

Article

Endogenous Modal Shift and Technology Change in Spanish Passenger Transport: A System Dynamics Scenario Analysis to 2050

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Abstract

The decarbonization of passenger transport remains one of the most challenging sectors for climate policy, as supply-side technological solutions alone are insufficient to meet stringent climate targets. This paper presents an extended system dynamics model of the Spanish passenger transport sector, built on the WILLIAM integrated assessment framework, that for the first time endogenizes modal shift, allowing transport mode shares to emerge from the interaction of policy instruments, price signals, and infrastructure provision. Four scenarios are evaluated to 2050: a Baseline, a scenario calibrated to the Spanish National Integrated Energy and Climate Plan (GG-PNIEC), a more ambitious electrification and modal-shift scenario (GG+), and a Decent Living Standards scenario (DLS) combining technological change with deep demand reduction. Relative to 2023, direct CO₂ emissions in 2050 fall by 64% under GG-PNIEC, 75% under GG+, and 84% under DLS. While GG-PNIEC and GG+ deliver substantial reductions through electrification, only DLS approaches deep decarbonization, combining rapid electrification with a reduction of over 55% in light-duty vehicle travel demand relative to the Baseline. These results indicate that technological substitution alone is insufficient, and that sufficiency-oriented demand reduction is decisive for reaching the deepest emission cuts in passenger transport.

Keywords: system dynamics; passenger transport; decarbonization; modal shift; electric vehicles; green growth; sufficiency; decent living standards; scenario analysis; Spain

1. Introduction

Human activities have been releasing greenhouse gases (GHGs) into the atmosphere at an unprecedented pace, driving climate change to levels that now constitute one of the defining challenges of our time. In response, the international community adopted the Paris Agreement in 2015, which commits its signatories to keeping global mean temperature rise well below 2 °C above pre-industrial levels, and to pursue efforts to limit it to 1.5 °C [1]. Achieving these targets requires deep, rapid, and wide-ranging transformations across all sectors of the economy. Among them, the transport sector stands out as one of the most difficult to decarbonize: globally, transport accounts for approximately 16% of total GHG emissions [2], and road transport alone is responsible for roughly three-quarters of those emissions, with passenger vehicles representing the largest single contributor within road transport [3].



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Unlike the power sector, where clean energy alternatives are increasingly cost-competitive and well established, transport continues to be dominated by fossil fuels, and its emissions have grown by nearly 80% since 1990 [2].

The European Union (EU) has positioned itself as a leader in climate action and has set legally binding targets to address this challenge. With the adoption of the European Climate Law on 30 June 2021, the EU committed to achieving climate neutrality by 2050 [4]. As part of the ‘Fit for 55’ package, the EU aims to reduce net GHG emissions by at least 55% by 2030 relative to 1990 levels [5].

Transport, which accounts for around a quarter of total EU GHG emissions—or even up to a third according to some estimates, including non-exhaust and upstream emissions [6,7]—is a critical focus of this effort. Despite decades of policy attention, transport emissions in the EU have shown little overall reduction since 2005, even as other sectors have achieved substantial cuts [7]. Passenger cars continue to dominate, accounting for around 73% of pkm in the EU in 2022 [8], while the share of public transport modes has barely changed over the past two decades [6]. The EU’s Sustainable and Smart Mobility Strategy further calls for a 90% reduction in transport GHG emissions by 2050, the electrification of the vehicle fleet, and tripling the traffic of high-speed rail by 2050 [9].

To advance these goals, the EU has also promoted the expansion of renewable energy use in transport through the revision of Directive (EU) 2018/2001 on renewable energy, which specifically strengthens targets for advanced biofuels and other renewable fuels of non-biological origin [10].

Spain represents a particularly relevant case study within this EU framework. Beyond its regulatory relevance, it offers a demanding empirical test bed for the endogenous framework proposed here: it combines one of Europe’s most extensive high-speed rail networks, whose scale creates a genuine large-capacity alternative to road and short-haul air travel, with a substantial share of domestic air demand serving the Canary and Balearic Islands that cannot be shifted to rail at all, and a national decarbonization target for transport that exceeds the EU’s own minimum obligations. Under the Governance Regulation (EU) 2018/1999, EU member states are required to design National Energy and Climate Plans that include specific measures to reduce transport emissions in line with the EU’s climate objectives [11]. Within the Spanish energy system, transport represents approximately 26% of total GHG emissions, and emissions from this sector grew by 41% between 1990 and the reference year of the plan [12]. The underlying modeling framework, however, is not country-specific: it is implemented as the passenger transport module of the multiregional WILLIAM model, which covers thirty-five world regions [13], and the same equations and calibration procedure described in Section 2 can in principle be recalibrated for any of them given the requisite data; Spain is used here as a detailed first application, chosen for the reasons outlined above and for the availability of granular fleet and mobility data.

Under Spain’s National Integrated Energy and Climate Plan (PNIEC), the country has set ambitious goals for the decarbonization of transport, including a 34% reduction in CO₂ emissions by 2030, 60% by 2040, and 90% by 2050, which significantly exceeds the EU’s minimum obligations. Among the key levers identified in the PNIEC, the plan foresees that 35% of the pkm currently performed in conventional vehicles will shift to non-emitting modes, and targets the deployment of five million electric vehicles—including three million passenger cars—by 2030 [12,14]. Additionally, the plan promotes modal shift towards public transport, the expansion of low-emission zones in urban areas, the penetration of hydrogen, and the adoption of biofuels and biomethane.

The updated PNIEC for 2023–2030 raises the overall GHG reduction target to 32% compared to 1990 levels and introduces new specific actions covering rail, aviation, and

maritime transport for the first time [15]. Beyond the direct GHG emissions from fuel combustion, a comprehensive assessment of the environmental impacts of passenger transport must also account for the full lifecycle of the vehicle fleet: the extraction of raw materials, manufacturing, and eventual disposal of a large stock of vehicles involves substantial material flows, energy use, and additional emissions not captured in tailpipe figures.

Research has increasingly underscored this point, showing that a massive substitution of internal combustion engine vehicles with electric ones—while reducing direct emissions—creates new pressures in terms of critical mineral demand, manufacturing energy, and infrastructure investment [16].

These findings point to the need to complement supply-side measures—which dominate most policy assessments—with demand-side interventions [17,18]. In this context, the concept of sufficiency—understood as policies and practices that avoid unnecessary demand for energy and materials while ensuring wellbeing for all within planetary boundaries [19]—has gained traction as a necessary component of a genuinely sustainable transport transition. Sufficiency in transport encompasses a variety of strategies, including modal shift towards public transport, cycling, and walking, reductions in vehicle ownership, carpooling, teleworking, and trip reduction [20–22].

A broad literature has documented the mitigation potential of these demand-side measures across different regions and methods: combining various behavioral factors has been shown to potentially reduce direct transport CO₂ emissions by approximately 50% by the end of the century compared to a baseline [23]; and in the European context, behavioral changes could contribute more than 20% of the overall GHG reductions required for net-zero by 2050 [24], while also limiting the surge in electricity demand, material requirements, and infrastructure costs that would arise from an exclusively technology-driven electrification strategy. Building on this tradition, the Decent Living Standards (DLS) framework has operationalized the concept of minimum material and energy needs consistent with human wellbeing, enabling the quantification of scenarios in which the global population achieves a good quality of life with far lower resource consumption than current patterns imply [25–28].

A variety of modeling approaches have been developed to this end, each with distinct characteristics and strengths. Among integrated assessment models (IAMs) incorporating a transport sector, most are top-down equilibrium models. These include partial equilibrium models such as IMAGE [29] and TIAM-UCL, as well as general equilibrium models such as, MESSAGE-Transport [30]. The GCAM model, is a dynamic recursive economic model that uses price signals to explore the implications of different policies applied to transport and other sectors [31]. While the models described above have provided important insights into transport decarbonization pathways, each carries inherent limitations: equilibrium frameworks struggle to capture the feedback dynamics and path-dependencies that characterize long-run fleet transitions, while sectoral models often lack links to broader energy and economic systems.

System dynamics (SD) models address these gaps precisely because they represent complex systems through stocks, flows, feedback loops, and time delays, making them especially well-suited to transport policy analysis: they capture the temporal and sectoral interactions—such as the long lags between policy implementation and fleet turnover—and can naturally represent rebound effects that are difficult to incorporate in equilibrium frameworks. SD models have been applied across a broad range of transport problems: Struben and Sterman [32] developed a foundational SD model of alternative fuel vehicle diffusion, capturing how social network effects and complementary infrastructure co-evolve with fleet adoption; and Ghisolfi et al. [33] applied SD to freight decarbonization, showing that combining modal shift with electrification produces the steepest emissions reductions.

