit significant volatility, presumably as fleet renewal cycles match when large numbers of vehicles are replaced simultaneously.

7.1.3 INFRASTRUCTURE AND POWER DEMAND

The transition to an electrified fleet will bring about a massive expansion of charging infrastructure, which will put more pressure on the power grid.

As expected, the peak power demand is equal to the adoption rate of BEVs. The Accelerated scenarios experience highest demand for all fleets.

One important finding is from the Infrastructure Deficit assessment of the private car fleet. This chart shows that even the most extreme market-led uptake of BEVs doesn't come close to beating the planned provision of charging power, even with the government's most cautious Delayed infrastructure plan. This would mean that, according to this model, the principal hindrance to private car electrification is not an insufficiency of grid capacity planned for but rather slower-than-anticipated market uptake of BEVs.

7.2 HYPOTHETICAL SCENARIO 1: CHINA STARTS EXPORTING NEW ELECTRIC CARS AT A LOWER PRICE

This will be simulated by changing the price parameter of BEV from €45,000 to €25,000. The simulation is therefore designed to quantify the effects of this demand-side shock, testing whether a purely rational, market-driven adoption rate would massively outpace the planned deployment of charging infrastructure and deviate from established policy transition timelines.

7.2.1 FINDING 1: POLICY EFFECTIVENESS IS CONFIRMED, BUT WITH CLEAR TRADE-OFFS

The three policy scenarios demonstrate a direct correlation between the speed of the mandate and the environmental and economic outcomes. As shown in Figure 57 and Figure 58, the Accelerated policy leads to the fastest reduction in emissions. This benefit, however, comes at the cost of higher upfront capital expenditure, as seen in the pronounced cost spikes in Figure 59, and requires a more aggressive build-out of charging infrastructure (Figure 60).

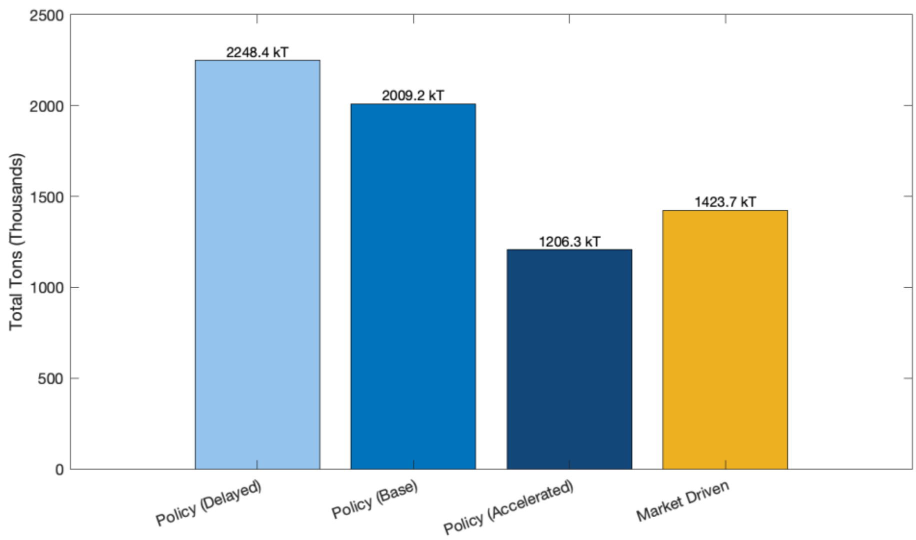


Figure 57: Total Cumulative CO2 Emissions (Taxi / VTC Model) - Hypothetical 1

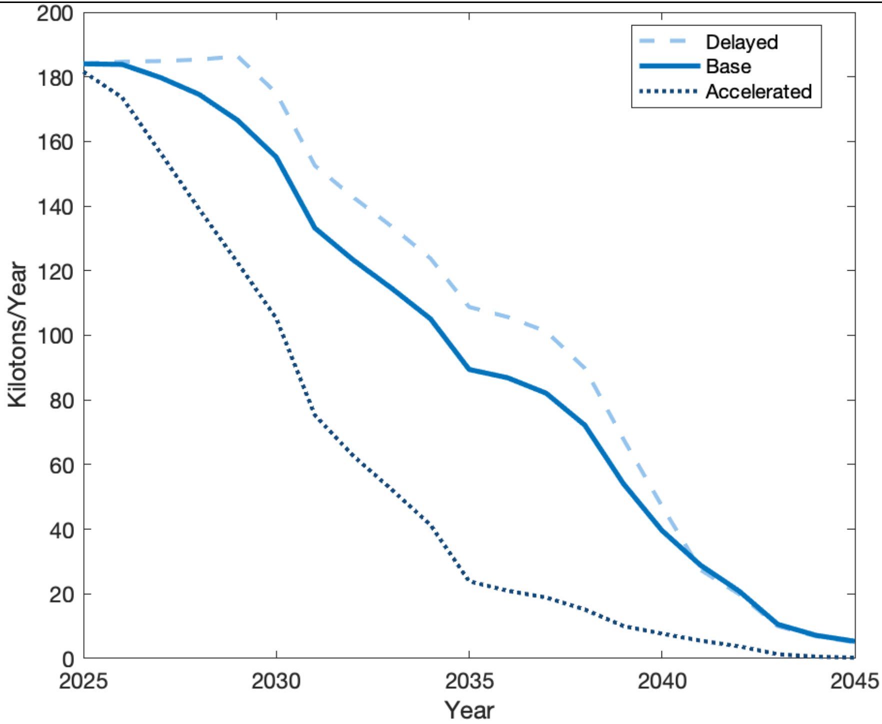


Figure 58: Annual CO2 Emissions for Taxi / VTC Model (Lower BEV Price Hypothetical Scenario)

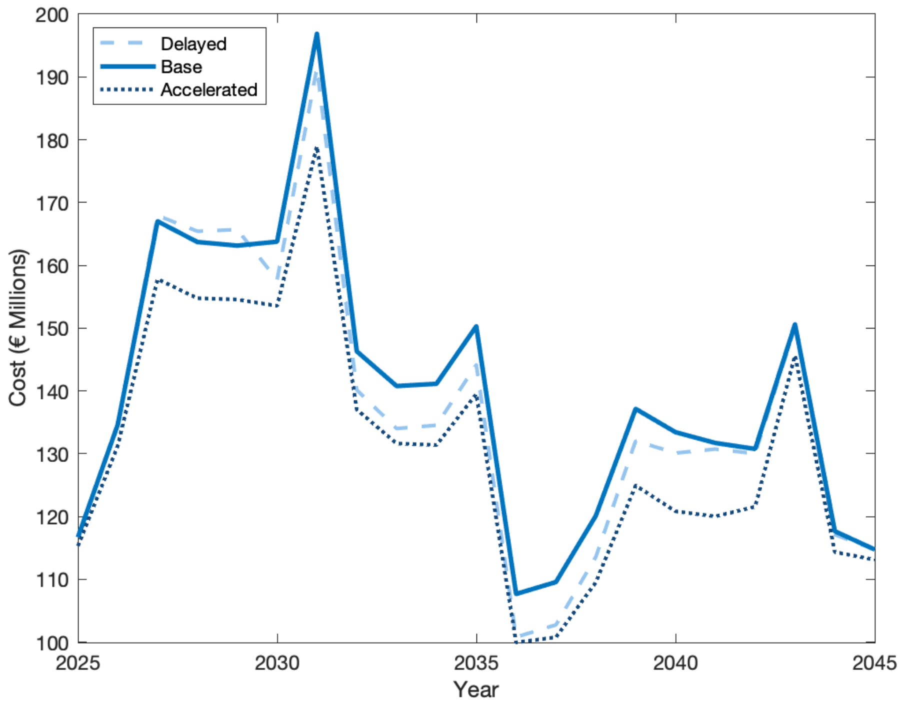


Figure 59: Total Annual Fleet Cost for Taxi / VTC Model (Lower BEV Price Hypothetical Scenario)

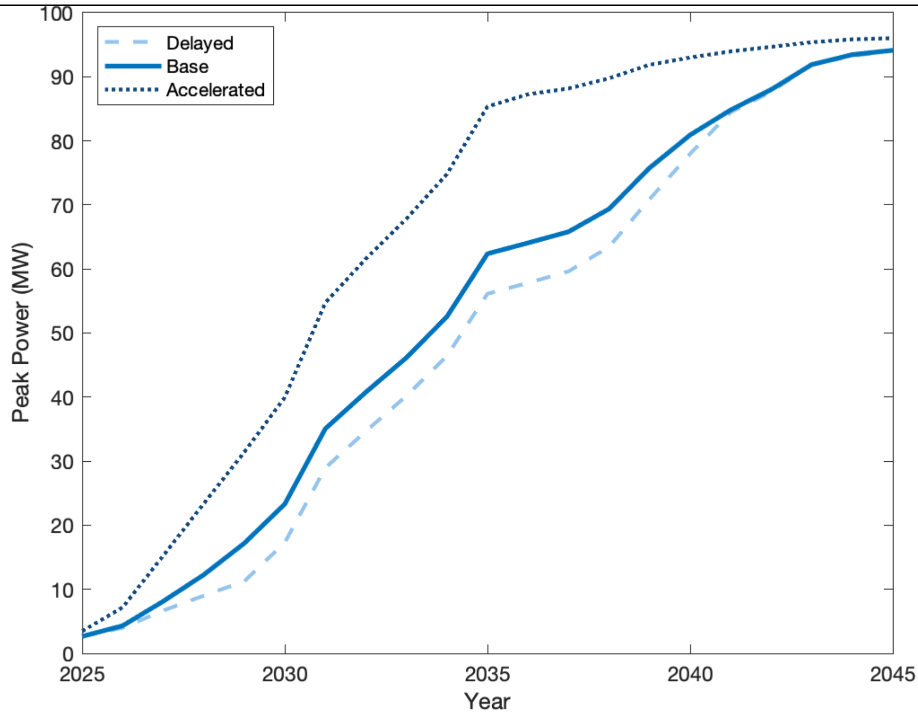


Figure 60: Charging Power Demand for Taxi / VTC Model (Lower BEV Price Hypothetical Scenario)

7.2.2 FINDING 2: MARKET ADOPTION, DRIVEN BY TCO, IS PROJECTED TO OUTPACE POLICY TARGETS

The Market-Driven scenario (Figure 61) shows a transition governed by economic viability. The strategic comparison in Figure 62 is the most illuminating finding of this study. The market's adoption rate for BEVs (yellow line) is projected to be significantly faster than the Base policy plan (blue line) and even exceeds the Accelerated plan in the early years. This suggests that for high-utilization vehicles like taxis, the lower operational costs (fuel, maintenance) of BEVs quickly offset their higher initial purchase price, making them the superior economic choice sooner than policymakers anticipate.

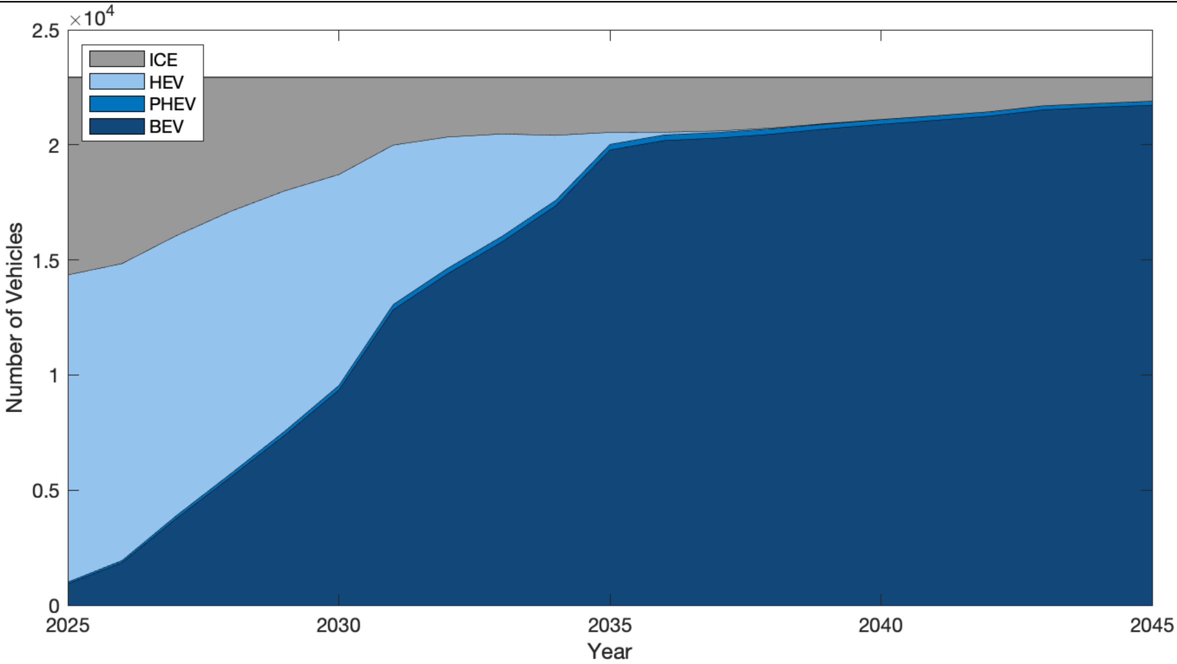


Figure 61: Taxi / VTC Fleet Composition (Market Projections for Lower BEV Price Hypothetical Scenario)

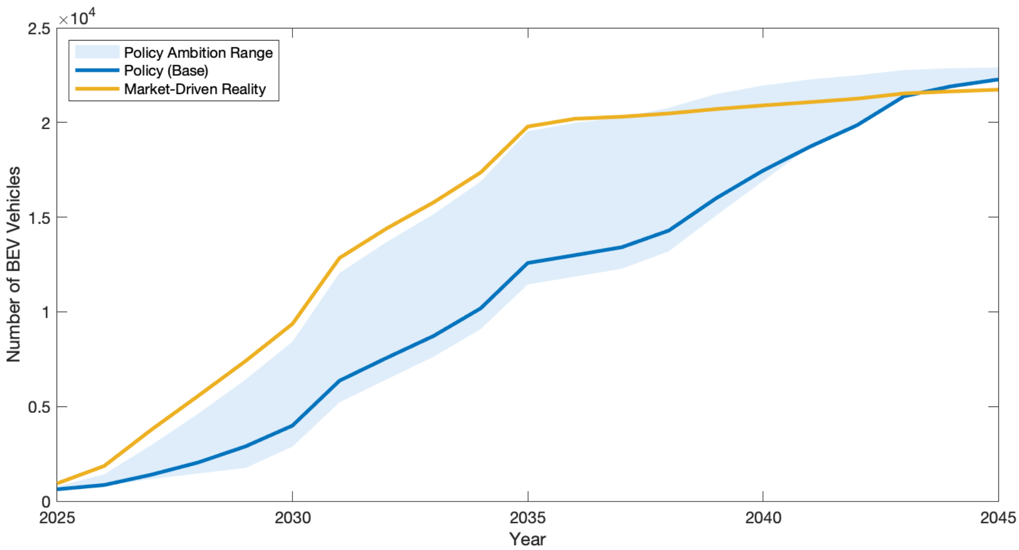


Figure 62: BEV Adoption Policy Ambition vs Market Reality (Lower BEV Price Hypothetical Scenario)

7.2.3 FINDING 3: A CRITICAL CHARGING INFRASTRUCTURE DEFICIT IS A PRIMARY RISK

The consequence of the market outpacing policy is a significant projected shortfall in charging capacity.

Figure Figure 63 shows a power deficit peaking at about 27 MW around the year 2034. This deficit represents the gap between the power needed by the rapidly adopting market and the supply planned under government policy.

It highlights a critical strategic risk where the city's infrastructure is unprepared for the success and speed of organic EV adoption.