In the context of passenger transport decarbonization, Álvarez-Antelo et al. [13] developed a detailed SD model of the Spanish passenger transport sector as part of the multiregional WILLIAM integrated assessment model. That model combines technological change across different powertrains with behavioral measures following the Avoid–Shift–Improve framework, and calculates energy demand, direct emissions, and additional material requirements. However, the modal split between transport modes in that model was treated as an exogenous input, meaning it was imposed as an external scenario assumption rather than being determined endogenously by the dynamics of the model itself. The present article extends this model by endogenizing changes in transport mode shares, allowing modal shift to emerge from the interaction of price signals, infrastructure provision, and policy incentives represented within the model structure. The contribution of this article is threefold. First, it endogenizes modal and powertrain competition jointly: at both levels, shares emerge from pairwise comparisons of relative attractiveness, damped by fleet-renewal inertia and bounded by structural floors and saturation ceilings, rather than following trajectories imposed by the modeler. Second, policy instruments—purchase subsidies, charging-infrastructure deployment and internal-combustion phase-out dates—act on the determinants of choice rather than on its outcome, so that both the magnitude and the timing of their effect become model outputs rather than scenario assumptions; this also closes feedback loops that an exogenous formulation cannot represent, most notably the experience curve, whereby the electric fleet generated by the module raises global accumulated capacity, lowers vehicle prices and thereby further expands the fleet. Third, the resulting framework allows technology-centered and sufficiency-oriented pathways to be assessed consistently within a single model, so that the relative contribution of supply-side and demand-side levers to transport decarbonization can be compared on equal terms. Using this enhanced model, we propose and evaluate alternative scenarios for the Spanish passenger transport sector that go beyond the targets established in the PNIEC [34].

Our scenarios are designed to improve upon the emissions outcomes of the PNIEC baseline while remaining feasible in terms of infrastructure, behavior, and material requirements. The article is structured as follows. Section 2 presents the methodology, including a brief description of the transport model, the endogenization of modal shift, the calibration procedure, and the scenarios simulated. Section 3 presents the results of the scenario analysis. Section 4 discusses the implications of the findings in the context of Spain's climate targets and the broader literature on transport decarbonization. Finally, Section 5 synthesizes the main conclusions.

2. Model and Methods

2.1. The Transport Model

To carry out the research, the transport model presented in Álvarez-Antelo et al. [13] was used, with modifications to endogenize behavioral changes in transport usage. The model is implemented in the system dynamics software Vensim DSS 10.3.4 (Ventana Systems, Inc., Harvard, MA, USA). The general operation of the transport model is as follows:

First, the model receives aggregate passenger transport demand, measured in pkm, as an exogenous scenario input. In the original version of the model this was derived endogenously as a function of GDP; in the version used for this article it is treated as exogenous, which is a deliberate design choice rather than a simplification. Taking total demand directly from the PNIEC anchors the scenarios to the official planning trajectory and keeps their outcomes comparable with Spain's stated targets, whereas deriving it from GDP would make the results contingent on growth assumptions that lie outside the scope of this article. It also isolates the contribution of this work: because total demand follows a common trajectory across the Baseline, GG-PNIEC and GG+ scenarios, the differences

between them are attributable to the endogenous modal and technological response to policy rather than to divergent assumptions about how much people travel. In three of the scenarios total transport demand is therefore as specified by the PNIEC; in the Fourth, the DLS scenario, a substantially lower trajectory is simulated, so that demand itself becomes the variable under test against the same supply-side ambition as GG+.

For clarity, three distinct demand concepts are used throughout the model. Aggregate passenger transport demand refers to the total volume of mobility, expressed in passenger-kilometers, introduced exogenously for each scenario. Allocated passenger transport demand refers to the portion of this aggregate demand assigned endogenously to each mode–powertrain combination through the nested share equations. Satisfied passenger transport demand refers to the portion of the allocated demand that can be provided by the available fleet, given vehicle stocks, occupancy rates, annual mileage, and other capacity constraints; allocated demand may therefore exceed satisfied demand when the required fleet or transport capacity is insufficient.

The aggregate demand for each transport mode and each propulsion technology is then allocated endogenously through the nested share equations. There are 11 transport modes and 10 propulsion technologies, resulting in 110 possible combinations in theory, although many transport modes are incompatible with several of the propulsion technologies.

The transport modes are: light-duty vehicles, buses, two- and three-wheelers, urban rail, conventional rail, high-speed rail, domestic aviation, intra-EU aviation, international aviation, maritime transport, and non-motorized transport. The propulsion technologies are: gasoline engines, diesel engines, LPG engines, natural gas engines, battery-electric vehicles, plug-in hybrid electric vehicles, conventional hybrid vehicles, fuel-cell vehicles, generic electric traction vehicles (e.g., trams and trolleybuses), and human-powered vehicles.

The allocated demand for each mode–powertrain combination is not necessarily fully satisfied. The model compares allocated demand with the maximum transport service that can be supplied by the corresponding vehicle fleet, which depends on the number of available vehicles, their maximum annual mileage, and their maximum occupancy or load factor. When available capacity is lower than allocated demand, only part of that demand is satisfied; the remainder is recorded as unsatisfied demand. Fleet additions respond to allocated demand under normal, rather than maximum, mileage and occupancy conditions, while retirements depend on the average service life of each vehicle category. Energy consumption and emissions are calculated from satisfied—rather than aggregate or allocated—passenger transport demand: for each mode–powertrain combination, satisfied demand is combined with the corresponding energy intensity and emission factors, ensuring that reported energy use and emissions represent transport activity delivered by the available fleet. With the energy demand known, passenger transport emissions can then be estimated, assuming a specific electricity mix and emission factors for each energy type. Figure 1 shows a general schematic of the transport model. For a more detailed description of the model, see Álvarez-Antelo et al. [13].

2.2. The Distribution of Transport Demand

The allocation of total transport demand among transport modes and propulsion technologies is governed by a matrix that determines the proportion each mode–technology combination represents within total transport demand. This matrix evolves endogenously, which constitutes the main improvement of the present model relative to its earlier versions. Its evolution is resolved through a two-level nested structure: the first level determines the change in the relative use of the transport modes (the modal split), and the second level determines, within each mode, the change in the relative use of the competing propulsion technologies.