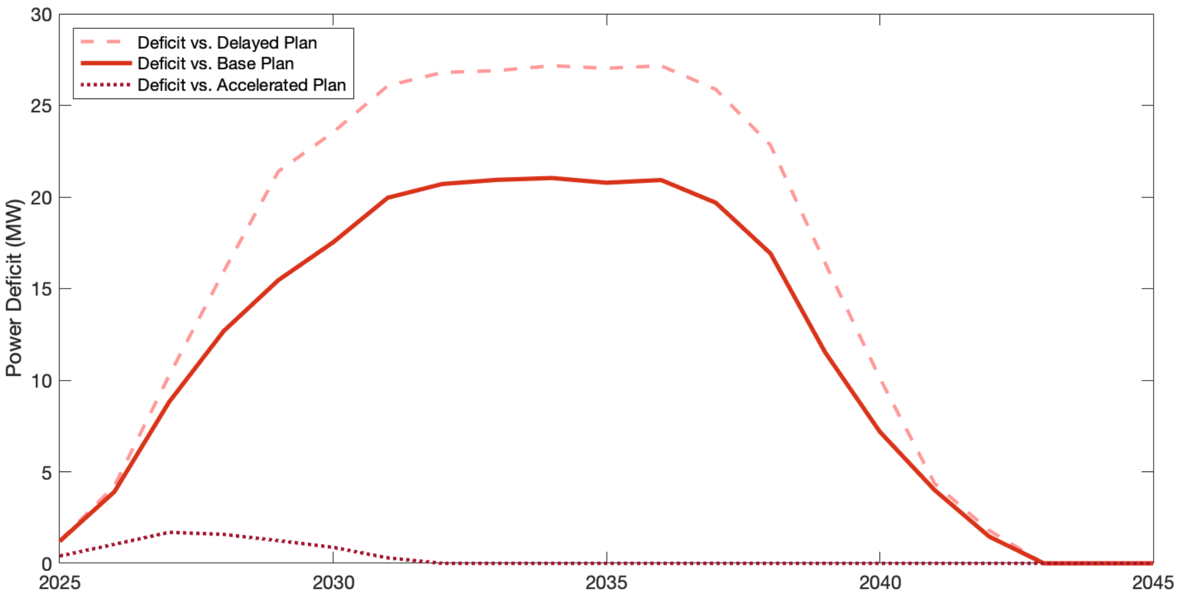


Figure 63: Infrastructure Deficit (Market Demand vs Planned Supply under Lower BEV Price Hypothetical Scenario)

7.3 HYPOTHETICAL SCENARIO 2: BATTERY DURABILITY CRISIS

Scenario of accelerated battery degradation is not predicted by standard consumer models. This premature wear necessitates a significant, unplanned capital outlay for battery pack replacement of €15,000.

This cost is annualized in the MATLAB code in the following way:

$$OPEX_{BEV,new} = OPEX_{BEV,initial} + \frac{€15,000}{L_{vehicle}} \tag{13}$$

The code now tells the TCO model that, on average, owning a BEV has an extra cost of (€15,000 / 11 years) around €1,364 per year. This cost is now factored into every purchase decision from the very beginning.

7.3.1 KEY TAKEAWAY: LONG-TERM COSTS CAN INVERT THE MARKET AND STALL DECARBONIZATION.

The shift from BEV adoption (Figure 25: Taxi / VTC Fleet Composition (Market Projections)) to a complete rejection in Figure 64 is happening because the TCO-based market model is behaving rationally. The €15,000 battery replacement cost, which hits every BEV in its 8th year, makes its lifetime ownership cost much higher than a PHEV or conventional vehicle.

The market learns this, and rational economic actors (the taxi drivers) stop buying the vehicle that has a built-in monetary time bomb. The direct consequence is that the decarbonization pathway of the fleet is missing; emissions plateau instead of continuing their decline, and the city does not meet environmental goals for this fleet.

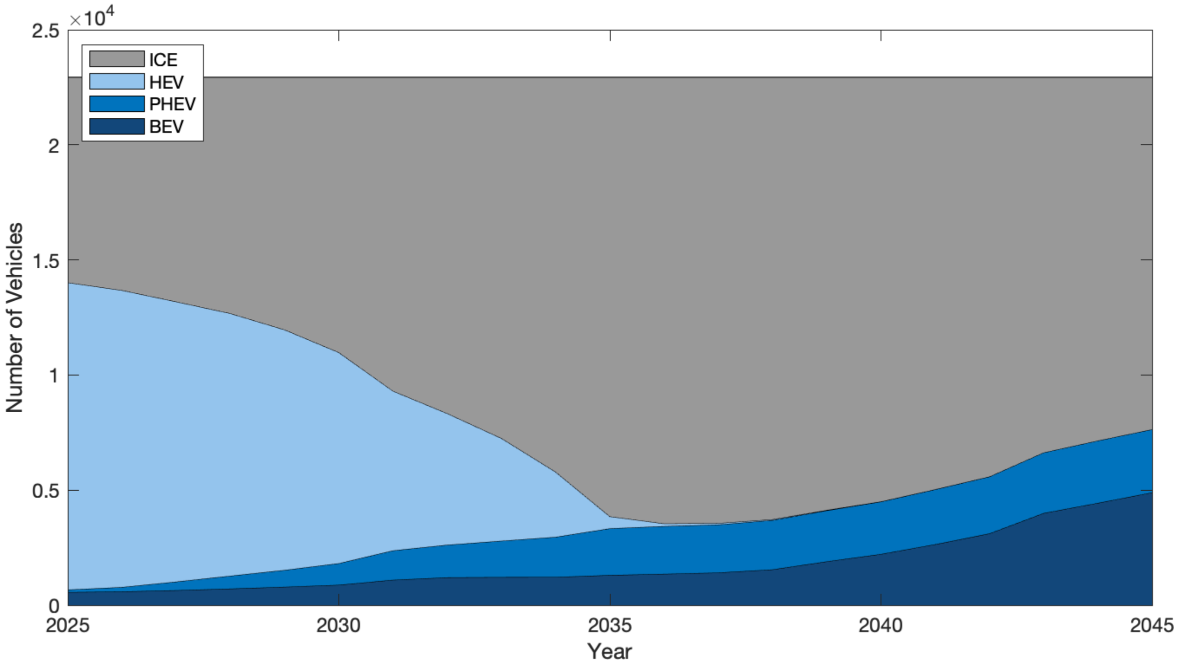


Figure 64: Taxi / VTC Fleet Composition (Market Projections for Lower Battery Durability Hypothetical Scenario)

As shown in Figure 65, total cumulative market-driven emissions of CO2 are now 4,849.2 kilotons, whereas in the base scenario (Figure 13: Total Cumulative CO2 Emissions (Taxi / VTC Model)) they were 4,125.6 kilotons. A 17.5% increase is noted.

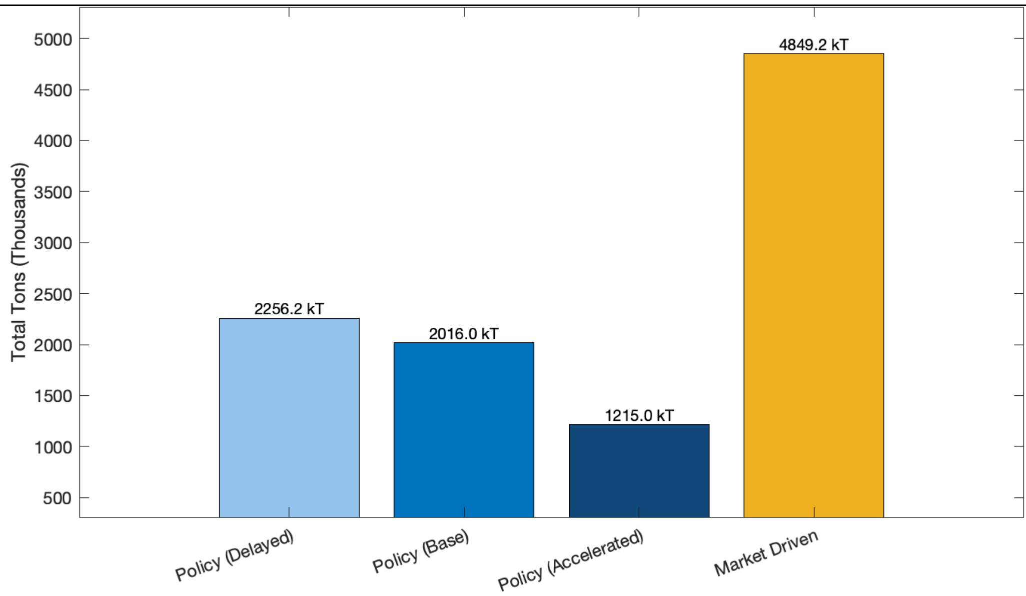


Figure 65: Total Cumulative CO2 Emissions (Taxi / VTC Model) - Hypothetical 2

Figure 16: Total Cumulative Fleet Cost (Taxi / VTC Model) and Figure 66 determine the model's precision in Market-Driven decisions: As BEV now proposes a higher cost of ownership, they are no longer an affordable option, therefore, to keep spending low other alternatives are chosen to renew the vehicles.

Both graphs represent a total cumulative market-driven cost of 2.9 billion euros, which stands for the robustness of the model.

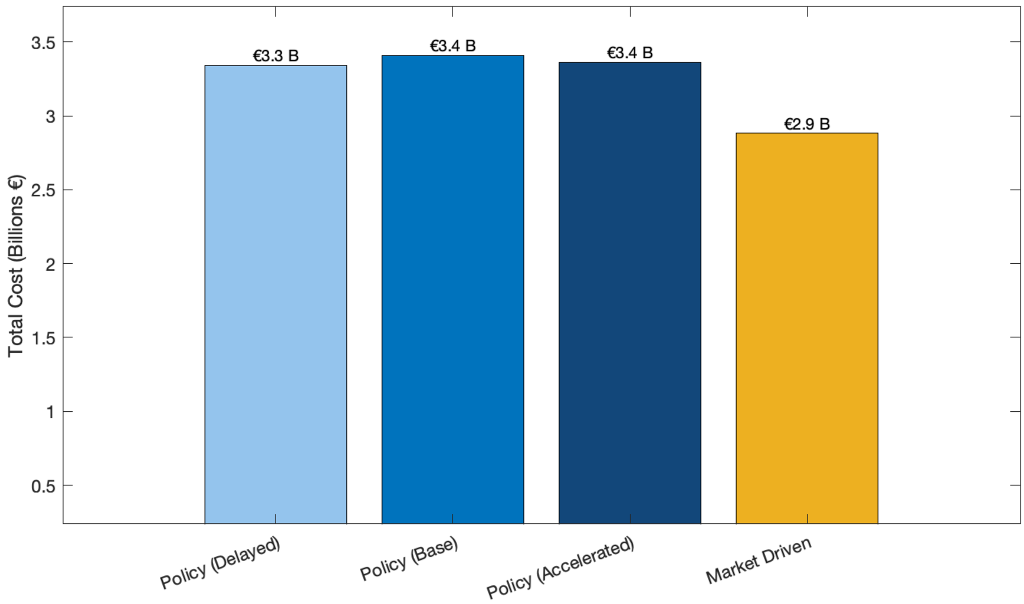


Figure 66: Total Cumulative Fleet Cost – Battery Deterioration Case (Taxi / VTC Model)

CHAPTER 8: CONCLUSION AND RECOMMENDATIONS

By contrasting policy-driven demands and market-driven behavior, this study provided fundamental knowledge on the complex interplay of technology, economics, and policy. The key implications of the simulation results and stylized cases form the foundation for actionable recommendations that can ensure a successful, efficient, and resilient transition towards a zero-emission public transport system.

8.1 MAIN CONCLUSIONS

8.1.1 THE TOTAL COST OF OWNERSHIP (TCO) IS THE DEFINITIVE DRIVER OF PRIVATE FLEET ADOPTION

For the private commercial fleets of VTC and taxi, becoming electric is not an issue of environmental idealism but economic prudence. The simulations indicate that TCO is the decisive factor (or primary driver). The base case indicated that with no clear win for TCO, BEV market penetration is way off policy goals. Conversely, the theoretical potential for lower-cost BEVs demonstrated that competitive TCO would induce market take-up at a scale that dwarfs even the most optimistic government aspirations. The changeover, therefore, hinges on attaining TCO parity.

8.1.2 A CRITICAL MISMATCH EXISTS BETWEEN POLICY AMBITION AND MARKET DYNAMICS

The study reveals a critical mismatch between how policy is designed and how the market works. Whereas government plans are constructed around certain, straight-line adoption goals, the market evolves non-linearly and responds dynamically to signals in the economy. This can result in two critical failures:

i. **Ambition Failure:** As in the base case, if BEV economics are not compelling, policy targets will be missed, and emissions will be high because operators will stick with cheaper ICE vehicles.
ii. **Preparation Failure:** As demonstrated in the first hypothetical scenario, if BEV economics suddenly become highly favorable overnight, the market can outpace regulatory planning to induce acute infrastructure shortages.

8.1.3 INFRASTRUCTURE PLANNING MUST ANTICIPATE MARKET TIPPING POINTS, NOT JUST FOLLOW POLICY ROADMAPS

Charging infrastructure is a secondary but necessary enabler, one of the key findings of this research. The base simulation established that intended rollout of infrastructure was adequate for the projected market uptake. However, the low-cost BEV variant showed this to be an at-risk assumption. A rapid, market-driven take-up brings an abrupt infrastructure deficit, translating provision of charging into the dominant constraint of the entire decarbonization program. Thus, an unfocused passive policy following approach to infrastructure is risky by nature.

8.1.4 The Economic Case for Electrification is Fragile and Sensitive to Long-Term Risks

The Battery Durability Crisis scenario showed how unanticipated, long-term costs can completely disrupt the transition. One substantial future cost, such as battery replacement, can tip the TCO calculation and make BEVs economically unviable for high-mileage professional users. This slows down and even reverses BEV adoption, resulting in higher emissions and ***FOSSIL FUEL*** lock-in. This outcome emphasizes that long-term dependability and low-cost ownership costs are just as important as the initial cost of purchase in driving operator adoption.

8.2 Strategic Recommendations

Based on these conclusions, the following recommendations are proposed for key stakeholders:

8.2.1 Recommendations For Municipal and Regional Policymakers

i. **Move from Target-Based to TCO-Focused Policies**. Instead of focusing on mandating adoption ratios for BEVs, policy must be shifted towards proactively managing professional operators' Total Cost of Ownership. This involves implementing dynamic subsidies that are extremely high when BEV costs are higher and reduced as TCO parity is reached, maintaining electricity prices commercial charging competitive, and using tax structures to maximize the OPEX advantages of BEVs.

ii. **Develop a Proactive and "Over-Provisioned" Plan for Infrastructure**. Planning for infrastructure needs to be disentangled from linear policy timelines and instead planned to achieve reasonable stress tests of the market, as imagined in this research through the rapid uptake scenario. The city would want to deploy charging capacity in advance of projected demand, thereby creating a buffer that eliminates infrastructure as a probable chokepoint. This makes it possible to ensure the resilience to allow an efficient, market-enabled transition.

iii. **De-Risk the Long-Term Ownership of BEVs**. As a countermeasure to risks under the battery durability scenario, public authorities must create a more secure investment environment for VTC and taxi operators. This can take the form of providing a guarantee for extended warranty programs for commercial vehicles, backing battery-as-a-service (BaaS) or leasing models that separate the cost of the vehicle from the battery, and laying out specific policies for battery health and residual value.

8.2.2 For Public Transport Authorities

Electrify Public Fleets at Faster Rate. Inter-urban bus and EMT fleet modeling shows that faster electrification is not just the green choice but also economically rational in the long run, as cost savings in OPEX equalize higher initial CAPEX. Public authorities should lead by example, making their fleet transformation timetables priorities at the earliest possible moment in order to achieve optimum environmental and long-term economic benefits.