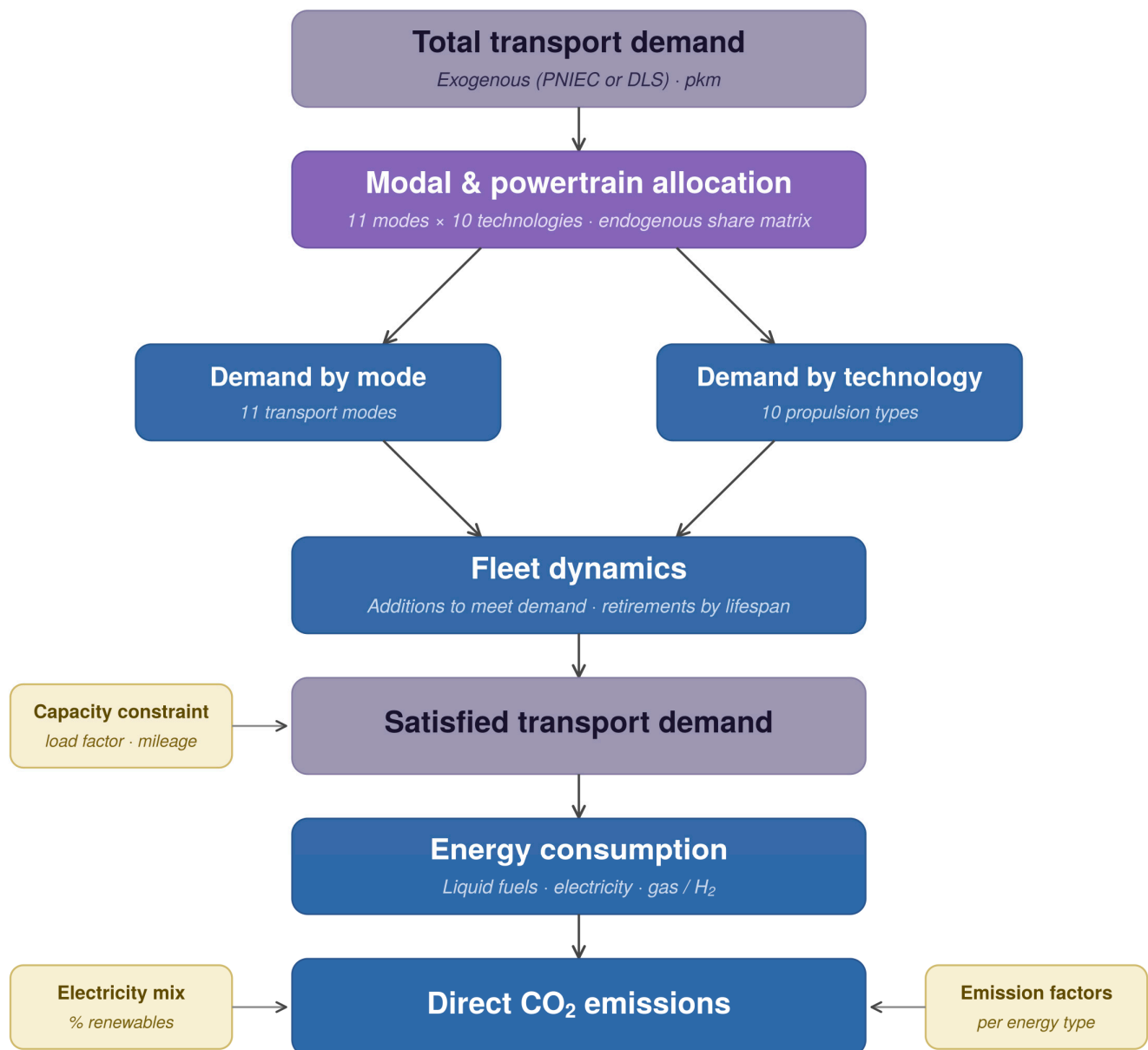


Figure 1. General structure of the passenger transport model. Aggregate passenger transport demand is introduced exogenously, allocated endogenously across modes and powertrains, and subsequently constrained by the available fleet to determine satisfied demand, energy consumption and emissions. Box colours indicate the role of each element in the model: light purple boxes are the aggregate demand variables that open and close the transport chain (the exogenously imposed demand and the demand actually satisfied by the fleet); the dark purple box is the allocation module, the only stage at which modal and powertrain shares are determined endogenously; blue boxes are the variables computed sequentially by the model (demand by mode and by technology, fleet stock, energy consumption and emissions); yellow boxes are exogenous parameters and assumptions provided to the model rather than calculated by it. Arrows indicate the direction of information flow: vertical and diagonal arrows follow the sequential calculation chain, so that the output of each block is the input of the next; horizontal arrows entering from the sides represent exogenous parameters that condition the corresponding step—load factors and annual mileage determine how much of the allocated demand the existing fleet can actually satisfy, while the electricity mix and the energy-specific emission factors convert final energy consumption into direct CO₂ emissions.

Both levels follow the family of dynamic share equations derived from the Future Technology Transformations (FTT) framework and its underlying Lotka–Volterra (replicator)

dynamics [35,36], in which the rate of change of a share depends on the pairwise comparison of the relative attractiveness of the competing options, weighted by the shares already present in the market. The module is fully coupled to a multi-regional master transport model and to an emissions module, exchanging fleet, occupancy, energy-consumption and accumulated-capacity variables, which closes several feedback loops described below. The empirical validity of this formulation is assessed step by step in Section 2.3, which reports goodness-of-fit against historical data for both the calibration period and an out-of-sample validation window.

2.2.1. Share Dynamics

At both levels, the net change in the share of any option results from the balance of inflows from less attractive alternatives and outflows to more attractive ones. For the modal level, the attractiveness differential driving the substitution from mode i to mode j is:

$$A_{ij} = \alpha_i \cdot TC_{ij} + (1 - \alpha_i) \cdot TA_{ij} + (V_j^m - V_i^m) + (P_j^m - P_i^m) \quad (1)$$

where $\alpha_i \in [0, 1]$ is the weight given to the cyclical cost term of mode i ; TC_{ij} and TA_{ij} are, respectively, the cyclical and the absolute cost components of the pairwise comparison, defined in Equations (2) and (3); and V_j^m and P_j^m are the non-pecuniary preference term and the policy effect for the destination mode j , so that their differences $(V_j^m - V_i^m)$ and $(P_j^m - P_i^m)$ capture the net advantage of the destination mode over the origin mode. For most modes, α_i takes the boundary values 0 or 1, so that a single cost signal, either the absolute cost level or its recent trend, dominates the competition; only for high-speed rail and international air, where both signals are jointly informative, was an intermediate value calibrated.

The absolute component captures the structural gap between the total costs of ownership of the two modes:

$$TA_{ij} = \frac{z_{ij}}{1 + |z_{ij}|}, \text{ with } z_{ij} = \lambda^m \cdot \frac{(TCO_i - TCO_j)}{\frac{1}{2} \cdot (TCO_i + TCO_j)} \quad (2)$$

where λ^m is the modal cost-sensitivity parameter and TCO_i is the total cost of ownership of mode i per passenger-kilometer. Normalizing the cost difference by the mean of the two costs makes the comparison symmetric and scale-free, while the algebraic sigmoid bounds TA_{ij} within $(-1, 1)$, so that extreme cost ratios cannot dominate the comparison.

The cyclical component captures instead how each mode's cost is evolving relative to the level that the market perceives as normal:

$$TC_{ij} = \Delta TCO_i - \Delta TCO_j, \text{ with } \Delta TCO_i = (TCO_i - TCO_i^{\text{hist}}) / TCO_i^{\text{hist}} \text{ and } d(TCO_i^{\text{hist}}) / dt = (TCO_i - TCO_i^{\text{hist}}) / \tau \quad (3)$$

where TCO_i^{hist} is an exponentially smoothed memory of past costs with characteristic time τ , representing the period over which consumers retain a historical price level, and ΔTCO_i is the relative deviation of the current cost from that memory. The two components therefore encode complementary signals—how expensive an option currently is (TA_{ij}) and in which direction its cost is moving (TC_{ij})—and α_i sets their relative influence. All divisions are protected against zero denominators. The corresponding share flow from mode i to mode j per unit time is:

$$F_{ij} = \max(0, S_i - S_i^{\min}) \cdot (S_j + \omega_m) \cdot (S_j^{\max} - S_j) \cdot \max(0, A_{ij}) \cdot (1 - \rho_j) \cdot \Phi_{ij} \quad (4)$$

where S_i and S_j are the modal shares of modes i and j ; $S_i^{\min}$ and $S_j^{\max}$ are the structural floor of the origin mode and the ceiling of the destination mode; ω_m is a seeding parameter

that allows near-zero shares to emerge; ρ_j is the inertia parameter of the destination mode, capturing the structural pace of infrastructure and fleet turnover; and $\Phi_{ij} \in \{0, 1\}$ is a feasibility indicator restricting substitution to pairs of modes between which a transfer is physically meaningful. The floor $S_i^{\min}$ ensures that the private car retains a minimum share corresponding to captive mobility not serviceable by public transport. Flows are truncated at zero, so that only net-positive attractiveness differentials generate substitution.

The net rate of change of any modal share is the sum of all inflows from less attractive modes minus all outflows to more attractive ones, integrated at each time step:

$$\frac{dS_i}{dt} = \sum_j F_{ji} - \sum_j F_{ij} \quad (5)$$

An analogous structure governs the evolution of powertrain shares within each mode. The attractiveness differential driving the substitution from technology i to technology k within mode m is:

$$A_{m,ik} = \beta_m \cdot TC_{m,ik} + (1 - \beta_m) \cdot TA_{m,ik} + (V_{m,k}^t - V_{m,i}^t) + (P_{m,k}^t - P_{m,i}^t) \quad (6)$$

where β_m is the weight given to the cyclical cost term at the technological level within mode m ; $TC_{m,ik}$ and $TA_{m,ik}$ are, respectively, the cyclical and the absolute cost components of the pairwise technological comparison, defined as in Equations (2) and (3) with the modal costs replaced by the total cost of ownership of technologies i and k within the mode m , and λ^m by the technological cost-sensitivity parameter λ^t ; and $V_{m,k}^t$ and $P_{m,k}^t$ are the behavioral change term and the policy effect for technology k in mode m . The corresponding share flow is:

$$F_{m,ik} = S_{m,i}^t \cdot (S_{m,k}^t + \omega_t) \cdot (S_{m,k}^{\max} - S_{m,k}^t) \cdot \max(0, A_{m,ik}) \cdot (1 - \rho_{m,k}^t) \cdot \Phi_{m,ik} \quad (7)$$

where $S_{m,i}^t$ and $S_{m,k}^t$ are the shares of technologies i and k within mode m ; $S_{m,k}^{\max}$ is the saturation ceiling of technology k in mode m ; ω_t is the technological seeding parameter; $\rho_{m,k}^t$ is the inertia of the destination technology within mode m , reflecting the pace of vehicle fleet turnover; and $\Phi_{m,ik} \in \{0, 1\}$ is a mode-specific feasibility indicator that restricts substitution to technology pairs that are physically and commercially viable within each mode. Unlike the modal flow equation, the technological flow does not impose a structural floor on the origin technology share, since no powertrain is guaranteed a minimum market presence in the projection.