8.3 Limitations and Lines for Future Research

This research provides a robust framework, but it is subject to certain limitations that create room for future work:

i. **Scope:** For consistency with much of the existing literature, the analysis was limited to a tank-to-wheel boundary. Future studies should include a well-to-wheel" analysis, coupling the model to the changing carbon intensity of Spain's national electricity grid to give a more comprehensive view of total GHG emissions.

ii. **Model Assumptions:** The model makes the assumptions of constant fleet sizes and generalized emission factors. The future versions can implement dynamic fleet sizing according to demand forecasts and employ finer data on vehicle models and driving cycle-specific emissions.

iii. **New Technologies:** The analysis does not include an estimation of the possible effect of Vehicle-to-Grid (V2G) technology, which would enable fleet cars to supply grid stabilization services, generating a new stream of revenue and changing the TCO calculation Incorporating V2G economics is the next natural step for this research.

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ANNEX

9.1 TAXI & VTC MATLAB DOCUMENTATION

9.1.1 FLEET COMPOSITION (TAXI/VTC)

Comprised of 22935 vehicles, with the following structure:

```
%tipo_vehiculo taxi(1)/VTC(2), año_matriculación, categoría_DGT,
categoría_combustible, c.c., potencia,
%plazas
matrizflotadetalle = [1    2018   2      13     1997   13.19  5      ;
1      2021   1      6      1997   11.19  5      ;
1      2018   1      4      1798   73     5      ;
1      2013   1      4      1798   73     5      ;
1      2016   2      13     1598   85     5      ;
1      2016   2      13     1598   85     5      ;
1      2017   2      13     1598   85     5      ;
1      2017   2      13     1598   85     5      ;
1      2018   1      6      1395   81     5      ;
1      2018   1      4      1798   73     5      ;
1      2018   1      4      1798   73     5      ;
1      2018   1      4      1798   73     5      ;
1      2019   1      8      1598   80     5      ;
1      2019   1      4      1798   73     5      ;
1      2019   1      4      1798   73     5      ;
1      2019   1      4      1798   73     5      ;
1      2021   1      4      1798   73     5      ;
1      2021   1      4      1798   73     5      ;
.
.
.
.
.
```

9.1.2 SEGMENT ASSIGNMENT FUNCTION (TAXI/VTC)

Assigns each vehicle to a segment, based on physical aspects. It helps to calculate emissions not only by fuel categories, but also by other logical traits of each vehicle.

```
function segment_id = assign_segment(cc, hp, plazas, fuel_category)
%Assigns vehicle to a segment based on technical specs
%
% Inputs:
%   cc             - engine displacement (cubic centimeters)
%   hp             - horsepower
%   plazas         - number of seats
%   fuel_category  - fuel type (1=BEV, 2=PHEVg, etc.)
%
% Output:
%   segment_id     - integer code of segment (1=small car, etc.)

% Logic for segmentation

if plazas > 5
    segment_id = 5; % Light Commercial
elseif fuel_category == 1 && hp > 200
    segment_id = 4; % Premium EV
elseif cc < 1400 && hp < 100
    segment_id = 1; % Small Car
elseif cc >= 1400 && cc < 2000 && hp >= 100 && hp < 160
    segment_id = 2; % Medium Car
elseif cc >= 2000 || hp >= 160
    segment_id = 3; % Large Car / SUV
else
    segment_id = 6; % Undefined / fallback
end

end
```

9.1.3 EMISSION DATA (TAXI/VTC)

Here, what was talked about in the previous point can be seen. The emission profile is calculated by vehicle types, and later multiplied for a factor depending on which category the vehicle falls into.

```
% Base emissions by fuel type
% Base emissions by fuel type co2 (g/km) nox (mg/km) pm (mg/km)
base_emissions = [
    0 0 0;     % BEV
    37 10 0.3; % PHEVg
    35 11 0.3; % PHEVd
    100 100 1.5; % HEVg
    100 100 1.5; % HEVd
    178 56 1.1; % GNCg
    178 56 1.1; % GNCd
    200 88 1.3; % GLPg
    200 88 1.3; % GLPd
    150 100 1.4; % E7g
    150 100 1.4; % E7d
    181 126 1.6; % E6g
    173 168 1.5; % E6d
    200 200 1.8; % E5g
    200 200 1.8  % E5d
];

% Segment modifiers
segment_multipliers = [
    0.9; % Small Car
    1.0; % Medium Car
    1.2; % Large Car / SUV
    1.1; % Premium EV (only for energy later, emissions = 0 for BEV)
    1.3; % Light Commercial
    1.0; % Other
];

% Initialize new emissions matrix
emissions = zeros(15, 6, 3); % 15 fuels × 6 segments × 3 pollutants
```

```
% Fill emissions matrix
for fuel = 1:15
    for segment = 1:6
        emissions(fuel, segment, :) = base_emissions(fuel,:) .*
segment_multipliers(segment);
    end
end
```

9.1.4 CONSUMPTION DATA (TAXI/VTC)

A matrix with consumption factors for Urban, Suburban and Extra-Urban driving scenarios for each fuel type.

```
% Consumption matrix includes driving cycles
% Each fuel type now has 3 consumption values:
% 1. Urban (Stop-and-Go) - Highest consumption
% 2. Suburban (Mixed)
% 3. Extra-Urban (Cruising) - Lowest consumption

% Columns are grouped by fuel type:
% [Gas_Urb, Gas_Sub, Gas_EU, Die_Urb, Die_Sub, Die_EU, ..., Elec_Urb, Elec_Sub,
Elec_EU]
% All units are l/100km, except for electricity (kWh/100km)

consumptions = [
%    Gasoline (U, S, EU)  Diesel (U, S, EU) GNC (U, S, EU) GLP (U, S, EU)
Electricity (U, S, EU)
    0   0   0,           0   0   0,        0   0  0,       0   0  0,     22  18
15;   % 1: BEV
    5   4   3.5,         0   0   0,        0   0  0,       0   0  0,     12  10
8;    % 2: PHEVg
    0   0   0,           4.5 3.5 3,        0   0  0,       0   0  0,     12  10
8;    % 3: PHEVd
    6   5   4,           0   0   0,        0   0  0,       0   0  0,     0   0
0;    % 4: HEVg
    0   0   0,           5.5 4.5 3.5,      0   0  0,       0   0  0,     0   0
0;    % 5: HEVd
    0.2 0.1 0.1,         0   0   0,        12  10 8,       0   0  0,     0   0
0;    % 6: GNCg
```

```
    0    0    0,            0.2 0.1 0.1,        12   10 8,          0    0   0,       0    0
0;    % 7: GNCd
    0.2 0.1 0.1,            0    0    0,         0    0   0,        15   13 11,       0    0
0;    % 8: GLPg
    0    0    0,            0.2 0.1 0.1,         0    0   0,        15   13 11,       0    0
0;    % 9: GLPd
    11   9    7,            0    0    0,         0    0   0,         0    0   0,       0    0
0;    % 10: E7g
    0    0    0,            9    7    5,         0    0   0,         0    0   0,       0    0
0;    % 11: E7d
    13   11   9,            0    0    0,         0    0   0,         0    0   0,       0    0
0;    % 12: E6g
    0    0    0,            11   9    7,         0    0   0,         0    0   0,       0    0
0;    % 13: E6d
    14   12   10,           0    0    0,         0    0   0,         0    0   0,       0    0
0;    % 14: E5g
    0    0    0,            12   10   8,         0    0   0,         0    0   0,       0    0
0;    % 15: E5d
];

% Scaling by vehicle segment
consumptions_scaled = zeros(15, 6, size(consumptions,2));
for fuel = 1:15
    for segment = 1:6
        consumptions_scaled(fuel, segment, :) = consumptions(fuel,:) .*
segment_multipliers(segment);
    end

End
```

9.1.4 *SIMULATION (TAXI/VTC)*

This is the yearly simulation for the model, it gets information from the 4 previous files and generates the outputs.

```
clear; clc; close all;



%% 1. PARAMETERS TO CONTROL



% 1.1    Simulation Control
start_year = 2025;
end_year = 2045;
scenarios_to_run = [1, 2, 3]; % 1: Delayed, 2: Base, 3: Accelerated

% 1.2    Switches for Modelling
use_dynamic_adoption = true; % Set to true to use TCO-based S-curve, false to use
fixed target_table
use_seasonal_effects = true; % Set to true to apply seasonal adjustments to
EV/PHEV consumption

% 1.3    Sensitivity Analysis Multipliers
    %Impact of economic assumptions / 1.0 = base case
battery_cost_reduction_multiplier = 1.0; % >1 accelerates cost reduction
fossil_fuel_price_increase_multiplier = 1.0; % >1 accelerates price increase
electricity_price_increase_multiplier = 1.0; % >1 accelerates price increase
vehicle_purchase_cost_multiplier = 1.0; % >1 increases initial vehicle prices

% 1.4    Seasonal Vehicle Consumption Parameters
winter_months_factor = 3/12; % 3 months of winter
summer_months_factor = 3/12; % 3 months of summer
shoulder_months_factor = 6/12; % 6 months of mild weather
winter_consumption_increase = 1.25; % 25% increase in consumption
summer_consumption_increase = 1.15; % 15% increase in consumption

% 1.5    Dynamic Adoption Parameters
market_sensitivity = 0.0002; % Higher value = faster market reaction to TCO
differences
tco_projection_years = 5;    % How many years of OPEX to include in purchase
decision
```

```
% 1.6    Driving Cycle & Behavior Parameters
drive_cycle_mix_occupied = [0.70, 0.30, 0.0];
drive_cycle_mix_searching = [0.50, 0.40, 0.1];




% 1.7    Fleet Dynamics & Operational Parameters
vehicle_lifespan_years = 11;
empty_taxi_ratio = 0.5438;
empty_vtc_ratio = empty_taxi_ratio;
distance_Taxi_daily = [89.8, 112.33];
distance_VTC_daily = distance_Taxi_daily * (220 / 174);


% 1.8   Initial Economic Parameters with Subsidies and Split Maintenance
% Columns: [sticker_price(€), subsidy(€), battery_cost(€), electricity(€/kWh),
fuel_price(€/unit), routine_maint_cost(€/km), insurance_risk_cost(€/km)]
vehicle_costs_initial = [
% Price   Subsidy Battery  Elec    Fuel    Routine Insure
  45000, 7000,   8000,    0.15,   0,      0.009,  0.0045; % 1: BEV
  33000, 4500,   4000,    0.15,   1.42,   0.025,  0.0042; % 2: PHEVg
  33000, 4500,   4000,    0.15,   1.42,   0.025,  0.0042; % 3: PHEVd
  35000, 2000,   0,       0,      1.42,   0.015,  0.0040; % 4: HEVg
  35000, 2000,   0,       0,      1.42,   0.015,  0.0040; % 5: HEVd
  23000, 1000,   0,       0,      1.20,   0.035,  0.0040; % 6: GNCg
  23000, 1000,   0,       0,      1.20,   0.035,  0.0040; % 7: GNCd
  22000, 1000,   0,       0,      0.85,   0.035,  0.0040; % 8: GLPg
  22000, 1000,   0,       0,      0.85,   0.035,  0.0040; % 9: GLPd
  26000, 0,      0,       0,      1.42,   0.04,   0.0040; % 10: E7g
  26000, 0,      0,       0,      1.42,   0.04,   0.0040; % 11: E7d
  30000, 0,      0,       0,      1.42,   0.018,  0.0040; % 12: E6g
  30000, 0,      0,       0,      1.42,   0.018,  0.0040; % 13: E6d
  30000, 0,      0,       0,      1.42,   0.018,  0.0040; % 14: E5g
  30000, 0,      0,       0,      1.42,   0.018,  0.0040  % 15: E5d
];
```

```
vehicle_costs_initial(:,1) = vehicle_costs_initial(:,1) *
vehicle_purchase_cost_multiplier;


% 1.9   YoY Costs Variations
cost_change_rates = [
% Price   Subsidy  Battery Elec.    Fuel    Routine Insure
  -0.02, -0.05,    -0.04,  +0.01,   0,      -0.01,  +0.005;  % 1: BEV
  -0.01, -0.07,    -0.03,  +0.01,   +0.015, +0.005, +0.005;  % 2: PHEVg
  -0.01, -0.07,    -0.03,  +0.01,   +0.015, +0.005, +0.005;  % 3: PHEVd
  -0.005, -0.10,   0,      0,       +0.015, +0.01,  +0.005;  % 4: HEVg
  -0.005, -0.10,   0,      0,       +0.015, +0.01,  +0.005;  % 5: HEVd
  +0.005, -0.10,   0,      0,       +0.01,  +0.01,  +0.005;  % 6: GNCg
  +0.005, -0.10,   0,      0,       +0.01,  +0.01,  +0.005;  % 7: GNCd
  +0.005, -0.10,   0,      0,       +0.01,  +0.01,  +0.005;  % 8: GLPg
  +0.005, -0.10,   0,      0,       +0.01,  +0.01,  +0.005;  % 9: GLPd
  +0.01, 0,        0,      0,       +0.015, +0.01,  +0.005;  % 10: E7g
  +0.01, 0,        0,      0,       +0.015, +0.01,  +0.005;  % 11: E7d
  +0.01, 0,        0,      0,       +0.015, +0.01,  +0.005;  % 12: E6g
  +0.01, 0,        0,      0,       +0.015, +0.01,  +0.005;  % 13: E6d
  +0.01, 0,        0,      0,       +0.015, +0.01,  +0.005;  % 14: E5g
  +0.01, 0,        0,      0,       +0.015, +0.01,  +0.005   % 15: E5d
];


% 1.10  Sensitivity Multiplier Logic
cost_change_rates(1, 3) = cost_change_rates(1, 3) *
battery_cost_reduction_multiplier; % BEV Battery
cost_change_rates(2:3, 3) = cost_change_rates(2:3, 3) *
battery_cost_reduction_multiplier; % PHEV Battery
cost_change_rates(:, 4) = cost_change_rates(:, 4) *
electricity_price_increase_multiplier; % Electricity
cost_change_rates([2:5, 10:15], 5) = cost_change_rates([2:5, 10:15], 5) *
fossil_fuel_price_increase_multiplier; % Fossil Fuels



cost_change_multiplier = 1 + cost_change_rates;


% 1.11  Electrification Targets
target_table_base = [
```

```
    15 20; 20 22; 25 24; 30 26; 40 28; 50 30; 60 25; 70 20; 80 15;
    85 10; 90 5;  93 3;  95 2;  97 1;  99 0;  100 0; 100 0; 100 0;
    100 0; 100 0; 100 0;
];

%% 2. INITIALIZATION

% 2.1   Load Data Files
flotadetalle;
emissionfile;
consumptionfile;
initial_fleet_data = matrizflotadetalle;

% 2.2   Get Initial counts
initial_taxi_count = sum(initial_fleet_data(:,1) == 1);
initial_vtc_count = sum(initial_fleet_data(:,1) == 2);

% 2.3   Preallocate results structure
results = struct();

% 2.4   Calculate annual consumption adjustment for seasonal effects
if use_seasonal_effects
    annual_consumption_adjustment_factor = (winter_months_factor *
winter_consumption_increase) + ...
                                          (summer_months_factor *
summer_consumption_increase) + ...
                                          (shoulder_months_factor * 1.0);
else
    annual_consumption_adjustment_factor = 1.0; % No effect
end
```

```
%% 3. SIMULATION LOOPS

% Run 1: Policy-Driven Simulation (using fixed target_table)
disp('--- Running POLICY-DRIVEN Simulation (Fixed Targets) ---');
results_policy = run_fleet_simulation(false, initial_fleet_data,
vehicle_costs_initial, cost_change_multiplier, ...
    target_table_base, scenarios_to_run, start_year, end_year,
vehicle_lifespan_years, ...
    distance_Taxi_daily, distance_VTC_daily, empty_taxi_ratio, empty_vtc_ratio,
...
    drive_cycle_mix_occupied, drive_cycle_mix_searching, consumptions_scaled,
emissions, ...
    annual_consumption_adjustment_factor, market_sensitivity,
tco_projection_years);

% Run 2: Market-Driven Simulation (using dynamic TCO adoption)
disp('--- Running MARKET-DRIVEN Simulation (Dynamic TCO) ---');
results_market = run_fleet_simulation(true, initial_fleet_data,
vehicle_costs_initial, cost_change_multiplier, ...
    target_table_base, scenarios_to_run, start_year, end_year,
vehicle_lifespan_years, ...
    distance_Taxi_daily, distance_VTC_daily, empty_taxi_ratio, empty_vtc_ratio,
...
    drive_cycle_mix_occupied, drive_cycle_mix_searching, consumptions_scaled,
emissions, ...
    annual_consumption_adjustment_factor, market_sensitivity,
tco_projection_years);

function results = run_fleet_simulation(use_dynamic_adoption, initial_fleet_data,
vehicle_costs_initial, cost_change_multiplier, target_table_base,
scenarios_to_run, start_year, end_year, vehicle_lifespan_years,
distance_Taxi_daily, distance_VTC_daily, empty_taxi_ratio, empty_vtc_ratio,
drive_cycle_mix_occupied, drive_cycle_mix_searching, consumptions_scaled,
```

```
emissions, annual_consumption_adjustment_factor, market_sensitivity,
tco_projection_years)
    results = struct();
    for scenario = scenarios_to_run
        fleet = initial_fleet_data;
        vehicle_costs = vehicle_costs_initial;
        years = start_year:end_year;
        N_years = length(years);
        fleet_composition = zeros(N_years, 15);
        annual_CO2 = zeros(N_years, 1);
        annual_NOx = zeros(N_years, 1);
        annual_PM = zeros(N_years, 1);
        annual_energy_demand = zeros(N_years, 1);
        annual_cost = zeros(N_years, 1);

        target_table = target_table_base;
        if scenario == 1, target_table(1:5,:) = repmat(target_table_base(1,:), 5,
1);
        elseif scenario == 3, target_table = [target_table_base(6:end,:);
repmat(target_table_base(end,:),5,1)];
        end

        fprintf('Running Scenario %d...\n', scenario);

        for y = 1:N_years
            current_year = years(y);
            if y > 1, vehicle_costs = vehicle_costs .* cost_change_multiplier;
end

            if use_dynamic_adoption
                avg_yearly_km = (mean(distance_Taxi_daily)) * 300;
                tco = zeros(3,1);



                % TCO for BEV (Type 1)
                net_capex_bev = vehicle_costs(1,1) - vehicle_costs(1,2);
                cons_bev = squeeze(consumptions_scaled(1, 2, 13:15));
```

```
                weighted_cons_bev = dot(cons_bev, (drive_cycle_mix_occupied + drive_cycle_mix_searching)/2);

                opex_bev = (avg_yearly_km * weighted_cons_bev / 100 * vehicle_costs(1,4) * annual_consumption_adjustment_factor) + (avg_yearly_km * (vehicle_costs(1,6) + vehicle_costs(1,7)));

%                 %  BATTERY DURABILITY CRISIS (START)

% % Add the annualized cost of a future battery replacement to the projected OPEX

% annualized_battery_replacement_cost = 15000 / vehicle_lifespan_years;

% opex_bev = opex_bev + annualized_battery_replacement_cost;

% %   BATTERY DURABILITY CRISIS (END)

                tco(1) = net_capex_bev + (opex_bev * tco_projection_years);


                % TCO for PHEV (Type 2)

                net_capex_phev = vehicle_costs(2,1) - vehicle_costs(2,2);

                cons_phev_gas = squeeze(consumptions_scaled(2, 2, 1:3));

                cons_phev_elec = squeeze(consumptions_scaled(2, 2, 13:15));

                weighted_cons_phev_gas = dot(cons_phev_gas, (drive_cycle_mix_occupied + drive_cycle_mix_searching)/2);

                weighted_cons_phev_elec = dot(cons_phev_elec, (drive_cycle_mix_occupied + drive_cycle_mix_searching)/2);

                opex_phev = (avg_yearly_km * weighted_cons_phev_gas / 100 * vehicle_costs(2,5)) + (avg_yearly_km * weighted_cons_phev_elec / 100 * vehicle_costs(2,4) * annual_consumption_adjustment_factor) + (avg_yearly_km * (vehicle_costs(2,6) + vehicle_costs(2,7)));

                tco(2) = net_capex_phev + (opex_phev * tco_projection_years);


                % TCO for ICE (Type 13)

                net_capex_ice = vehicle_costs(13,1) - vehicle_costs(13,2);

                cons_ice = squeeze(consumptions_scaled(13, 2, 7:9));

                weighted_cons_ice = dot(cons_ice, (drive_cycle_mix_occupied + drive_cycle_mix_searching)/2);

                opex_ice = (avg_yearly_km * weighted_cons_ice / 100 * vehicle_costs(13,5)) + (avg_yearly_km * (vehicle_costs(13,6) + vehicle_costs(13,7)));

                tco(3) = net_capex_ice + (opex_ice * tco_projection_years);


                utilities = exp(-market_sensitivity * tco);

                market_shares = utilities / sum(utilities);

                BEV_share = market_shares(1); PHEV_share = market_shares(2);

            else
```

```
        targets = target_table(min(y, size(target_table,1)), :);
        BEV_share = targets(1)/100; PHEV_share = targets(2)/100;
    end

    current_ages = current_year - fleet(:, 2);
    retired_idx = current_ages > vehicle_lifespan_years;
    retired_taxis = sum(retired_idx & fleet(:,1) == 1);
    retired_vtcs = sum(retired_idx & fleet(:,1) == 2);
    fleet(retired_idx, :) = [];

    for r = 1:retired_taxis
        rnd = rand();
        if rnd < BEV_share, fuel_type = 1;
        elseif rnd < BEV_share + PHEV_share, fuel_type = 2;
        else, fuel_type = 13; end
        new_vehicle = [1, current_year, 1, fuel_type, 2000, 100, 5];
        fleet = [fleet; new_vehicle];
    end
    for r = 1:retired_vtcs
        rnd = rand();
        if rnd < BEV_share, fuel_type = 1;
        elseif rnd < BEV_share + PHEV_share, fuel_type = 2;
        else, fuel_type = 13; end
        new_vehicle = [2, current_year, 1, fuel_type, 2000, 100, 5];
        fleet = [fleet; new_vehicle];
    end

    N = size(fleet, 1);
    vehicle_emissions_per_km = zeros(N, 3);
    daily_distance = zeros(N, 1);
    current_annual_cost = 0;
    current_annual_kwh = 0;

    for i = 1:N
        vehicle_type = fleet(i,1); fuel_category = fleet(i,4);
        cc = fleet(i,5); hp = fleet(i,6); plazas = fleet(i,7);
```

```
                segment = assign_segment(cc, hp, plazas, fuel_category);
                if vehicle_type == 1, mu_busy = distance_Taxi_daily(1);
empty_ratio = empty_taxi_ratio;
                else, mu_busy = distance_VTC_daily(1); empty_ratio =
empty_vtc_ratio;
                end
                busy_km = max(normrnd(mu_busy, 15), 0);
                empty_km = busy_km * (empty_ratio / (1 - empty_ratio));
                daily_distance(i) = busy_km + empty_km;
                distance_yearly = daily_distance(i) * 300;



                net_capex = (fleet(i,2) == current_year) *
(vehicle_costs(fuel_category, 1) - vehicle_costs(fuel_category, 2));
                total_maint_cost = distance_yearly *
(vehicle_costs(fuel_category, 6) + vehicle_costs(fuel_category, 7));



                cons_vector = squeeze(consumptions_scaled(fuel_category, segment,
:));
                fuel_cost = 0;

                if fuel_category == 1 % BEV
                    cons_per_km = dot(cons_vector(13:15),
drive_cycle_mix_occupied)*busy_km + dot(cons_vector(13:15),
drive_cycle_mix_searching)*empty_km;
                    total_kwh = (cons_per_km/100 * 300) *
annual_consumption_adjustment_factor;
                    fuel_cost = total_kwh * vehicle_costs(fuel_category, 4);
                    current_annual_kwh = current_annual_kwh + total_kwh;
                elseif ismember(fuel_category, [2,3]) % PHEV
                    gas_cons_per_km = dot(cons_vector(1:3),
drive_cycle_mix_occupied)*busy_km + dot(cons_vector(1:3),
drive_cycle_mix_searching)*empty_km;
                    elec_cons_per_km = dot(cons_vector(13:15),
drive_cycle_mix_occupied)*busy_km + dot(cons_vector(13:15),
drive_cycle_mix_searching)*empty_km;
                    total_fuel = gas_cons_per_km/100 * 300;
                    total_kwh = (elec_cons_per_km/100 * 300) *
annual_consumption_adjustment_factor;
```

```
                    fuel_cost = total_fuel * vehicle_costs(fuel_category, 5) +
total_kwh * vehicle_costs(fuel_category, 4);
                    current_annual_kwh = current_annual_kwh + total_kwh;
                else % Conventional ICE/HEV
                    if ismember(fuel_category, [4, 6, 8, 10, 12, 14]), cols =
1:3; else, cols = 7:9; end
                    cons_per_km = dot(cons_vector(cols),
drive_cycle_mix_occupied)*busy_km + dot(cons_vector(cols),
drive_cycle_mix_searching)*empty_km;
                    total_fuel = cons_per_km/100 * 300;
                    fuel_cost = total_fuel * vehicle_costs(fuel_category, 5);
                end

                current_annual_cost = current_annual_cost + net_capex + fuel_cost
+ total_maint_cost;
                vehicle_emissions_per_km(i,:) = squeeze(emissions(fuel_category,
segment, :));
            end

            annual_cost(y) = current_annual_cost;
            annual_energy_demand(y) = current_annual_kwh / 1000;
            daily_emissions = vehicle_emissions_per_km .* daily_distance;
            daily_emissions(:,2:3) = daily_emissions(:,2:3) / 1000;
            annual_CO2(y) = sum(daily_emissions(:,1)) * 300 / 1e3;
            annual_NOx(y) = sum(daily_emissions(:,2)) * 300 / 1e3;
            annual_PM(y)  = sum(daily_emissions(:,3)) * 300 / 1e3;
            for ft = 1:15, fleet_composition(y, ft) = sum(fleet(:,4) == ft); end
        end
        results(scenario).years = years;
        results(scenario).annual_CO2 = annual_CO2;
        results(scenario).annual_NOx = annual_NOx;
        results(scenario).annual_PM = annual_PM;
        results(scenario).annual_energy_demand = annual_energy_demand;
        results(scenario).annual_cost = annual_cost;
        results(scenario).fleet_composition = fleet_composition;
    end
end
```

```
%% 4. PLOTTING & COMPARISON

disp('Simulations complete. Generating comprehensive analysis plots...');

% 4.1   Infrastructure Demand Calculation
charging_window_hours = 8;
simultaneity_factor = 0.5;
charging_loss = 0.15;
years = results_policy(1).years;

% 4.2 Calculate peak power demand for all policy and market scenarios
for scenario = scenarios_to_run
    % Policy Scenarios
    annual_mwh_policy = results_policy(scenario).annual_energy_demand;
    avg_daily_mwh_policy = annual_mwh_policy / 300;
    results_policy(scenario).peak_power_demand_mw = (avg_daily_mwh_policy / charging_window_hours) * simultaneity_factor / (1-charging_loss);

    % Market Scenarios
    annual_mwh_market = results_market(scenario).annual_energy_demand;
    avg_daily_mwh_market = annual_mwh_market / 300;
    results_market(scenario).peak_power_demand_mw = (avg_daily_mwh_market / charging_window_hours) * simultaneity_factor / (1-charging_loss);
end

% SETUP: DEFINE COLOR PALETTES & STYLES

disp('Setting up color palettes and styles...');
```

```
% Blue Palette for Policy Scenarios (Light to Dark)
% Used for comparing Delayed, Base, and Accelerated scenarios
policy_blues = [
    0.58, 0.77, 0.93;  % Light Blue (for 'Delayed')

    0.00, 0.45, 0.74;  % Standard MATLAB Blue (for 'Base')
    0.07, 0.28, 0.48   % Dark Navy Blue (for 'Accelerated')
];

% Red Palette for Deficit Scenarios (Light to Dark)
% Used to highlight shortfalls or negative outcomes
deficit_reds = [
    1.00, 0.60, 0.60;  % Light Red
    0.85, 0.20, 0.10;  % Strong Red
    0.64, 0.08, 0.18   % Dark Crimson
];

% Fleet Composition Palette (Area Charts)
% Blues for electric/hybrid types, grey for internal combustion
fleet_colors = [
    0.07, 0.28, 0.48;  % Dark Navy Blue (for BEV)
    0.00, 0.45, 0.74;  % Standard Blue (for PHEV)
    0.58, 0.77, 0.93;  % Light Blue (for HEV)
    0.60, 0.60, 0.60   % Medium Grey (for ICE)
];

% Distinct Color for Market Scenario
market_color = [0.93, 0.69, 0.13]; % Gold/Orange

% Global Style Settings
base_line_width = 2;
thick_line_width = 2.5;

% Set default font size for all axes for readability
set(groot, 'defaultAxesFontSize', 11);
```

```
% FIGURE 1: DEEP DIVE ON GOVERNMENT POLICY SCENARIOS (EMISSIONS FOCUSED)

disp('Generating Figure 1: Government Policy Scenarios...');
figure('Name', 'Analysis of Government Policy Scenarios', 'WindowState',
'maximized');
sgtitle('Government Plan Scenarios: Fleet Evolution and Emissions', 'FontSize',
18, 'FontWeight', 'bold');

% Plot 1.1: Fleet Composition (Delayed)
ax1 = subplot(2,3,1);
fleet_data = results_policy(1).fleet_composition;
BEV=fleet_data(:,1); PHEV=sum(fleet_data(:,2:3),2); HEV=sum(fleet_data(:,4:5),2);
ICE=sum(fleet_data(:,6:end),2);
area(years, [BEV, PHEV, HEV, ICE]);
colororder(ax1, fleet_colors);
%title('Fleet Composition (Policy - Delayed)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Vehicles');
legend({'BEV', 'PHEV', 'HEV', 'ICE'}, 'Location','northwest'); box on;

% Plot 1.2: Fleet Composition (Base)
ax2 = subplot(2,3,2);
fleet_data = results_policy(2).fleet_composition;
BEV=fleet_data(:,1); PHEV=sum(fleet_data(:,2:3),2); HEV=sum(fleet_data(:,4:5),2);
ICE=sum(fleet_data(:,6:end),2);
area(years, [BEV, PHEV, HEV, ICE]);
colororder(ax2, fleet_colors);
%title('Fleet Composition (Policy - Base)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Vehicles');
box on;

% Plot 1.3: Fleet Composition (Accelerated)
ax3 = subplot(2,3,3);
fleet_data = results_policy(3).fleet_composition;
BEV=fleet_data(:,1); PHEV=sum(fleet_data(:,2:3),2); HEV=sum(fleet_data(:,4:5),2);
ICE=sum(fleet_data(:,6:end),2);
```

```
area(years, [BEV, PHEV, HEV, ICE]);
colororder(ax3, fleet_colors);
%title('Fleet Composition (Policy - Accelerated)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Vehicles');
box on;

% Plot 1.4: CO2 Emissions
subplot(2,3,4); hold on;
plot(years, results_policy(1).annual_CO2/10^6, '--', 'Color', policy_blues(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Delayed');
plot(years, results_policy(2).annual_CO2/10^6, '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base');
plot(years, results_policy(3).annual_CO2/10^6, ':', 'Color', policy_blues(3,:),
'LineWidth', base_line_width, 'DisplayName', 'Accelerated');
%title('Annual CO₂ Emissions', 'FontWeight', 'normal');
xlabel('Year');
ylabel('Kilotons/Year');
legend('Location', 'best'); box on; hold off;

% Plot 1.5: NOx Emissions
subplot(2,3,5); hold on;
plot(years, results_policy(1).annual_NOx/10^3, '--', 'Color', policy_blues(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Delayed');
plot(years, results_policy(2).annual_NOx/10^3, '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base');
plot(years, results_policy(3).annual_NOx/10^3, ':', 'Color', policy_blues(3,:),
'LineWidth', base_line_width, 'DisplayName', 'Accelerated');
%title('Annual NOₓ Emissions', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Tons/Year');
legend('Location', 'best'); box on; hold off;

% Plot 1.6: PM Emissions
subplot(2,3,6); hold on;
plot(years, results_policy(1).annual_PM/10^3, '--', 'Color', policy_blues(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Delayed');
plot(years, results_policy(2).annual_PM/10^3, '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base');
plot(years, results_policy(3).annual_PM/10^3, ':', 'Color', policy_blues(3,:),
'LineWidth', base_line_width, 'DisplayName', 'Accelerated');
```

```
%title('Annual PM Emissions', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Tons/Year');

legend('Location', 'best'); box on; hold off;



% FIGURE 2 & 3: POLICY SCENARIO IMPACTS (COST & POWER)


disp('Generating Figures 2 & 3: Policy Cost and Power Demand...');


% FIGURE 2: Total Annual Fleet Cost

figure('Name', 'Total Annual Fleet Cost by Policy');

ax_cost = gca;

hold on;

plot(years, results_policy(1).annual_cost / 1e6, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results_policy(2).annual_cost / 1e6, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results_policy(3).annual_cost / 1e6, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

%title('Total Annual Fleet Cost by Scenario', 'FontSize', 14, 'FontWeight', 'bold');

xlabel('Year'); ylabel('Cost (€ Millions)');

legend('Location', 'northwest'); box on; hold off;


% FIGURE 3: Planned Charging Power Demand

figure('Name', 'Planned Charging Power Demand by Policy');

ax_power = gca;

hold on;

plot(years, results_policy(1).peak_power_demand_mw, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results_policy(2).peak_power_demand_mw, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results_policy(3).peak_power_demand_mw, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

%title('Planned Charging Power Demand by Scenario', 'FontSize', 14, 'FontWeight', 'bold');

xlabel('Year'); ylabel('Peak Power (MW)');

legend('Location', 'northwest'); box on; hold off;
```

```
% FIGURE 4: DEEP DIVE ON THE MARKET-DRIVEN SCENARIO

disp('Generating Figure 4: Market-Driven Scenario...');
figure('Name', 'Analysis of Market-Driven Scenario', 'WindowState', 'maximized');
sgtitle('Market-Driven Scenario: Fleet Evolution and Impacts', 'FontSize', 18,
'FontWeight', 'bold');

subplot(2,2,1);
ax_market_fleet = gca;
fleet_data = results_market(2).fleet_composition;
BEV=fleet_data(:,1); PHEV=sum(fleet_data(:,2:3),2); HEV=sum(fleet_data(:,4:5),2);
ICE=sum(fleet_data(:,6:end),2);
area(years, [BEV, PHEV, HEV, ICE]);
colororder(ax_market_fleet, fleet_colors);
%title('Fleet Composition (Market-Driven)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Vehicles');
legend({'BEV', 'PHEV', 'HEV', 'ICE'}, 'Location','northwest'); box on;

subplot(2,2,2);
plot(years, results_market(2).annual_CO2/10^6, '-', 'Color', market_color,
'LineWidth', thick_line_width);
%title('Annual CO₂ Emissions (Market-Driven)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Kilotons/Year'); box on;

subplot(2,2,3);
plot(years, results_market(2).annual_cost / 1e6, '-', 'Color', market_color,
'LineWidth', thick_line_width);
%title('Total Annual Fleet Cost (Market-Driven)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Cost (€ Millions)'); box on;

subplot(2,2,4);
plot(years, results_market(2).peak_power_demand_mw, '-', 'Color', market_color,
'LineWidth', thick_line_width);
%title('Realistic Charging Power Demand', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Peak Power (MW)'); box on;
```

```
% FIGURE 5: STRATEGIC COMPARISON: POLICY vs. MARKET

disp('Generating Figure 5: Policy vs. Market Comparison...');
figure('Name', 'COMPARISON: Policy Ambition vs. Market Reality', 'WindowState',
'maximized');
sgtitle('Strategic Comparison: Government Plan vs. Market Reality', 'FontSize',
18, 'FontWeight', 'bold');

% Plot 5.1: BEV Adoption Comparison
subplot(2,1,1);
hold on;
fleet_delayed = results_policy(1).fleet_composition(:,1);
fleet_accelerated = results_policy(3).fleet_composition(:,1);
% Use a light, transparent blue for the policy range
fill([years fliplr(years)], [fleet_delayed' fliplr(fleet_accelerated')],
policy_blues(1,:), 'FaceAlpha', 0.3, 'EdgeColor', 'none', 'DisplayName', 'Policy
Ambition Range');
plot(years, results_policy(2).fleet_composition(:,1), '-', 'Color',
policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Policy
(Base)');
plot(years, results_market(2).fleet_composition(:,1), '-', 'Color', market_color,
'LineWidth', thick_line_width, 'DisplayName', 'Market-Driven Reality');
%title('BEV Adoption: Policy Ambition vs. Market Reality');
xlabel('Year'); ylabel('Number of BEV Vehicles');
legend('Location', 'northwest'); box on; hold off;

% Plot 5.2: Infrastructure Deficit Comparison (USING RED SHADES)
subplot(2,1,2);
hold on;
market_demand = results_market(2).peak_power_demand_mw;
deficit_vs_delayed_plan = max(0, market_demand -
results_policy(1).peak_power_demand_mw);
deficit_vs_base_plan = max(0, market_demand -
results_policy(2).peak_power_demand_mw);
deficit_vs_accelerated_plan = max(0, market_demand -
results_policy(3).peak_power_demand_mw);
% Plot deficits using the red palette
plot(years, deficit_vs_delayed_plan, '--', 'Color', deficit_reds(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Deficit vs. Delayed Plan');
```

```
plot(years, deficit_vs_base_plan, '-', 'Color', deficit_reds(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Deficit vs. Base Plan');

plot(years, deficit_vs_accelerated_plan, ':', 'Color', deficit_reds(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Deficit vs. Accelerated Plan');

%title('Infrastructure Deficit (Market Demand vs. Planned Supply)');

xlabel('Year'); ylabel('Power Deficit (MW)');

legend('Location', 'northwest'); box on; hold off;



% FIGURE 6: CUMULATIVE IMPACT COMPARISON (BAR CHARTS)


disp('Generating Figure 6: Cumulative Impact Comparison...');

figure('Name', 'Cumulative Impact Comparison', 'WindowState', 'maximized');

sgtitle('Total Impact Over Simulation Period (2025-2045)', 'FontSize', 18, 'FontWeight', 'bold');


%  Consolidate Total Emissions and Cost Data

total_CO2 = [sum(results_policy(1).annual_CO2), sum(results_policy(2).annual_CO2), sum(results_policy(3).annual_CO2), sum(results_market(2).annual_CO2)];

total_NOx = [sum(results_policy(1).annual_NOx), sum(results_policy(2).annual_NOx), sum(results_policy(3).annual_NOx), sum(results_market(2).annual_NOx)];

total_PM = [sum(results_policy(1).annual_PM), sum(results_policy(2).annual_PM), sum(results_policy(3).annual_PM), sum(results_market(2).annual_PM)];

total_Cost = [sum(results_policy(1).annual_cost), sum(results_policy(2).annual_cost), sum(results_policy(3).annual_cost), sum(results_market(2).annual_cost)];


%  Define shared properties for consistency

scenario_labels = {'Policy (Delayed)', 'Policy (Base)', 'Policy (Accelerated)', 'Market Driven'};

% New bar colors for consistent storytelling

comparison_bar_colors = [

    policy_blues(1,:); % Delayed

    policy_blues(2,:); % Base

    policy_blues(3,:); % Accelerated

    market_color;      % Market

];

% Function to add data labels to bars
```

```
add_bar_labels = @(bar_obj, format_str) {
    text(bar_obj.XEndPoints, bar_obj.YEndPoints, ...
    arrayfun(@(value) sprintf(format_str, value), bar_obj.YData, 'UniformOutput',
false), ...
    'HorizontalAlignment', 'center', 'VerticalAlignment', 'bottom', 'FontSize',
10);
};

%  Plot 6.1: Total CO2 Emissions
subplot(2, 2, 1);
b1 = bar(total_CO2 / 1e6, 'FaceColor', 'flat'); % In Million Tons
b1.CData = comparison_bar_colors;
%title('Total Cumulative CO_2 Emissions', 'FontWeight', 'normal');
ylabel('Total Tons (Thousands)');
set(gca, 'xticklabel', scenario_labels, 'XTickLabelRotation', 20);
box on;
add_bar_labels(b1, '%.1f kT');

%  Plot 6.2: Total NOx Emissions
subplot(2, 2, 2);
b2 = bar(total_NOx/ 1e3, 'FaceColor', 'flat');
b2.CData = comparison_bar_colors;
%title('Total Cumulative NO_x Emissions', 'FontWeight', 'normal');
ylabel('TTotal Tons');
set(gca, 'xticklabel', scenario_labels, 'XTickLabelRotation', 20);
box on;
add_bar_labels(b2, '%.1f T');

%  Plot 6.3: Total PM Emissions
subplot(2, 2, 3);
b3 = bar(total_PM/ 1e3, 'FaceColor', 'flat');
b3.CData = comparison_bar_colors;
%title('Total Cumulative PM Emissions', 'FontWeight', 'normal');
ylabel('Total Tons');
set(gca, 'xticklabel', scenario_labels, 'XTickLabelRotation', 20);
box on;
add_bar_labels(b3, '%.1f T');
```

```
%  Plot 6.4: Total Fleet Cost
subplot(2, 2, 4);
b4 = bar(total_Cost / 1e9, 'FaceColor', 'flat'); % Convert to Billions of Euros
b4.CData = comparison_bar_colors;
%title('Total Cumulative Fleet Cost', 'FontWeight', 'normal');
ylabel('Total Cost (Billions €)');
set(gca, 'xticklabel', scenario_labels, 'XTickLabelRotation', 20);
box on;
add_bar_labels(b4, '€%.1f B');

disp('All plots generated successfully.');
```