2.2.2. Cost of Ownership and Endogenous Learning

The pecuniary attractiveness derives from the total cost of ownership (TCO) per passenger-kilometer, aggregating the levelized capital cost of the vehicle, energy costs and, where relevant, dedicated infrastructure costs. Capital costs are levelized over the vehicle service life and the common annual distance of each mode and divided by the average real occupancy of the mode, so that costs per passenger-kilometer are comparable across modes. Two cost components required particular attention. First, the occupancy of each mode was set to its average real load factor rather than its design capacity; using the design capacity of high-speed rail instead of its average occupancy would have artificially depressed its cost per passenger-kilometer. Second, the dedicated high-speed rail infrastructure cost was explicitly internalized at 0.08 euros per passenger-kilometer. Spain's high-speed network has an average construction cost of approximately 17.7 million euros per kilometer and annual maintenance costs of around 150,000 euros per kilometer [37]; amortized over the service life of the civil works and divided by the annual passenger-kilometers carried by the network, this yields an infrastructure cost on the order of 0.08–0.11 euros per passenger-

kilometer, consistent with the low utilization of much of the network. This magnitude is conservative within that range. Unlike buses, which use the shared road network, and aviation, which uses shared airports, high-speed rail requires exclusive, dedicated infrastructure whose construction cost—of the order of 18 million euros per kilometer over a network of approximately 3900 km [37,38] is fully attributable to the mode.

Vehicle capital costs follow an endogenous experience curve in which the price of each vehicle declines as a power function of global accumulated capacity:

$$P = P_0 \left(\frac{C}{C_0} \right)^{-b}, b = -\log_2(1 - LR) \quad (8)$$

where P is the vehicle price, P_0 the reference price, C the global accumulated capacity, C_0 the reference capacity, b the learning exponent, and LR the learning rate per doubling of capacity. The accumulated capacity is computed as the sum of the private and public passenger vehicle fleets across the thirty-five regions of the master model, closing a key feedback loop: the electric fleet generated by the module feeds back through the master model into the global accumulated capacity, which lowers the vehicle price, reduces the TCO, raises attractiveness, and further expands the fleet. Learning rates are set at 8% for battery-electric and 6% for plug-in hybrid vehicles, consistent with full-vehicle estimates in the experience-curve literature [39]; mature internal combustion technologies are assigned a zero learning rate.

2.2.3. Behavioral Change, Recharging Infrastructure and Range Anxiety

The non-pecuniary component of the attractiveness function captures preferences and perceived barriers not reflected in monetary costs. Each term enters additively and carries its own sign, so that effects reducing the appeal of an option are negative—consistent with the sign convention used for the diesel-stigma term, which is negative throughout—while effects increasing appeal are positive. For the technological level, the non-pecuniary effect for technology k in mode m is:

$$V_{m,k}^t = \gamma_{m,k} + R_{m,k} + D_{m,k} \quad (9)$$

where $\gamma_{m,k}$ is the residual preference parameter capturing non-monetary factors such as brand perception or eco-label premiums; $R_{m,k}$ is a recharging or refueling anxiety term (negative for battery-electric and fuel-cell vehicles, zero otherwise); and $D_{m,k}$ is a diesel-perception term (negative for diesel powertrains, ramped from 2015 onwards to capture the post-dieselgate stigma, zero otherwise).

The recharging anxiety term is a decreasing function of an explicit infrastructure level rather than a direct function of the electric-vehicle share. Making anxiety depend directly on the electric-vehicle share would produce an undamped self-reinforcing cycle and would implicitly embed infrastructure policy in the baseline; routing it through an explicit infrastructure level keeps policy-driven deployment as the dominant lever while retaining a moderate, damped market response to adoption [40]:

$$R_{m,BEV} = -R_{m,BEV}^{max} \left[1 - \frac{I}{I + \mu} \right] \quad (10)$$

where $R_{m,BEV}^{max}$ is the maximum anxiety amplitude, I is the normalized recharging-infrastructure level (between 0 and 1), and μ is the saturation parameter defining the infrastructure level at which anxiety is halved. The infrastructure level combines an initial level, a policy-driven deployment component whose annual rate is the main infrastructure

lever distinguishing scenarios, and a moderate market-induced component proportional to the battery-electric share:

$$I = \min(1, I_0 + I_{pol} + I_{mkt}) \quad (11)$$

where I_0 is the initial infrastructure level, I_{pol} the policy-driven deployment component, and I_{mkt} the market-induced component. In the baseline, where the policy deployment rate is low, infrastructure grows slowly, anxiety persists and battery-electric adoption is delayed; in the policy scenarios, accelerated deployment lowers anxiety earlier, bringing the electric take-off forward so that the difference is attributable to the infrastructure lever.

2.2.4. Policy Levers

Policy interventions are represented as levers that remain neutral over the historical period and are activated from their implementation years in the projection scenarios. At the technological level, the policy effect $P_{m,k}^t$ in Equation (6) aggregates three distinct instruments. Purchase subsidies reduce the perceived TCO of target vehicles by a percentage of the sale price, entering the cost component after the learning curve so as not to contaminate the experience curve. Low-emission zone restrictions add a negative attractiveness penalty to internal combustion engine vehicles in the affected share of the fleet. The phase-out of new internal combustion engine vehicle sales is implemented through a prohibition factor, indexed by powertrain and mode, that multiplies the fleet inflow rather than the stock:

$$\Psi_{m,ik} = \Psi_{m,ik}^{post} \cdot \mathbb{1}(t \geq t_m^*) \quad (12)$$

where $\Psi_{m,ik}^{post}$ is the post-prohibition feasibility vector (0 for prohibited powertrains, 1 for permitted ones), and $\mathbb{1}(t \geq t_m^*)$ is the indicator function activating from the prohibition year t_m^* in mode m . This specification captures fleet inertia: vehicles sold before the prohibition continue circulating and emitting for the remainder of their physical service life, so that a sales ban produces gradual rather than immediate decarbonization. The bidimensional indexing by mode and powertrain allows the prohibition to apply to private cars while leaving other modes on their own calendars.

At the modal level, the policy effect P_j^m in Equation (1) captures instruments that alter the relative attractiveness of modes: investments in public transport frequency and coverage (positive for bus and rail), urban access restrictions on private cars (negative for light-duty vehicles), and road pricing. The private-car floor S_i^{min} is allowed to relax under strong modal-shift policy through a captive-mobility reduction factor that represents the share of car-dependent mobility rendered serviceable by improved public transport.

2.3. Data and Calibration

The behavioral parameters of the nested share equations were calibrated against historical data for Spain over the period 2000–2019, with the subsequent years 2020–2023 retained as an out-of-sample validation window. Historical modal and technological shares were drawn from the JRC-IDEES 2021 database [41] for the period up to 2021; the series was extended to 2023 using data from the Spanish Observatory of Transport and Logistics [42], specifically the online statistical database [43] and the Annual Report 2022 [42]. Energy-consumption intensities by mode and powertrain (MJ/km) were also drawn from JRC-IDEES 2021. Vehicle capital costs (CAPEX) for emerging powertrain technologies were taken from the supplementary material of Khalili et al. [44], which provides technology-specific cost trajectories to 2050. Fuel and energy prices were sourced from three complementary datasets: weekly retail fuel prices from the European Commission's Weekly Oil Bulletin [45], electricity prices from Eurostat [46], and natural gas and other energy carrier prices from MITECO [15]. Calibration used the Powell conjugate-direction

algorithm implemented in Vensim with multiple random restarts, minimizing a payoff defined between simulated and observed modal and technological shares. For the projection of the policy scenarios, the model is re-initialized at the year 2023, taken as the base year and initialized with the observed shares and fleet stocks; the scenarios therefore share an identical base-year state and diverge only through the activation of their respective policy levers.

2.3.1. Calibration Strategy

The calibration process followed the model's hierarchical structure, moving sequentially from the modal level, down to the technological level, and finally to the non-pecuniary preference parameters.

Throughout this process, a key methodological rule was established: before behavioral parameters were estimated, the monetary-cost calculations were verified to prevent preference parameters from compensating for inconsistencies in the TCO formulation. If a behavioral parameter hit the upper or lower limit of its acceptable range, it usually indicated an underlying error in the calculated Total Cost of Ownership (TCO) that the parameter was artificially trying to compensate.

To structure the process, parameters were grouped into four categories based on their function:

- Level parameters (e.g., preferences and anxiety factors): Shift market shares and remain active during future projections.
- Speed parameters (e.g., substitution rates and cost sensitivities): Determine how quickly the system responds to changes.
- Timing parameters (e.g., take-off years and saturation midpoints): Define the timeline of technology adoption.
- Limit parameters (e.g., ceilings and floors): Set the maximum and minimum market bounds.