9.2 EMT DOCUMENTATION

9.2.1 EMT FLEET DATA

Fleet data has been downloaded as an Excel file directly from the EMT website. The data is presented in the file in two distinct sheets:

First one is a historical record of every bus in the fleet since 1989 to 2024

Second one is a current snaphot of the fleet as of 2024

Relación histórica de la flota de autobuses (1989-2024)

Matrícula (1)	Nº EMT (2)	Marca	Modelo	Versión	Tipo de combustible	Clasificación Ecológica	Plataforma (3)	Plazas cálculo ocupac	Fecha de alta	Fecha de baja	Información actualizada a fech
4021MRH	258	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/31/24	12/31/99	5/31/24
4027MRH	256	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/30/24	12/31/99	5/31/24
3058MRB	3561	SOLARIS	Urbino 12 Eléctrico	2	Eléctrico	Sin emisiones	Doble plat. doble	72	5/30/24	12/31/99	5/31/24
4007MRH	251	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/29/24	12/31/99	5/31/24
3885MRF	252	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/29/24	12/31/99	5/31/24
3841MRF	254	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/29/24	12/31/99	5/31/24
4090MRH	246	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/25/24	12/31/99	5/31/24
4017MRF	247	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/25/24	12/31/99	5/31/24
3721MRF	242	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/24/24	12/31/99	5/31/24
3949MRF	250	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/24/24	12/31/99	5/31/24
3983MRF	249	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/23/24	12/31/99	5/31/24
4022MRH	240	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/22/24	12/31/99	5/31/24
4081MRH	248	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/22/24	12/31/99	5/31/24
4037MRH	236	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/21/24	12/31/99	5/31/24
4060MRH	238	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/21/24	12/31/99	5/31/24
4064MRH	243	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/21/24	12/31/99	5/31/24
3649MRF	244	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/21/24	12/31/99	5/31/24
4050MRH	245	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/21/24	12/31/99	5/31/24
2651MPT	231	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/10/24	12/31/99	5/31/24
2969MPT	233	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/10/24	12/31/99	5/31/24
3553MPT	237	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/10/24	12/31/99	5/31/24
3678MPT	239	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/9/24	12/31/99	5/31/24
2759MPT	232	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/8/24	12/31/99	5/31/24
3137MPT	234	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/8/24	12/31/99	5/31/24
3334MPT	235	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/8/24	12/31/99	5/31/24
3741MPT	241	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	5/8/24	12/31/99	5/31/24
2482MPT	228	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	4/26/24	12/31/99	5/31/24
2559MPT	230	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	4/26/24	12/31/99	5/31/24
1628MPC	192	IRIZAR	IEBUS	3	Eléctrico	Sin emisiones	Plat. doble	87	4/24/24	12/31/99	5/31/24
1664MPC	193	IRIZAR	IEBUS	3	Eléctrico	Sin emisiones	Plat. doble	87	4/17/24	12/31/99	5/31/24
2418MPC	229	IRIZAR	IEBUS	5	Eléctrico	Sin emisiones	Plat. doble	87	4/13/24	12/31/99	5/31/24
1573MPC	189	IRIZAR	IEBUS	3	Eléctrico	Sin emisiones	Plat. doble	87	4/11/24	12/31/99	5/31/24

Figure 67: Historical record of every bus in the EMT fleet since 1989 to 2024

DISTRIBUCIÓN DEL PARQUE DE MATERIAL MÓVIL DE EXPLOTACIÓN A DÍA 31 DE MAYO DE 2024

Tipo de combustible	Marca	Modelo	Vehículos	%
PARQUE VERDE			**2,108**	**100.00%**
GAS NATURAL			**1,794**	**85.10%**
Convencional			**1,794**	**85.10%**
	BREDAMENARINIBUS	Vivacity GNC	19	0.90%
	IVECO	Citelis GNC	36	1.71%
	MAN	Lion's City GNC	42	1.99%
	MAN	NG/313-F GNC Articulado	32	1.52%
	MAN	NL/313-F GNC	83	3.94%
	MERCEDES	Cit-GNC	718	34.06%
	MERCEDES	Citaro G GNC Articulado	54	2.56%
	SCANIA	N280 UB GNC	543	25.76%
	SCANIA	N280 GNC Aeropuerto	17	0.80%
	SOLARIS	Urbino 12 GNC	250	11.86%
ELÉCTRICO			**314**	**14.90%**
	BYD	K9UB	65	3.08%
	CAR-BUS	Wolta	18	0.86%
	IRIZAR	I2E	35	1.66%
	IRIZAR	IEBUS	116	5.50%
	IRIZAR	IETRAM	12	0.57%
	RAMPINI	E60	6	0.29%
	SOLARIS	Urbino 12 Eléctrico	61	2.89%
	TECNOBÚS	Gulliver	1	0.05%
TOTAL PARQUE MÓVIL			**2,108**	**100.00%**

Figure 68: Snapshot of the fleet as of 2024

9.2.2 EMISSION FILE (EMT - MATLAB)

```
% Data is aligned with the fuel category codes from the EMTFleetS1 file:
% 1: CNG (Compressed Natural Gas)
% 2: BEV (Battery Electric Vehicle)




% Pollutants are in the order: [CO2 (g/km), NOx (g/km), PM (g/km)]
base_emissions_bus = zeros(15, 3);

% Define Emissions for CNG Buses
% Values are representative of a modern Euro VI CNG bus.
% CO2 is derived from consumption: ~0.40 kg/km * 2750 gCO2/kg_CNG = 1100 g/km
```

```
base_emissions_bus(1, :) = [1100, 2.0, 0.05];


% Define Emissions for BEV Buses
% BEVs have zero tailpipe emissions.
base_emissions_bus(2, :) = [0, 0, 0];
```

9.2.3 CONSUMPTION FILE (EMT - MATLAB)

```
% Revisar tamaño de matriz
consumptions_bus = zeros(15, 15);


% Define Consumption for CNG Buses
% Units: kg / 100km
% Columns: 7=Urban, 8=Suburban, 9=Extra-Urban
% Values are based on industry averages, reflecting higher consumption
% in stop-and-go urban traffic.
consumptions_bus(1, 7:9) = [40, 35, 30];


% Define Consumption for BEV Buses
% Units: kWh / 100km
% Columns: 13=Urban, 14=Suburban, 15=Extra-Urban
% Values are based on industry averages, reflecting higher efficiency from
% regenerative braking in urban/suburban cycles.
consumptions_bus(2, 13:15) = [130, 120, 140];
```

9.2.4 SIMULATION FILE (EMT - MATLAB)

```
%Required Files
%     - EMTFleetS1.mat
%     - consumption_bus_file.m
%     - emission_bus_file.m




clear; clc; close all;
```

```
% 1. PARAMETERS TO CONTROL

% Simulation Control
start_year = 2025;
end_year = 2045;
scenarios_to_run = [1, 2, 3]; % 1: Delayed, 2: Base, 3: Accelerated

% Operational Parameters
vehicle_lifespan_years = 15;
daily_distance_mean = 126;
drive_cycle_mix = [0.85, 0.15, 0.0]; % [Urban, Suburban, Extra-Urban]

% Initial Economic Parameters (for start_year)
% Rows: 1=CNG, 2=BEV. Other rows are placeholders.
% Columns: [purchase(€), elec(€/kWh), fuel(€/kg), maint_new(€/km),
maint_old(€/km)]
vehicle_costs_initial = zeros(15, 5);
vehicle_costs_initial(1, :) = [350000, 0,    1.0,  0.25, 0.64]; % CNG Bus
vehicle_costs_initial(2, :) = [650000, 0.09, 0,    0.18, 0.35]; % BEV Bus

% Dynamic Economic Annual Change Rates
cost_change_rates = zeros(15, 5);
%            [Purchase, Elec,   Fuel, Maint_New, Maint_Old]
cost_change_rates(1, :) = [+0.01,  0,     +0.02, +0.01, +0.01]; % CNG
cost_change_rates(2, :) = [-0.03,  +0.01, 0,     -0.02, -0.02]; % BEV
cost_change_multiplier = 1 + cost_change_rates;

% TCO Model Enhancements
downtime_capex_multiplier = 1.10; % 10% CAPEX increase for new BEVs
early_retirement_rate_gnc = 0.1; % NUEVO: Retirar un % extra de los buses GNC más
antiguos cada año



%  Electrification Targets (% of new sales that are BEV)
target_table_base_bus = [60; 65; 70; 75; 80; 85; 90; 95; 100; 100; 100; 100; 100;
100; 100; 100; 100; 100; 100; 100; 100];
```

```
% --- Charging Infrastructure Assumptions ---
charging_window_hours = 8;
simultaneity_factor = 1;
charging_loss = 0.15;



% 2. INITIALIZATION

fprintf('Initializing simulation with robust table structure...\n');

% Load Data Files
try
    load('EMTFleetS1.mat');
    consumption_bus_file;
    emission_bus_file;
catch
    error('A required data file (EMTFleetS1.mat, consumption_bus_file.m, or
emission_bus_file.m) is missing.');
end

% Create a TABLE for the initial fleet
try
    % Columns from EMTFleetS1.mat: 3:Fuel Type, 4:EcoClass, 5:Seats, 6:Year
    col_names = {'FuelCategory', 'EcoClass', 'Seats', 'RegistrationYear'};
    initial_fleet = array2table(EMTFleetS1(:, [3, 4, 5, 6]), 'VariableNames',
col_names);
catch
    error('Failed to create table from EMTFleetS1.mat. Ensure it is a 2108x6
numerical matrix.');
end

% Preallocate results structure
results = struct();



% 3. SIMULATION LOOPS
```

```
for scenario = scenarios_to_run

    fleet = initial_fleet; % Reset fleet for each new scenario
    vehicle_costs = vehicle_costs_initial;

    years = start_year:end_year;
    N_years = length(years);

    % Preallocate annual results arrays
    fleet_composition = zeros(N_years, 15);
    annual_CO2 = zeros(N_years, 1);
    annual_NOx = zeros(N_years, 1);
    annual_PM = zeros(N_years, 1);
    annual_energy_demand_mwh = zeros(N_years, 1);
    annual_cost = zeros(N_years, 1);

    % Adjust targets based on scenario using a 5-YEAR time-shift
    target_table = target_table_base_bus;
    if scenario == 1 % Delayed
        delay_years = 5;
        target_table = [repmat(target_table(1), delay_years, 1);
target_table(1:end-delay_years)];
    elseif scenario == 3 % Accelerated
        acceleration_years = 5;
        target_table = [target_table(acceleration_years+1:end);
repmat(target_table(end), acceleration_years, 1)];
    end

    fprintf('Running EMT Bus Scenario %d...\n', scenario);

    for y = 1:N_years
        current_year = years(y);

        % DEBUGGING CONTROL: To see the raw CAPEX difference, comment out the
following IF block
        % By doing this, prices will remain static at 2025 levels, and the
        % cost curves will diverge significantly based on purchase decisions.
```

```
        if y > 1
            vehicle_costs = vehicle_costs .* cost_change_multiplier;
        end

    % --- Fleet Aging and Renewal (con Retirada Anticipada) ---
fleet.Age = current_year - fleet.RegistrationYear;

% 1a. Retirar autobuses por fin de vida útil
retired_idx_age = fleet.Age > vehicle_lifespan_years;

% 1b. Forzar retirada de un 5% de los buses GNC más antiguos
is_gnc = fleet.FuelCategory == 1; % El código para GNC es 1 en tu tabla
num_gnc_buses = sum(is_gnc);
num_to_retire_early = floor(num_gnc_buses * early_retirement_rate_gnc);

retired_idx_early = false(height(fleet), 1); % Inicializar como falso
if num_to_retire_early > 0
    gnc_indices = find(is_gnc);
    % Ordenar los buses GNC por año de compra (del más antiguo al más nuevo)
    [~, sorted_order] = sort(fleet.RegistrationYear(gnc_indices));
    % Obtener los índices de la tabla de los buses más antiguos a retirar
    indices_to_retire_early = gnc_indices(sorted_order(1:num_to_retire_early));
    retired_idx_early(indices_to_retire_early) = true;
end

% Combinar ambos criterios de retirada
retired_idx = retired_idx_age | retired_idx_early;
num_to_replace = sum(retired_idx);

        fleet = fleet(~retired_idx, :);

        BEV_share = target_table(min(y, size(target_table, 1))) / 100;
        new_buses_cell = cell(num_to_replace, width(fleet));

        for r = 1:num_to_replace
            if rand() < BEV_share
```

```
                fuel_type = 2; % BEV
            else
                fuel_type = 1; % CNG
            end
            new_buses_cell(r, :) = {fuel_type, 3, 80, current_year, 0};
        end

        if num_to_replace > 0
            new_buses_table = cell2table(new_buses_cell, 'VariableNames',
fleet.Properties.VariableNames);
            fleet = [fleet; new_buses_table];
        end

        %  Per-Vehicle Calculations
        N = height(fleet);
        current_annual_kwh = 0;
        current_annual_cost = 0;
        total_annual_emissions = zeros(1, 3);

        for i = 1:N
            fuel_category = fleet.FuelCategory(i);
            age = fleet.Age(i);

            % Consumption
            if fuel_category == 2 % BEV
                cons_vector = consumptions_bus(fuel_category, 13:15);
            else % CNG
                cons_vector = consumptions_bus(fuel_category, 7:9);
            end
            weighted_cons_per_100km = dot(cons_vector, drive_cycle_mix);

            % Economics
            distance_yearly = daily_distance_mean * 365;
            energy_yearly = (weighted_cons_per_100km / 100) * distance_yearly;

            if fuel_category == 2 % BEV
```

```
                energy_price = vehicle_costs(fuel_category, 2);
                current_annual_kwh = current_annual_kwh + energy_yearly;
            else % CNG
                energy_price = vehicle_costs(fuel_category, 3);
            end
            energy_cost = energy_yearly * energy_price;

            % Age-dependent maintenance
            maint_new = vehicle_costs(fuel_category, 4);
            maint_old = vehicle_costs(fuel_category, 5);
            maint_slope = (maint_old - maint_new) / vehicle_lifespan_years;
            maint_cost_per_km = maint_new + maint_slope * age;
            maint_cost = distance_yearly * maint_cost_per_km;

            capex = 0;
            if fleet.RegistrationYear(i) == current_year
                capex = vehicle_costs(fuel_category, 1);
                if fuel_category == 2
                    capex = capex * downtime_capex_multiplier;
                end
            end
            current_annual_cost = current_annual_cost + capex + energy_cost +
maint_cost;

            % Emissions
            emissions_per_km = base_emissions_bus(fuel_category, :);
            annual_vehicle_emissions_grams = emissions_per_km * distance_yearly;
            total_annual_emissions = total_annual_emissions +
(annual_vehicle_emissions_grams / 1e6);
        end

        annual_cost(y) = current_annual_cost;
        annual_energy_demand_mwh(y) = current_annual_kwh / 1000;
        annual_CO2(y) = total_annual_emissions(1);
        annual_NOx(y) = total_annual_emissions(2);
        annual_PM(y) = total_annual_emissions(3);
```

```
        for fuel_type = 1:15
            fleet_composition(y, fuel_type) = sum(fleet.FuelCategory == fuel_type);
        end
    end

    results(scenario).years = years;
    results(scenario).annual_CO2 = annual_CO2;
    results(scenario).annual_NOx = annual_NOx;
    results(scenario).annual_PM = annual_PM;
    results(scenario).annual_energy_demand_mwh = annual_energy_demand_mwh;
    results(scenario).annual_cost = annual_cost;
    results(scenario).fleet_composition = fleet_composition;
end

%  4. COMPREHENSIVE PLOTTING & ANALYSIS (Adapted from Taxi/VTC Model)

fprintf('Simulations complete. Generating comprehensive analysis plots for EMT fleet...\n');

% 4.1 Infrastructure Demand Calculation
% Use the existing parameters from the bus script.
% charging_window_hours = 8;
% simultaneity_factor = 1;
% charging_loss = 0.15;
years = results(1).years;
total_fleet_size = height(initial_fleet);

% Calculate peak power demand for all scenarios
for scenario = scenarios_to_run
    annual_mwh = results(scenario).annual_energy_demand_mwh;
    avg_daily_mwh = annual_mwh / 365;
    % Use charging parameters defined at the top of the script
    results(scenario).peak_power_demand_mw = (avg_daily_mwh / charging_window_hours) / (1-charging_loss) * simultaneity_factor;
end
```

```
% SETUP: DEFINE COLOR PALETTES & STYLES

fprintf('Setting up color palettes and styles...\n');

% Blue Palette for Policy Scenarios (Light to Dark)
policy_blues = [0.58, 0.77, 0.93; 0.00, 0.45, 0.74; 0.07, 0.28, 0.48];

% Fleet Composition Palette (Area Charts for Buses)
fleet_colors = [0.07, 0.28, 0.48; 0.85, 0.33, 0.10]; % Dark Blue (BEV), Burnt
Orange (CNG)

%  Global Style Settings
base_line_width = 2;
thick_line_width = 2.5;
set(groot, 'defaultAxesFontSize', 11);


% FIGURE 1: DEEP DIVE ON FLEET SCENARIOS (EMISSIONS FOCUSED)

fprintf('Generating Figure 1: Scenario Deep Dive...\n');
figure('Name', 'EMT Bus: Analysis of Fleet Scenarios', 'WindowState',
'maximized');
sgtitle('EMT Bus Scenarios: Fleet Evolution and Emissions', 'FontSize', 18,
'FontWeight', 'bold');

% Plot 1.1: Fleet Composition (Delayed)
ax1 = subplot(2,3,1);
fleet_data = results(1).fleet_composition;
BEV=fleet_data(:,2); CNG=fleet_data(:,1);
area(years, [BEV, CNG]);
colororder(ax1, fleet_colors);
% title('Fleet Composition (Delayed)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
legend({'BEV', 'CNG'}, 'Location','northwest'); box on;

% Plot 1.2: Fleet Composition (Base)
```

```
ax2 = subplot(2,3,2);
fleet_data = results(2).fleet_composition;
BEV=fleet_data(:,2); CNG=fleet_data(:,1);
area(years, [BEV, CNG]);
colororder(ax2, fleet_colors);
% title('Fleet Composition (Base)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
box on;

% Plot 1.3: Fleet Composition (Accelerated)
ax3 = subplot(2,3,3);
fleet_data = results(3).fleet_composition;
BEV=fleet_data(:,2); CNG=fleet_data(:,1);
area(years, [BEV, CNG]);
colororder(ax3, fleet_colors);
% title('Fleet Composition (Accelerated)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
box on;

% Plot 1.4: CO2 Emissions
subplot(2,3,4); hold on;
plot(years, results(1).annual_CO2, '--', 'Color', policy_blues(1,:), 'LineWidth',
base_line_width, 'DisplayName', 'Delayed');
plot(years, results(2).annual_CO2, '-', 'Color', policy_blues(2,:), 'LineWidth',
thick_line_width, 'DisplayName', 'Base');
plot(years, results(3).annual_CO2, ':', 'Color', policy_blues(3,:), 'LineWidth',
base_line_width, 'DisplayName', 'Accelerated');
% title('Annual CO₂ Emissions', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Tons/Year');
legend('Location', 'best'); box on; hold off;

% Plot 1.5: NOx Emissions
subplot(2,3,5); hold on;
plot(years, results(1).annual_NOx, '--', 'Color', policy_blues(1,:), 'LineWidth',
base_line_width, 'DisplayName', 'Delayed');
plot(years, results(2).annual_NOx, '-', 'Color', policy_blues(2,:), 'LineWidth',
thick_line_width, 'DisplayName', 'Base');
```

```
plot(years, results(3).annual_NOx, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Annual NOₓ Emissions', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Tons/Year');



legend('Location', 'best'); box on; hold off;


% Plot 1.6: PM Emissions

subplot(2,3,6); hold on;

plot(years, results(1).annual_PM, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).annual_PM, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');



plot(years, results(3).annual_PM, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Annual PM Emissions', 'FontWeight', 'normal');

xlabel('Year');

ylabel('Tons/Year');

legend('Location', 'best'); box on; hold off;


% FIGURE 2 & 3: SCENARIO IMPACTS (COST & POWER)


fprintf('Generating Figures 2 & 3: Cost and Power Demand...\n');


% FIGURE 2: Total Annual Fleet Cost

figure('Name', 'EMT Bus: Total Annual Fleet Cost by Scenario');

hold on;

plot(years, results(1).annual_cost / 1e6, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).annual_cost / 1e6, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');
```

```
plot(years, results(3).annual_cost / 1e6, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Total Annual Fleet Cost by Scenario (CAPEX + OPEX)', 'FontSize', 14, 'FontWeight', 'bold');

xlabel('Year'); ylabel('Cost (€ Millions)');

legend('Location', 'northwest'); box on; hold off;


% FIGURE 3: Charging Power Demand

figure('Name', 'EMT Bus: Charging Power Demand by Scenario');

hold on;

plot(years, results(1).peak_power_demand_mw, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).peak_power_demand_mw, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results(3).peak_power_demand_mw, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Estimated Peak Charging Power Demand by Scenario', 'FontSize', 14, 'FontWeight', 'bold');

xlabel('Year'); ylabel('Peak Power (MW)');

legend('Location', 'northwest'); box on; hold off;



% FIGURE 4: DEEP DIVE ON THE BASE SCENARIO

%

fprintf('Generating Figure 4: Base Scenario Deep Dive...\n');

figure('Name', 'EMT Bus: Analysis of Base Scenario', 'WindowState', 'maximized');

sgtitle('EMT Bus: Deep Dive on the Base Scenario', 'FontSize', 18, 'FontWeight', 'bold');


% Plot 4.1: Fleet Composition

subplot(2,2,1);

ax_base_fleet = gca;

fleet_data = results(2).fleet_composition;

BEV=fleet_data(:,2); CNG=fleet_data(:,1);

area(years, [BEV, CNG]);

colororder(ax_base_fleet, fleet_colors);

% title('Fleet Composition (Base)', 'FontWeight', 'normal');
```

```
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
legend({'BEV', 'CNG'}, 'Location','northwest'); box on;

% Plot 4.2: CO2 Emissions
subplot(2,2,2);
plot(years, results(2).annual_CO2, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width);
% title('Annual CO₂ Emissions (Base)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Tons/Year'); box on;

% Plot 4.3: Annual Cost
subplot(2,2,3);
plot(years, results(2).annual_cost / 1e6, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width);
% title('Total Annual Fleet Cost (Base)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Cost (€ Millions)'); box on;

% Plot 4.4: Power Demand
subplot(2,2,4);
plot(years, results(2).peak_power_demand_mw, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width);
% title('Peak Charging Power Demand (Base)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Peak Power (MW)'); box on;



% FIGURE 5: STRATEGIC SCENARIO COMPARISON



fprintf('Generating Figure 5: Strategic Scenario Comparison...\n');
figure('Name', 'EMT Bus: Strategic Scenario Comparison', 'WindowState', 'maximized');
sgtitle('EMT Bus: Strategic Comparison of Scenarios', 'FontSize', 18, 'FontWeight', 'bold');

% Plot 5.1: BEV Adoption Comparison
subplot(2,1,1);
hold on;
```

```
fleet_delayed = results(1).fleet_composition(:,2); % BEV is category 2
fleet_accelerated = results(3).fleet_composition(:,2);
fill([years fliplr(years)], [fleet_delayed' fliplr(fleet_accelerated')],
policy_blues(1,:), 'FaceAlpha', 0.3, 'EdgeColor', 'none', 'DisplayName', 'Range
(Delayed to Accelerated)');
plot(years, results(2).fleet_composition(:,2), '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base Scenario');
% title('BEV Adoption Across Scenarios');
xlabel('Year'); ylabel('Number of BEV Buses');
legend('Location', 'northwest'); box on; hold off;


% Plot 5.2: Total Annual Cost Comparison
subplot(2,1,2);
hold on;
plot(years, results(1).annual_cost/1e6, '--', 'Color', policy_blues(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Delayed');
plot(years, results(2).annual_cost/1e6, '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base');
plot(years, results(3).annual_cost/1e6, ':', 'Color', policy_blues(3,:),
'LineWidth', base_line_width, 'DisplayName', 'Accelerated');
% title('Total Annual Fleet Cost Across Scenarios');
xlabel('Year'); ylabel('Cost (€ Millions)');
legend('Location', 'northwest'); box on; hold off;



% FIGURE 6: CUMULATIVE IMPACT COMPARISON (BAR CHARTS)


fprintf('Generating Figure 6: Cumulative Impact Comparison...\n');
figure('Name', 'EMT Bus: Cumulative Impact Comparison', 'WindowState',
'maximized');
sgtitle('EMT Bus: Total Impact Over Simulation Period (2025-2045)', 'FontSize',
18, 'FontWeight', 'bold');


% Consolidate Data
total_CO2 = [sum(results(1).annual_CO2), sum(results(2).annual_CO2),
sum(results(3).annual_CO2)];
total_NOx = [sum(results(1).annual_NOx), sum(results(2).annual_NOx),
sum(results(3).annual_NOx)];
total_PM  = [sum(results(1).annual_PM), sum(results(2).annual_PM),
sum(results(3).annual_PM)];
```

```
total_Cost = [sum(results(1).annual_cost), sum(results(2).annual_cost),
sum(results(3).annual_cost)];


% Define shared properties
scenario_labels = {'Delayed', 'Base', 'Accelerated'};
comparison_bar_colors = policy_blues;
add_bar_labels = @(bar_obj, format_str) text(bar_obj.XEndPoints,
bar_obj.YEndPoints, arrayfun(@(v) sprintf(format_str, v), bar_obj.YData,
'UniformOutput', false), 'HorizontalAlignment', 'center', 'VerticalAlignment',
'bottom', 'FontSize', 10);


% Plot 6.1: Total CO2 Emissions
subplot(2, 2, 1);
b1 = bar(total_CO2/1e3, 'FaceColor', 'flat');
b1.CData = comparison_bar_colors;
% title('Total Cumulative CO_2 Emissions (Thousands)', 'FontWeight', 'normal');
ylabel('Total Tons (Thousands)');
set(gca, 'xticklabel', scenario_labels); box on;
add_bar_labels(b1, '%.1f k');


% Plot 6.2: Total NOx Emissions
subplot(2, 2, 2);
b2 = bar(total_NOx, 'FaceColor', 'flat');
b2.CData = comparison_bar_colors;
% title('Total Cumulative NO_x Emissions', 'FontWeight', 'normal');
%
ylabel('Total Tons');
set(gca, 'xticklabel', scenario_labels); box on;
add_bar_labels(b2, '%.1f Tons');


% Plot 6.3: Total PM Emissions
subplot(2, 2, 3);
b3 = bar(total_PM, 'FaceColor', 'flat');
b3.CData = comparison_bar_colors;
% title('Total Cumulative PM Emissions', 'FontWeight', 'normal');
ylabel('Total Tons');
set(gca, 'xticklabel', scenario_labels); box on;
```

```
add_bar_labels(b3, '%.1f Tons');


% Plot 6.4: Total Fleet Cost
subplot(2, 2, 4);
b4 = bar(total_Cost / 1e9, 'FaceColor', 'flat'); % In Billions
b4.CData = comparison_bar_colors;
% title('Total Cumulative Fleet Cost', 'FontWeight', 'normal');
ylabel('Total Cost (Billion €)');
set(gca, 'xticklabel', scenario_labels); box on;
add_bar_labels(b4, '€%.1f B');


fprintf('All plots for EMT Bus fleet generated successfully.\n');
```