Finally, seeding parameters—used to initialize new technologies starting from near-zero shares—were treated as technical rather than behavioral inputs. Once the initial historical emergence pattern was successfully reproduced, these parameters were fixed and excluded from further calibration. The principal calibrated values are reported in Table A1 (Appendix A).

2.3.2. Technology Calibration

The three emerging powertrains (battery-electric, plug-in hybrid, and hybrid) required particular care during calibration, as their small historical shares make them highly sensitive to seeding and cost specifications. For instance, the effective energy price of plug-in hybrids was computed using a 30/70 electricity-to-gasoline utility-factor balance rather than relying on the electricity price alone. This calibration is consistent with real-world data on PHEV charging behavior in Europe, where private owners typically drive roughly one-third of their kilometers on electricity [47].

Furthermore, non-pecuniary preference parameters and their signs were structurally set to reflect observed adoption drivers and barriers. Attributes increasing a powertrain's appeal entered the attractiveness function with positive signs, such as the preference for hybrids (capturing their eco-label premium and commercial success in Spain), whereas plug-in hybrids received a near-zero preference reflecting their limited real-world uptake [48]. Conversely, barriers to adoption were modeled with negative signs to appropriately reduce market appeal. This included a diesel-perception term, ramped up from 2015 to capture the post-Dieselgate stigma, and a range-anxiety term for battery-electric vehicles. Modeled as a structural deterrent representing recharging limitations, the range-anxiety parameter

enters the function negatively, with its amplitude calibrated to 0.20 to accurately capture its braking effect on early electric vehicle adoption.

2.3.3. Vehicle Prices and the Endogenous Learning Curve

Initially, using a fixed, outdated price for battery-electric vehicles without a learning curve produced unrealistic results: diesel dominated until 2050, and electric vehicles never took off because their Total Cost of Ownership (TCO) remained higher than gasoline.

Activating the learning curve resolved this issue. By setting an 8% learning rate for the vehicle—driven by global accumulated capacity from the master model—the electric TCO drops below gasoline in the 2030s. This allows electric vehicles to gain market share gradually as they become economically competitive.

These reference prices and learning rates align with existing literature. Additionally, modeling technological learning as a global, rather than national, process reflects that local vehicle prices are driven by international market trends.

2.3.4. Goodness of Fit

Goodness of fit was assessed with three complementary metrics: the root-mean-square error (RMSE), which is the optimization payoff and measures the typical error in share units; the Theil inequality coefficient (U), bounded between zero and one, which is well-suited to dynamic simulation; and the coefficient of determination (R^2). The metrics were computed separately for the calibration period (2000–2019), in which the parameters were fitted, and for the out-of-sample validation period (2020–2023). Tables 1 and 2 report the modal and technological results, respectively.

Table 1. Modal-split goodness of fit, by mode and pooled across modes, for calibration period (Cal.) and validation period (Val.).

Mode	RMSE Cal.	Theil U Cal.	RMSE Val.	Theil U Val.
Light-duty vehicles	0.018	0.016	0.089	0.083
Buses	0.024	0.134	0.041	0.262
Two/three-wheelers	0.004	0.074	0.014	0.203
Urban rail	0.002	0.075	0.001	0.053
Conventional rail	0.012	0.203	0.012	0.202
High-speed rail	0.017	0.354	0.049	0.636
Domestic aviation	0.004	0.052	0.007	0.095
Intra-EU aviation	0.047	0.166	0.061	0.220
International aviation	0.022	0.205	0.033	0.290
Maritime	0.003	0.225	0.002	0.189
Non-motorized	0.012	0.135	0.036	0.341
Pooled (all modes)	0.020	0.056	0.041	0.119
Pooled R^2	0.983	—	0.932	—

Two interpretive caveats apply. First, the RMSE is the appropriate metric here, whereas the Theil coefficient and the per-series R^2 are uninformative for shares of very low variance or near-zero magnitude: when an observed share is nearly constant or close to zero, these relative metrics penalize any deviation disproportionately and can take extreme values despite a negligible absolute error—the error of the fuel-cell share, for example, is below 0.0013 in share units. For this reason, the R^2 is reported only in pooled form, where it is high (0.983 and 0.999 in calibration for the modal and technological levels, and 0.932 and 0.997 in validation), indicating a close aggregate correspondence between simulated and observed modal and technological shares over the periods considered. The mature, high-share technologies that dominate the fleet—diesel and gasoline—attain excellent fits (Theil U of 0.008 and 0.024 in calibration).

Table 2. Light-duty-vehicle technological goodness of fit. * Theil U and R^2 are not informative for shares of near-zero magnitude and are omitted for those technologies (indicated as n/a), for calibration period (Cal.) and validation period (Val.).

Technology (LDV)	RMSE Cal.	Theil U Cal.	RMSE Val.	Theil U Val.
ICE gasoline	0.0150	0.024	0.0221	0.051
ICE diesel	0.0115	0.008	0.0281	0.018
ICE LPG	0.0013	0.518	0.0051	0.927
ICE natural gas	0.0088	0.936	0.0004	0.203
Battery-electric	0.0003	n/a *	0.0034	n/a *
Plug-in hybrid	0.0002	0.444	0.0032	n/a *
Hybrid	0.0005	0.131	0.0038	0.167
Fuel-cell	0.0000	—	0.0013	n/a *
Pooled (all techs)	0.0074	0.014	0.0129	0.023
Pooled R^2	0.999	—	0.997	—

Second, the larger validation errors reflect two identifiable factors rather than a failure of the model. At the modal level, the 2020–2023 window encompasses the COVID-19 shock, which abruptly distorted the modal split—the car share rose sharply while aviation collapsed during the lockdowns—a transient that a model calibrated on pre-pandemic trends neither reproduces nor is intended to. At the technological level, the model is deliberately conservative in early electric adoption: the observed battery-electric and plug-in hybrid shares accelerate over 2020–2023 faster than the calibrated trend, an acceleration driven by purchase-incentive programs and price reductions postdating the calibration period. This conservative baseline behavior underpins the role of policy levers in the scenarios, which are precisely what bring forward the electric transition relative to the unaided baseline.

2.3.5. Structural Constraints and Limitations

Modal and technological shares were bounded by ceilings and floors reflecting structural limits derived from historical maxima and literature. The private-car floor represents captive mobility not serviceable by public transport; following the correction of the high-speed rail cost, the car no longer reaches this floor in the baseline, leaving natural headroom for modal-shift policy. Bus shares in passenger-kilometers were capped consistently with the observation that, even under high public-transport integration, the bus mode rarely exceeds 18–20% of passenger-kilometers, with the bulk of any modal shift accruing to rail.

Two limitations are acknowledged. The residual preference terms of the hybrid and plug-in hybrid technologies reached their calibration bounds, indicating that they absorb part of the uncertainty in the cost specification of these transition technologies; their effect on aggregate 2050 emissions is nonetheless limited, as the hybrid acts as a bridge technology whose share declines once battery-electric vehicles become competitive. In addition, the re-initialization of the model at the 2023 base year, rather than a continuous run from the start of the historical period, may introduce minor adjustment transients in the first projection years; the analysis therefore emphasizes medium- and long-term trends and the differences between scenarios, which are robust to this effect, rather than the absolute values of the earliest projection years.

2.4. Scenarios

The model is used to simulate four scenarios that explore contrasting pathways for the decarbonization of Spanish passenger transport towards 2050. All four share the same calibrated model structure, the same 2023 base-year state, and the same underlying behavioral parameters; they are distinguished solely by the policy measures introduced,

by their intensity and timing, and—in the most ambitious case—by the level of transport demand itself.

The scenarios are constructed cumulatively, each building on the previous one and adding a further layer of intervention, so that they span a gradient of increasing ambition.

Taken together, the scenarios allow two complementary decarbonization logics to be examined: a technology- and supply-driven transition, progressively intensified across the first three scenarios, and a demand-side or sufficiency-driven transition introduced in the fourth.

2.4.1. Baseline (BAU) Scenario

Starting from the calibrated model (cf. Section 2.3 Data and calibration), the BAU scenario is parametrized with the following assumptions, such as fuel and vehicle price trajectories (by transport mode and powertrain) based on the IEA Stated Policies Scenario (STEPS), a negative non-pecuniary attractiveness term for diesel powertrains reflecting the post-dieselgate stigma, and CO₂eq emission intensity factor for electricity following current trends.