9.3 Interurban MATLAB Files

9.3.1 Fleet Generation File (Interurban)

```
function interurban_fleet = create_interurban_fleet()


% This function generates the initial fleet table for the interurban bus
simulation,



% COLUMNS:
% 1: Bus_ID
% 2: Purchase_Year
% 3: Fuel_Category ('Diesel', 'CNG', 'Hybrid/EV')




total_fleet_size = 2114;
disp(['Generating initial Interurban fleet table for ',
num2str(total_fleet_size), ' buses...']);



% CORRECCIÓN: Distribución de años escalada a 2,114 autobuses
```

```
years_vector = [ ...
    2010*ones(1,30), 2011*ones(1,48), 2012*ones(1,71), 2013*ones(1,89), ...
    2014*ones(1,107), 2015*ones(1,119), 2016*ones(1,137), 2017*ones(1,149), ...
    2018*ones(1,167), 2019*ones(1,179), 2020*ones(1,196), 2021*ones(1,208), ...
    2022*ones(1,246), ... % Changed from 238 to 246 (238 + 8)
    2023*ones(1,190), 2024*ones(1,178) ...
];
years = years_vector'; % Transponer a vector columna

%  CORRECCIÓN: Distribución de combustibles escalada a 2,106 autobuses
% Proporciones: 80% Diesel, 15% CNG, 5% Hybrid/EV
num_diesel = round(total_fleet_size * 0.80);
num_cng = round(total_fleet_size * 0.15);
num_hybrid_ev = total_fleet_size - num_diesel - num_cng; % El resto para asegurar
que la suma es exacta

fuels_cell = [
    repmat({'Diesel'}, num_diesel, 1);
    repmat({'CNG'}, num_cng, 1);
    repmat({'Hybrid/EV'}, num_hybrid_ev, 1)
    ];

% Shuffle the fuels to distribute them randomly across the years
fuels_cell = fuels_cell(randperm(length(fuels_cell)));

bus_ids = (1:total_fleet_size)';

interurban_fleet = table(bus_ids, years, fuels_cell, 'VariableNames', {'ID',
'PurchaseYear', 'FuelType'});

fprintf('Interurban fleet table of %d buses created successfully.\n',
height(interurban_fleet));
end
```

9.3.2 *EMISSION FILE (INTERURBAN)*

```
% Fuel Category Codes: 1=CNG, 2=BEV, 13=Diesel
```

```
% Pollutants are in the order: [CO2 (g/km), NOx (g/km), PM (g/km)]



% Initialize a matrix for compatibility.
base_emissions_interurban = zeros(15, 3);

% Define Emissions for Diesel Coaches

base_emissions_interurban(13, :) = [1300, 2.5, 0.08];

% Define Emissions for CNG Coaches
% Using the same values as the EMT CNG buses for consistency.
base_emissions_interurban(1, :) = [1100, 2.0, 0.05];

% Define Emissions for BEV Coaches
% BEVs have zero tailpipe emissions.
base_emissions_interurban(2, :) = [0, 0, 0];
```

9.3.3 *CONSUMPTION FILE (INTERURBAN)*

```
% Fuel Category Codes: 1=CNG, 2=BEV, 13=Diesel
% Columns are for [Urban, Suburban, Extra-Urban] driving cycles.



% Initialize a matrix for compatibility.
consumptions_interurban = zeros(15, 3);

% Define Consumption for Diesel Buses
% Unit: Liters / 100km
% Based on 35 L/100km average, distributed across cycles.
consumptions_interurban(13, :) = [40, 35, 30];

% Consumption for CNG Buses
% Unit: kg / 100km
% Based on 30 kg/100km average, distributed across cycles.
consumptions_interurban(1, :) = [35, 30, 25];
```

```
% Consumption for BEV Buses
% Unit: kWh / 100km
% Based on 1.4 kWh/km (140 kWh/100km) average from the review.
% Higher consumption in extra-urban due to lack of regenerative braking.
```