2.4.2. GG-PNIEC Scenario

This scenario builds on the BAU scenario but introduces additional policy measures. The scenario is inspired by the objectives established in the Spanish National Energy and Climate Plan (PNIEC) for 2030 [15]. These targets are implemented up to 2030, after which the model is allowed to evolve endogenously until 2050. Economic growth and population projections are taken from the PNIEC and used to estimate passenger transport demand, expressed in pkm. The model is then parametrized to align with the PNIEC targets for passenger transport, mainly those related to EV fleet deployment. To achieve these targets, the scenario incorporates policy measures such as subsidies for EV purchases (15% on the sale price) and deployment of charge infrastructure. Moreover, regarding the decarbonization of electricity generation, and in line with a net-zero emissions objective by 2050, an exogenous CO₂eq emission intensity factor for electricity is introduced to estimate the indirect emissions associated with electricity consumption. This factor follows a linear trajectory from current values to zero emissions by 2050, representing a more ambitious decarbonization pathway than that implied by current trends.

2.4.3. GG+ Scenario

This scenario represents a more ambitious sustainable transport pathway, in which EVs and public transport play a more prominent role than in the previous scenarios. Building on the GG-PNIEC scenario, it assumes stronger policy support for modal shift towards public transport, particularly buses and rail, together with higher subsidies for EV purchases (30% on the sale price) and a more extensive deployment of charging infrastructure. In addition, the scenario assumes that the production of ICE passenger cars is prohibited from 2035 onwards. The scenario also includes an energy-efficiency improvement measure across several passenger transport modes: buses by 3%, 2W_3W by 28%, rail by 3%, aviation by 25%, and maritime by 9%, taking the Current Policies scenario (CPS) from WEO 2025 as a reference [49]. Finally, the decarbonization of electricity generation is assumed to occur more rapidly than in the GG-PNIEC scenario, with the CO₂eq emission intensity factor reaching zero by 2035.

2.4.4. DLS Scenario

This scenario operationalizes the Decent Living Standards (DLS) framework for passenger transport and can therefore also be interpreted as a “sufficiency” scenario consistent with a de-/post-growth narrative [18,50,51]. In this case, 2050 passenger transport demand,

expressed in pkm, follows the levels derived from Millward-Hopkins et al. [28]. Their approach defines pkm per capita as a function of adjusted population density, combining constrained levels of private and air travel with ambitious reliance on non-motorized modes and public transport (see SI of [28] for details). To ensure comparability with the other scenarios, supply-side assumptions, including efficiency improvements and powertrain shares, are kept consistent with the GG+ scenario. Moreover, the scenario includes an additional sustainable mobility measure that promotes a higher occupancy for passenger cars, thereby increasing load factors to a target of 1.5 passengers per vehicle. It should be noted that the resulting emissions reductions in this scenario reflect both the sufficiency-oriented demand reduction in the DLS framework and the supply-side technology assumptions carried over from GG+, and therefore cannot be attributed exclusively to the demand-side component.

3. Results

This section presents the simulation results of the four scenarios considered. From 2024 onwards, the scenarios begin to diverge according to their respective policy assumptions. Results are shown for the full period 2015–2050; in all figures, the dashed vertical line in 2023 separates the historical record (shaded in grey) from the forward simulation.

3.1. Evolution of Passenger Transport Demand by Mode of Transport

The modal distribution of passenger transport—expressed in billions of pkm per year—shows markedly different trajectories across scenarios after 2024, reflecting the degree of policy intervention assumed in each case. In the historical period, light-duty vehicles (LDVs) were the dominant mode, accounting for roughly 355 billion pkm in 2015, while rail contributed only about 25 billion pkm.

In both the Baseline and GG-PNIEC scenarios, the modal structure remains largely unchanged over the projection period (Figure 2). LDVs continue to account for approximately 260 billion pkm per year by 2050, a figure only marginally below the 2015 level, while rail grows steadily from around 53 billion pkm in 2025 to approximately 154 billion pkm by 2050, driven by planned investments in high-speed rail. Air travel declines moderately from a post-pandemic peak of around 232 billion pkm in 2025 to roughly 118 billion pkm by 2050, as improved rail connectivity displaces demand on medium-distance corridors. The near-identical modal outcomes in these two scenarios indicate that the PNIEC measures, as modeled here, do not induce significant shifts in the overall distribution of travel demand; their primary effect is the electrification of the vehicle fleet rather than a recomposition of travel behavior.

A more substantial modal shift emerges under GG+: LDV demand falls to approximately 157 billion pkm by 2050—nearly half the Baseline value—while rail increases to about 216 billion pkm and bus services expand to around 92 billion pkm. The GG+ scenario thus combines electrification with a meaningful redistribution of travel across modes, leading to a modestly lower total motorized mobility volume than the Baseline (approximately 614 billion pkm versus 637 billion pkm by 2050).

The DLS scenario produces the most radical reorganization of mobility. LDV travel declines sharply from around 326 billion pkm in 2025 to approximately 117 billion pkm by 2050, a reduction of over 55% relative to the Baseline scenario and around 64% relative to its own 2025 peak. Rail demand also contracts under this scenario, falling from approximately 38 billion pkm in 2025 to around 16 billion pkm by 2050, as the strong overall reduction in long-distance travel affects rail disproportionately relative to shorter-distance modes. The total DLS demand in 2050 reaches approximately 284 billion pkm, less than half the Baseline level, with buses (around 46 billion pkm) and motorcycles (around 35 billion pkm)

assuming a relatively larger role as locally accessible modes. Air travel is similarly curtailed (approximately 69 billion pkm by 2050), and maritime transport becomes negligible.

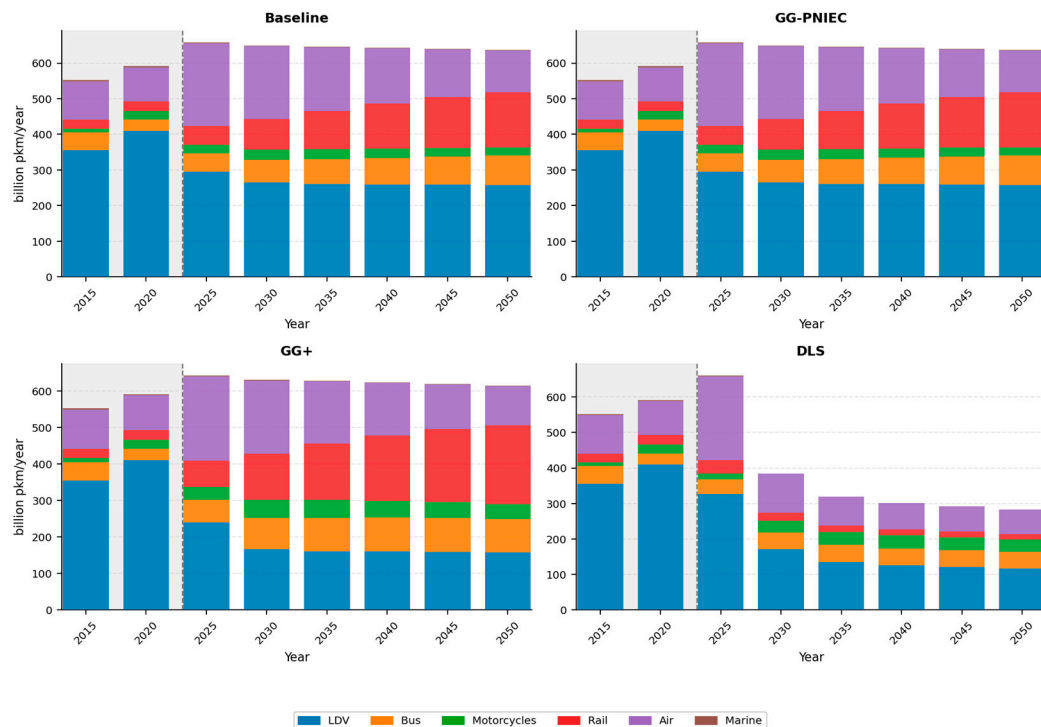


Figure 2. Passenger transport demand by mode of transport across the four scenarios (billion pkm/year), 2015–2050. The grey shaded area corresponds to historical data (as opposed to simulated data), with the dashed line indicating the final year of historical observations.

3.2. Evolution of LDV Power Train Composition

The composition of the light-duty vehicle fleet by powertrain technology evolves substantially in all scenarios, driven by progressive electrification. Because the four scenarios differ not only in fleet composition but also in total fleet size, powertrain shares are expressed as percentages of the total LDV stock in each scenario to enable meaningful comparison (Figure 3). In 2015, the fleet was almost entirely ICE-based, with diesel vehicles accounting for roughly 65% and gasoline vehicles for approximately 34% of the total. BEVs and PHEVs together represented a negligible fraction below 0.5%.