9.3.4 FLEET GENERATION FILE (INTERURBAN)

```
% 1. Place this script in a folder.
% 2. Add the required data files to the same folder:
%    - create_interurban_fleet.m
%    - consumption_interurban_file.m
%    - emission_interurban_file.m

clear; clc; close all;


%% 1. PARAMETERS TO CONTROL


% 1.1   Simulation Control
start_year = 2025;
end_year = 2045;
scenarios_to_run = [1, 2, 3]; % 1: Delayed, 2: Base, 3: Accelerated

% 1.2   Operational Parameters
vehicle_lifespan_years = 15;
daily_distance_mean = 300;
drive_cycle_mix = [0.3, 0.6, 0.1]; % More suburban/extra-urban driving

%  TCO Model Parameters
tco_projection_years = 10; % Number of years of OPEX to consider in a purchase
decision

% Initial Economic Parameters (for start_year)
% Columns: [purchase(€), elec(€/kWh), fuel(€/unit), maint(€/km)]
vehicle_costs_initial = zeros(15, 4);
```

```
vehicle_costs_initial(13, :) = [280000, 0,    1.42, 0.50]; % Diesel Coach (fuel unit = Liter)



vehicle_costs_initial(1, :)  = [350000, 0,    1.0,  0.45]; % CNG Coach (fuel unit = kg)

vehicle_costs_initial(2, :)  = [550000, 0.09, 0,    0.25]; % BEV Coach (fuel unit = kWh)


%  Dynamic Economic Annual Change Rates

cost_change_rates = zeros(15, 4);

%            [Purchase, Elec,    Fuel,  Maint]

cost_change_rates(13, :) = [+0.01,  0,     +0.02, +0.01]; % Diesel


cost_change_rates(1, :)  = [+0.01,  0,     +0.02, +0.01]; % CNG

cost_change_rates(2, :)  = [-0.04,  +0.01, 0,     -0.03]; % BEV

cost_change_multiplier = 1 + cost_change_rates;


%  DYNAMIC Regulatory Mandates Table (NEW)

% Defines the percentage of new purchases that must be zero-emission

% based on the EU Clean Vehicles Directive and future proposals.


mandate_years_base = [2025; 2026; 2030; 2035];

% The sub-target for zero-emission vehicles (as a % of total new fleet)


zero_emission_mandate_pct = [22.5; 32.5; 90; 100];


%  Charging Infrastructure Assumptions

charging_window_hours = 8;

simultaneity_factor = 0.7;

charging_loss = 0.15;



%  2. INITIALIZATION (CORRECTED FLEET GENERATION)


fprintf('Initializing simulation and generating corrected inter-urban fleet...\n');
```

```
% Load Data Files
try
    consumption_interurban_file;
    emission_interurban_file;
catch
    error('A required data file (consumption_interurban_file.m or
emission_interurban_file.m) is missing.');
end

% Step 1: Call the function to create the detailed fleet of 2,106 buses
fleet_from_file = create_interurban_fleet();

% Step 2: Convert the file's format to the format needed by the simulation
num_buses = height(fleet_from_file);
fuel_categories_numeric = zeros(num_buses, 1);

% Convert fuel names ('Diesel', 'CNG') to numeric codes (13, 1, 2)
for i = 1:num_buses
    if strcmp(fleet_from_file.FuelType{i}, 'Diesel')


        fuel_categories_numeric(i) = 13;
    elseif strcmp(fleet_from_file.FuelType{i}, 'CNG')
        fuel_categories_numeric(i) = 1;
    else % Assumes 'Hybrid/EV' maps to the BEV parameters
        fuel_categories_numeric(i) = 2;
    end
end

% Create the final, correctly formatted table for the simulation
initial_fleet = table(fuel_categories_numeric, fleet_from_file.PurchaseYear, ...
                      'VariableNames', {'FuelCategory', 'RegistrationYear'});

fprintf('%d buses correctly loaded and formatted.\n', height(initial_fleet));
```

```
% Preallocate results structure
results = struct();



% 3. SIMULATION LOOPS



for scenario = scenarios_to_run

    fleet = initial_fleet;
    vehicle_costs = vehicle_costs_initial;

    years = start_year:end_year;

    N_years = length(years);

    % Preallocate annual results arrays
    fleet_composition = zeros(N_years, 15);
    annual_CO2 = zeros(N_years, 1);

    annual_NOx = zeros(N_years, 1);
    annual_PM = zeros(N_years, 1);
    annual_energy_demand_mwh = zeros(N_years, 1);
    annual_cost = zeros(N_years, 1);

    %  Adjust Mandate Timing Based on Scenario
    scenario_time_shift = 0;
    if scenario == 1, scenario_time_shift = 5; end  % Delayed by 5 years
    if scenario == 3, scenario_time_shift = -5; end % Accelerated by 5 years

    mandate_table = table(mandate_years_base + scenario_time_shift,
zero_emission_mandate_pct, ...
                          'VariableNames', {'mandate_years',
'zero_emission_mandate_pct'});

    fprintf('Running Inter-urban Bus Scenario %d...\n', scenario);
```

```
    for y = 1:N_years
        current_year = years(y);

        if y > 1
            vehicle_costs = vehicle_costs .* cost_change_multiplier;
        end

        % Fleet Aging and Renewal
        fleet.Age = current_year - fleet.RegistrationYear;
        retired_idx = fleet.Age > vehicle_lifespan_years;
        num_to_replace = sum(retired_idx);
        fleet = fleet(~retired_idx, :);

        %  Fleet Renewal with Hybrid TCO-Regulatory Model
        new_buses_data = cell(num_to_replace, width(fleet));

        if num_to_replace > 0
            % 1. Find the current applicable mandate from the table
            current_mandate_row = mandate_table(current_year >=
mandate_table.mandate_years, :);
            current_zev_mandate_pct = 0; % Default to 0 if before first mandate
year
            if ~isempty(current_mandate_row)
                current_zev_mandate_pct =
current_mandate_row.zero_emission_mandate_pct(end);
            end

            % 2. Calculate the number of buses mandated to be zero-emission
            num_zero_emission_mandated = floor(num_to_replace *
(current_zev_mandate_pct / 100));
            num_remaining_to_replace = num_to_replace -
num_zero_emission_mandated;

            % 3. Fulfill the zero-emission mandate first
            for r = 1:num_zero_emission_mandated
                new_buses_data(r, :) = {2, current_year, 0}; % FuelCategory 2 =
BEV
            end
```

```
            % 4. For the rest, choose the most cost-effective option based on TCO
            if num_remaining_to_replace > 0
                % Calculate TCO for the remaining options (Diesel vs. CNG)
                op_cost_diesel = (dot(consumptions_interurban(13,:),
drive_cycle_mix)/100 * daily_distance_mean * 365 * vehicle_costs(13,3)) +
(daily_distance_mean * 365 * vehicle_costs(13,4));
                tco_diesel = vehicle_costs(13, 1) + (op_cost_diesel *
tco_projection_years);

                op_cost_cng = (dot(consumptions_interurban(1,:),
drive_cycle_mix)/100 * daily_distance_mean * 365 * vehicle_costs(1,3)) +
(daily_distance_mean * 365 * vehicle_costs(1,4));
                tco_cng = vehicle_costs(1, 1) + (op_cost_cng *
tco_projection_years);

                if tco_cng < tco_diesel
                    cheapest_conventional_fuel = 1; % CNG
                else
                    cheapest_conventional_fuel = 13; % Diesel
                end

                for r = (num_zero_emission_mandated + 1):num_to_replace
                    new_buses_data(r, :) = {cheapest_conventional_fuel,
current_year, 0};
                end
            end

            new_buses_table = cell2table(new_buses_data, 'VariableNames',
fleet.Properties.VariableNames);
            fleet = [fleet; new_buses_table];
        end

        %  Per-Vehicle Calculations
        N = height(fleet);
        current_annual_kwh = 0;
        current_annual_cost = 0;
        total_annual_emissions = zeros(1, 3);
```

```
        for i = 1:N
            fuel_category = fleet.FuelCategory(i);

            % Consumption
            cons_vector = consumptions_interurban(fuel_category, :);
            weighted_cons_per_100km = dot(cons_vector, drive_cycle_mix);

            % Economics
            distance_yearly = daily_distance_mean * 365;
            energy_yearly = (weighted_cons_per_100km / 100) * distance_yearly;

            if fuel_category == 2 % BEV
                energy_price = vehicle_costs(fuel_category, 2);
                current_annual_kwh = current_annual_kwh + energy_yearly;
            else % Diesel or CNG
                energy_price = vehicle_costs(fuel_category, 3);
            end
            energy_cost = energy_yearly * energy_price;

            maint_cost = distance_yearly * vehicle_costs(fuel_category, 4);

            capex = 0;
            if fleet.RegistrationYear(i) == current_year
                capex = vehicle_costs(fuel_category, 1);
            end
            current_annual_cost = current_annual_cost + capex + energy_cost +
maint_cost;

            % Emissions
            emissions_per_km = base_emissions_interurban(fuel_category, :);
            annual_vehicle_emissions_grams = emissions_per_km * distance_yearly;
            total_annual_emissions = total_annual_emissions +
(annual_vehicle_emissions_grams / 1e6);
        end

        annual_cost(y) = current_annual_cost;
        annual_energy_demand_mwh(y) = current_annual_kwh / 1000;
```

```
        annual_CO2(y) = total_annual_emissions(1);

        annual_NOx(y) = total_annual_emissions(2);

        annual_PM(y) = total_annual_emissions(3);


        for fuel_type = 1:15

            fleet_composition(y, fuel_type) = sum(fleet.FuelCategory ==
fuel_type);

        end

    end


    results(scenario).years = years;

    results(scenario).annual_CO2 = annual_CO2;

    results(scenario).annual_NOx = annual_NOx;

    results(scenario).annual_PM = annual_PM;

    results(scenario).annual_energy_demand_mwh = annual_energy_demand_mwh;

    results(scenario).annual_cost = annual_cost;

    results(scenario).fleet_composition = fleet_composition;

end



%  4. COMPREHENSIVE PLOTTING & ANALYSIS (Adapted from Taxi/VTC Model)


fprintf('Simulations complete. Generating comprehensive analysis plots for Inter-
urban fleet...\n');


% 4.1  Infrastructure Demand Calculation ---

% Use the existing parameters from the bus script.

% charging_window_hours = 8;

% simultaneity_factor = 0.7;

% charging_loss = 0.15;

years = results(1).years;

total_fleet_size = height(initial_fleet);


% Calculate peak power demand for all scenarios

for scenario = scenarios_to_run

    annual_mwh = results(scenario).annual_energy_demand_mwh;

    avg_daily_mwh = annual_mwh / 365;
```

```
    % Use charging parameters defined at the top of the script
    results(scenario).peak_power_demand_mw = (avg_daily_mwh /
charging_window_hours) / (1-charging_loss) * simultaneity_factor;
end

% SETUP: DEFINE COLOR PALETTES & STYLES
fprintf('Setting up color palettes and styles...\n');

%  Blue Palette for Policy Scenarios (Light to Dark)
policy_blues = [0.58, 0.77, 0.93; 0.00, 0.45, 0.74; 0.07, 0.28, 0.48];

%  Fleet Composition Palette (Area Charts for Buses)
fleet_colors = [0.07, 0.28, 0.48; 0.85, 0.33, 0.10; 0.5, 0.5, 0.5]; % Dark Blue
(BEV), Burnt Orange (CNG), Grey (Diesel)

%  Global Style Settings
base_line_width = 2;
thick_line_width = 2.5;
set(groot, 'defaultAxesFontSize', 11);



% FIGURE 1: DEEP DIVE ON FLEET SCENARIOS (EMISSIONS FOCUSED)

fprintf('Generating Figure 1: Scenario Deep Dive...\n');
figure('Name', 'Inter-urban Bus: Analysis of Fleet Scenarios', 'WindowState',
'maximized');
sgtitle('Inter-urban Bus Scenarios: Fleet Evolution and Emissions', 'FontSize',
18, 'FontWeight', 'bold');

% Plot 1.1: Fleet Composition (Delayed)
ax1 = subplot(2,3,1);
fleet_data = results(1).fleet_composition;
BEV=fleet_data(:,2); CNG=fleet_data(:,1); DIESEL=fleet_data(:,13);
area(years, [BEV, CNG, DIESEL]);
colororder(ax1, fleet_colors);
% title('Fleet Composition (Delayed)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
```

```
legend({'BEV', 'CNG', 'Diesel'}, 'Location','northwest'); box on;


% Plot 1.2: Fleet Composition (Base)
ax2 = subplot(2,3,2);
fleet_data = results(2).fleet_composition;
BEV=fleet_data(:,2); CNG=fleet_data(:,1); DIESEL=fleet_data(:,13);
area(years, [BEV, CNG, DIESEL]);
colororder(ax2, fleet_colors);
% title('Fleet Composition (Base)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
box on;


% Plot 1.3: Fleet Composition (Accelerated)
ax3 = subplot(2,3,3);
fleet_data = results(3).fleet_composition;
BEV=fleet_data(:,2); CNG=fleet_data(:,1); DIESEL=fleet_data(:,13);
area(years, [BEV, CNG, DIESEL]);
colororder(ax3, fleet_colors);
% title('Fleet Composition (Accelerated)', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);
box on;


% Plot 1.4: CO2 Emissions
subplot(2,3,4); hold on;
plot(years, results(1).annual_CO2, '--', 'Color', policy_blues(1,:), 'LineWidth',
base_line_width, 'DisplayName', 'Delayed');
plot(years, results(2).annual_CO2, '-', 'Color', policy_blues(2,:), 'LineWidth',
thick_line_width, 'DisplayName', 'Base');
plot(years, results(3).annual_CO2, ':', 'Color', policy_blues(3,:), 'LineWidth',
base_line_width, 'DisplayName', 'Accelerated');
% title('Annual CO₂ Emissions', 'FontWeight', 'normal');
xlabel('Year'); ylabel('Tons/Year');
legend('Location', 'best'); box on; hold off;


% Plot 1.5: NOx Emissions
subplot(2,3,5); hold on;
```

```
plot(years, results(1).annual_NOx, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).annual_NOx, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results(3).annual_NOx, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Annual NOₓ Emissions', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Tons/Year');

legend('Location', 'best'); box on; hold off;


% Plot 1.6: PM Emissions

subplot(2,3,6); hold on;

plot(years, results(1).annual_PM, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).annual_PM, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results(3).annual_PM, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Annual PM Emissions', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Tons/Year');

legend('Location', 'best'); box on; hold off;



% FIGURE 2 & 3: SCENARIO IMPACTS (COST & POWER)


fprintf('Generating Figures 2 & 3: Cost and Power Demand...\n');


%  FIGURE 2: Total Annual Fleet Cost

figure('Name', 'Inter-urban Bus: Total Annual Fleet Cost by Scenario');

hold on;

plot(years, results(1).annual_cost / 1e6, '--', 'Color', policy_blues(1,:), 'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).annual_cost / 1e6, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results(3).annual_cost / 1e6, ':', 'Color', policy_blues(3,:), 'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Total Annual Fleet Cost by Scenario (CAPEX + OPEX)', 'FontSize', 14, 'FontWeight', 'bold');

xlabel('Year'); ylabel('Cost (€ Millions)');
```

```
legend('Location', 'northwest'); box on; hold off;


%  FIGURE 3: Charging Power Demand

figure('Name', 'Inter-urban Bus: Charging Power Demand by Scenario');

hold on;

plot(years, results(1).peak_power_demand_mw, '--', 'Color', policy_blues(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).peak_power_demand_mw, '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results(3).peak_power_demand_mw, ':', 'Color', policy_blues(3,:),
'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Estimated Peak Charging Power Demand by Scenario', 'FontSize', 14,
'FontWeight', 'bold');

xlabel('Year'); ylabel('Peak Power (MW)');

legend('Location', 'northwest'); box on; hold off;



% FIGURE 4: DEEP DIVE ON THE BASE SCENARIO



fprintf('Generating Figure 4: Base Scenario Deep Dive...\n');

figure('Name', 'Inter-urban Bus: Analysis of Base Scenario', 'WindowState',
'maximized');

sgtitle('Inter-urban Bus: Deep Dive on the Base Scenario', 'FontSize', 18,
'FontWeight', 'bold');


% Plot 4.1: Fleet Composition

subplot(2,2,1);

ax_base_fleet = gca;

fleet_data = results(2).fleet_composition;

BEV=fleet_data(:,2); CNG=fleet_data(:,1); DIESEL=fleet_data(:,13);

area(years, [BEV, CNG, DIESEL]);

colororder(ax_base_fleet, fleet_colors);

% title('Fleet Composition (Base)', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Number of Buses'); ylim([0, total_fleet_size*1.1]);

legend({'BEV', 'CNG', 'Diesel'}, 'Location','northwest'); box on;


% Plot 4.2: CO2 Emissions
```

```
subplot(2,2,2);

plot(years, results(2).annual_CO2, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width);

% title('Annual CO₂ Emissions (Base)', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Tons/Year'); box on;


% Plot 4.3: Annual Cost

subplot(2,2,3);

plot(years, results(2).annual_cost / 1e6, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width);

% title('Total Annual Fleet Cost (Base)', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Cost (€ Millions)'); box on;


% Plot 4.4: Power Demand

subplot(2,2,4);

plot(years, results(2).peak_power_demand_mw, '-', 'Color', policy_blues(2,:), 'LineWidth', thick_line_width);

% title('Peak Charging Power Demand (Base)', 'FontWeight', 'normal');

xlabel('Year'); ylabel('Peak Power (MW)'); box on;



% FIGURE 5: STRATEGIC SCENARIO COMPARISON


%

fprintf('Generating Figure 5: Strategic Scenario Comparison...\n');

figure('Name', 'Inter-urban Bus: Strategic Scenario Comparison', 'WindowState', 'maximized');

sgtitle('Inter-urban Bus: Strategic Comparison of Scenarios', 'FontSize', 18, 'FontWeight', 'bold');


% Plot 5.1: BEV Adoption Comparison

subplot(2,1,1);

hold on;

fleet_delayed = results(1).fleet_composition(:,2); % BEV is category 2

fleet_accelerated = results(3).fleet_composition(:,2);

fill([years fliplr(years)], [fleet_delayed' fliplr(fleet_accelerated')], policy_blues(1,:), 'FaceAlpha', 0.3, 'EdgeColor', 'none', 'DisplayName', 'Range (Delayed to Accelerated)');
```

```
plot(years, results(2).fleet_composition(:,2), '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base Scenario');

% title('BEV Adoption Across Scenarios');

xlabel('Year'); ylabel('Number of BEV Buses');

legend('Location', 'northwest'); box on; hold off;


% Plot 5.2: Total Annual Cost Comparison

subplot(2,1,2);

hold on;

plot(years, results(1).annual_cost/1e6, '--', 'Color', policy_blues(1,:),
'LineWidth', base_line_width, 'DisplayName', 'Delayed');

plot(years, results(2).annual_cost/1e6, '-', 'Color', policy_blues(2,:),
'LineWidth', thick_line_width, 'DisplayName', 'Base');

plot(years, results(3).annual_cost/1e6, ':', 'Color', policy_blues(3,:),
'LineWidth', base_line_width, 'DisplayName', 'Accelerated');

% title('Total Annual Fleet Cost Across Scenarios');

xlabel('Year'); ylabel('Cost (€ Millions)');

legend('Location', 'northwest'); box on; hold off;


%%

% FIGURE 6: CUMULATIVE IMPACT COMPARISON (BAR CHARTS)

fprintf('Generating Figure 6: Cumulative Impact Comparison...\n');

figure('Name', 'Inter-urban Bus: Cumulative Impact Comparison', 'WindowState',
'maximized');

sgtitle('Inter-urban Bus: Total Impact Over Simulation Period (2025-2045)',
'FontSize', 18, 'FontWeight', 'bold');


% --- Consolidate Data ---

total_CO2 = [sum(results(1).annual_CO2), sum(results(2).annual_CO2),
sum(results(3).annual_CO2)];

total_NOx = [sum(results(1).annual_NOx), sum(results(2).annual_NOx),
sum(results(3).annual_NOx)];

total_PM  = [sum(results(1).annual_PM), sum(results(2).annual_PM),
sum(results(3).annual_PM)];

total_Cost = [sum(results(1).annual_cost), sum(results(2).annual_cost),
sum(results(3).annual_cost)];


% --- Define shared properties ---

scenario_labels = {'Delayed', 'Base', 'Accelerated'};
```

```
comparison_bar_colors = policy_blues;

add_bar_labels = @(bar_obj, format_str) text(bar_obj.XEndPoints,
bar_obj.YEndPoints, arrayfun(@(v) sprintf(format_str, v), bar_obj.YData,
'UniformOutput', false), 'HorizontalAlignment', 'center', 'VerticalAlignment',
'bottom', 'FontSize', 10);


% --- Plot 6.1: Total CO2 Emissions ---

subplot(2, 2, 1);

b1 = bar(total_CO2/1e3, 'FaceColor', 'flat');

b1.CData = comparison_bar_colors;

% title('Total Cumulative CO_2 Emissions', 'FontWeight', 'normal');

ylabel('Total Tons (Thousands)');

set(gca, 'xticklabel', scenario_labels); box on;

add_bar_labels(b1, '%.1f k');


% --- Plot 6.2: Total NOx Emissions ---

subplot(2, 2, 2);

b2 = bar(total_NOx, 'FaceColor', 'flat');

b2.CData = comparison_bar_colors;

% title('Total Cumulative NO_x Emissions', 'FontWeight', 'normal');

ylabel('Total Tons');

set(gca, 'xticklabel', scenario_labels); box on;

add_bar_labels(b2, '%.1f Tons');


% --- Plot 6.3: Total PM Emissions ---

subplot(2, 2, 3);

b3 = bar(total_PM, 'FaceColor', 'flat');

b3.CData = comparison_bar_colors;

% title('Total Cumulative PM Emissions', 'FontWeight', 'normal');

ylabel('Total Tons');

set(gca, 'xticklabel', scenario_labels); box on;

add_bar_labels(b3, '%.1f Tons');


% --- Plot 6.4: Total Fleet Cost ---

subplot(2, 2, 4);

b4 = bar(total_Cost / 1e9, 'FaceColor', 'flat'); % In Billions

b4.CData = comparison_bar_colors;
```

```
% title('Total Cumulative Fleet Cost', 'FontWeight', 'normal');
ylabel('Total Cost (Billion €)');
set(gca, 'xticklabel', scenario_labels); box on;
add_bar_labels(b4, '€%.1f B');

fprintf('All plots for Inter-urban Bus fleet generated successfully.\n');
```