In the Baseline scenario, ICE vehicles retain a dominant share throughout much of the projection period: diesel vehicles account for around 41% and gasoline vehicles for around 9% of the fleet in 2050, with BEVs reaching approximately 47%. The transition is gradual, with a meaningful BEV share not emerging until after 2030. Under GG-PNIEC, electrification accelerates markedly: BEVs rise from a share of roughly 3% in 2025 to approximately 73% of the total LDV fleet by 2050, consistent with the PNIEC targets for electric vehicle deployment. The combined ICE share (gasoline + diesel) falls to around 26% by 2050, reflecting that a substantial legacy fleet of conventional vehicles persists even under ambitious policy conditions.

The GG+ scenario produces a broadly similar BEV share to GG-PNIEC by 2050 (approximately 88%), but on a much smaller absolute fleet, meaning that the number of ICE vehicles in circulation is reduced far more dramatically. ICE vehicles (gasoline + diesel) fall to a combined share of around 12% by 2050. The DLS scenario is distinctive: BEVs reach approximately 87% of a drastically reduced fleet by 2050, with ICE vehicles accounting for around 12%.

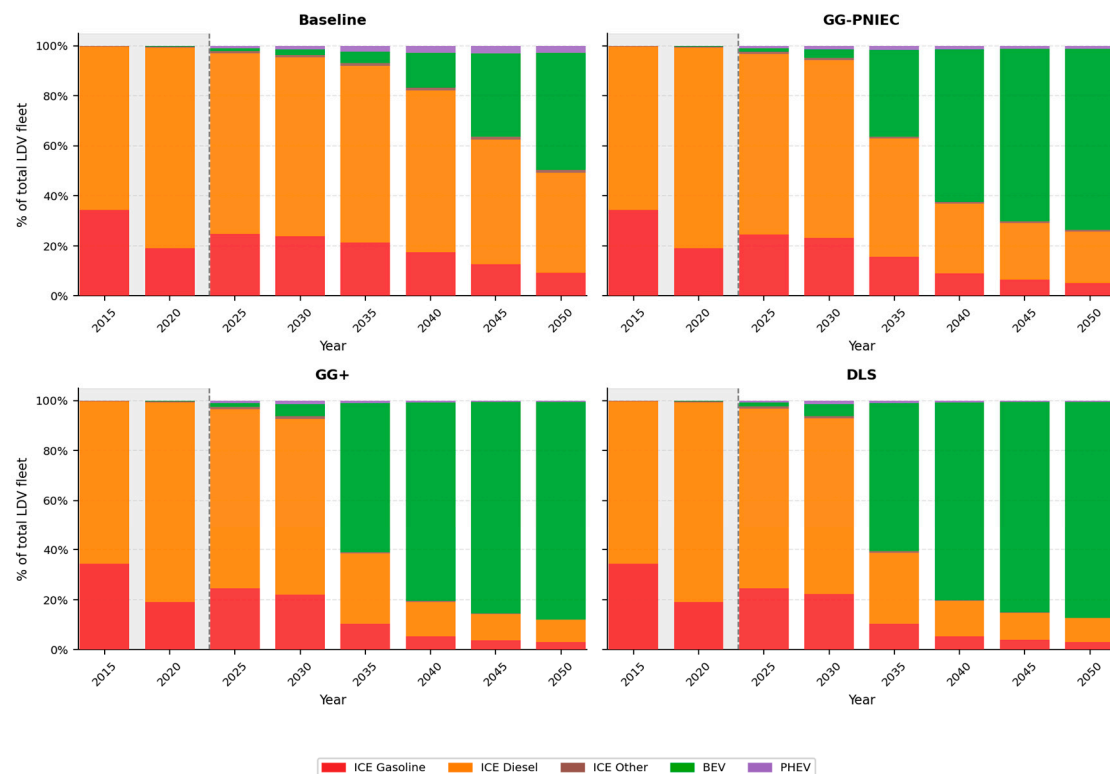


Figure 3. LDV fleet composition by powertrain technology as a share of total LDVs across the four scenarios (%), 2015–2050. ICE Other includes LPG, CNG, and conventional hybrid vehicles; PHEV: plug-in hybrid electric vehicle; BEV: battery-electric vehicle. The grey shaded area corresponds to historical data (as opposed to simulated data), with the dashed line indicating the final year of historical observations.

3.3. Evolution of Energy Consumption

Total energy consumption by the passenger transport sector reflects two opposing forces in all scenarios: the growth or stabilization of mobility demand on one hand, and progressive fleet electrification and efficiency improvements on the other (Figure 4). The historical record shows relatively stable total consumption of approximately 1.0–1.3 EJ/year between 2015 and 2019, with liquid fuels (gasoline and diesel) accounting for the dominant share. The post-pandemic rebound temporarily raised consumption in 2020–2021.

In the Baseline scenario, total energy demand evolves from approximately 1.2 EJ in 2023 towards around 1.0 EJ by 2050, as a slowly declining liquid fuel share is partially offset by rising electricity consumption. The GG-PNIEC scenario shows a more marked shift: liquid fuels fall to approximately 0.87 EJ in 2030 and continue declining to around 0.43 EJ by 2050, while electricity surges to roughly 146 PJ. The electrification dividend—reflecting the superior energy efficiency of electric drivetrains—produces a net decrease in total energy demand despite broadly stable transport volumes.

Under GG+, liquid fuels decline even more steeply, reaching approximately 0.27 EJ by 2050. Electricity peaks above 152 PJ by 2050, while hydrogen/gas consumption reaches around 22 PJ in the early 2030s before declining as BEVs consolidate as the dominant technology. The DLS scenario exhibits a qualitatively distinct pattern. The sharp contraction in LDV use causes liquid fuel demand to collapse after 2025, falling from approximately 1.0 EJ to around 0.42 EJ by 2030 and below 0.17 EJ by 2050. Electricity demand is comparatively low—peaking at only about 39 PJ by 2050—because the much smaller vehicle fleet performs far fewer total vehicle-kilometers. Total sectoral energy demand in 2050 is estimated at approximately 0.22 EJ, less than one-fifth of the Baseline projection.

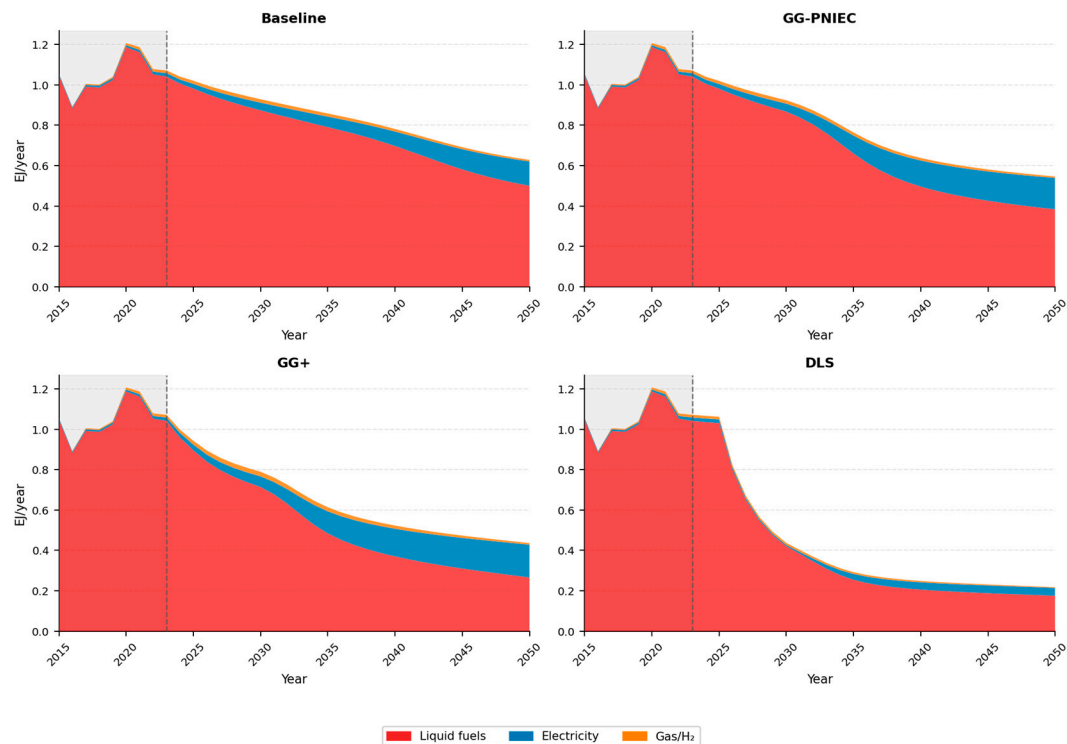


Figure 4. Total energy consumption of the passenger transport fleet by energy carrier across the four scenarios (EJ/year), 2015–2050. Electricity and gas/hydrogen values have been converted from PJ to EJ for comparability. The grey shaded area corresponds to historical data (as opposed to simulated data), with the dashed line indicating the final year of historical observations.

3.4. Evolution of Direct CO₂ Emissions

Direct CO₂ emissions from passenger transport follow sharply divergent trajectories across the four scenarios after 2024, driven by the combined effect of fleet electrification, modal shift, and changes in total travel demand (Figure 5). The historical period shows relatively stable emissions of approximately 75–78 Mt CO₂/year between 2015 and 2019, interrupted by the pandemic-related dip in 2020 and a rebound in 2021. All scenarios share an estimated value of approximately 77.5 Mt CO₂/year in 2023.

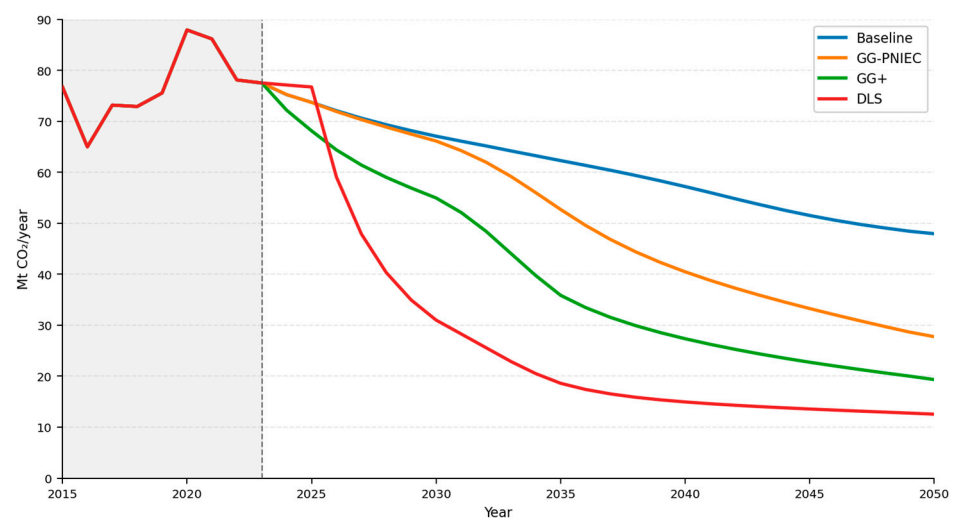


Figure 5. Direct CO₂ emissions from the passenger transport sector under the four scenarios (Mt CO₂/year), 2015–2050. The grey shaded area corresponds to historical data with the dashed line indicating the final year of historical observations.

In the Baseline scenario, emissions decline modestly from 77.5 Mt in 2023 to approximately 67 Mt in 2030 and around 48 Mt by 2050, a reduction of roughly 38% over the full period. This trajectory is too slow to meet Spain's sectoral climate goals, as it implies that more than 50 Mt CO₂/year would still be emitted in the early 2040s. The GG-PNIEC scenario achieves a considerably steeper decline: emissions reach approximately 66 Mt by 2030, broadly in line with the PNIEC's 2030 target, and continue falling to around 28 Mt by 2050, a cumulative reduction of 64% from 2023.

GG+ delivers faster and deeper decarbonization, with emissions falling to approximately 55 Mt by 2030 and around 19 Mt by 2050—a reduction of 75% from 2023. The acceleration relative to GG-PNIEC reflects both faster fleet electrification and the partial modal shift that reduces total motorized passenger-kilometers. The DLS scenario produces by far the most ambitious trajectory: driven by sharp demand reduction, rapid electrification, and lower aviation activity, emissions fall from 77.5 Mt in 2023 to approximately 31 Mt by 2030 (a reduction of 60% between 2023 and 2030, far exceeding the PNIEC 2030 target) and continue declining to around 13 Mt by 2050, representing a cumulative reduction of 84% from 2023 levels. The DLS scenario is the only one in which the emissions trajectory approaches levels compatible with deep decarbonization of the transport sector by mid-century.

4. Discussion

Across the four scenarios, the results reveal a consistent structural pattern. In GG-PNIEC and GG+, decarbonization relative to the Baseline is achieved predominantly through technological substitution—a shift in powertrain composition and, correspondingly, in the energy carriers consumed—while the underlying modal structure of demand changes comparatively little. The DLS scenario departs from this pattern: a substantial share of its emissions reduction stems from a restructuring of demand itself—lower travel volumes and a shift toward less energy-intensive modes—rather than from powertrain substitution alone, even though it shares the same technological ambition as GG+.

The results of the GG-PNIEC scenario show that a policy framework aligned with the current Spanish National Integrated Energy and Climate Plan can deliver a significant reduction in direct CO₂ emissions from passenger transport compared to the Baseline. This reduction is driven mainly by the electrification of the light-duty vehicle fleet, supported by purchase subsidies for electric vehicles, the deployment of public charging infrastructure, and fleet emission standards. By 2050, direct CO₂ emissions fall by 64% relative to 2023—a considerable reduction compared to the Baseline, but still well below the 90% target set by the PNIEC for transport by 2050. This gap suggests that the policy levers represented in GG-PNIEC, while broadly aligned with the plan's stated 2030 ambition, are not sufficient on their own to deliver on its longer-term goal, and that achieving the full PNIEC target would require either a faster pace of fleet electrification or complementary demand-side measures. Purchase subsidies have been shown to generate sizeable increases in EV uptake in multiple national contexts [52–54], and the availability of charging infrastructure is consistently identified as a key driver of adoption decisions [55,56]. The EU's original 2035 target of zero average tailpipe emissions for new cars—recently revised to a 90% reduction target, with some room for ICE vehicles running on synthetic e-fuels or biofuels [57]—has similarly been shown to have the potential to drive substantial fleet turnover and emissions reductions [58]. However, the effectiveness of fleet electrification in reducing total lifecycle CO₂ emissions is critically dependent on the parallel decarbonization of the electricity mix.

The GG+ scenario illustrates that deeper emissions reductions are attainable within the same technology-centered paradigm by intensifying the policy instruments already present in the PNIEC. This additional ambition, at the cost of a more demanding policy

effort, translates into faster EV deployment (reaching approximately 88% of the LDV fleet by 2050), more extensive charging infrastructure roll-out, stronger modal shift towards rail on medium-distance routes (LDV demand falling to around 157 billion pkm by 2050 versus 260 billion pkm in the Baseline), and a more accelerated phase-out of ICE vehicles. Countries that electrify their transport systems ahead of their grids risk achieving only modest net emissions reductions in the near term [59,60].

Despite the strong emissions reduction in the GG+ scenario, the supply-side approach it embodies carries a significant material cost. The rapid replacement of ICE vehicles with BEVs requires the production of tens of millions of new electric vehicles, each demanding substantial quantities of critical minerals—including lithium, cobalt, nickel, manganese, and copper—whose extraction and processing generate their own environmental and social pressures. Pulido-Sánchez et al. [61] quantified these requirements specifically for transport electrification, showing that a full transition of the global LDV fleet to BEVs entails cumulative material demands for lithium and cobalt that approach or exceed known reserves at current extraction rates. Xu et al. [62] similarly document that deploying EVs at 40–100% penetration by 2050 in 48 major countries can increase lithium demand by 2900–17,500% relative to 2020. The DLS scenario is distinctive precisely in its capacity to reconcile deep emissions reductions with a lower material footprint. By substantially reducing the total volume of motorized travel demand and by simultaneously increasing the load factor of existing vehicles, the DLS scenario achieves a drastically smaller fleet (approximately 10 million LDVs by 2050 versus around 21 million in GG-PNIEC). This means that fleet electrification in the DLS context demands a far smaller quantity of new vehicles and therefore a substantially lower material throughput, even as the BEV share of the remaining fleet approaches 87%. Fulton et al. [63] and Mattioli et al. [22] emphasize that the energy sufficiency dimension of transport transitions is systematically underweighted in mainstream policy assessments, and that combining supply-side technology change with meaningful demand reduction is indispensable for meeting stringent carbon budgets without displacing the problem upstream into material supply chains.

The depth of the behavioral transformation assumed in the DLS scenario—a reduction of over 55% in LDV travel demand by 2050 relative to the Baseline, alongside significant curtailment of aviation—presupposes a high degree of public engagement and societal willingness that goes well beyond the ambition of current transport policies. Road pricing and congestion charges have demonstrated capacity to reduce private vehicle use and shift trips to public transport, with co-benefits in terms of reduced urban air pollution and congestion [64]. Parking management—including parking restrictions, higher charges, and the conversion of parking spaces to cycling or pedestrian infrastructure—is consistently identified as one of the most effective deterrents against car use in urban environments [65,66]. Low-emission zones, already promoted in the Spanish PNIEC, can catalyze modal shift by restricting access for polluting vehicles, as demonstrated by the London ULEZ (Ultra-Low Emission Zone) experience. Improvements to public transport quality, frequency, and affordability—whether through subsidy or reduced fares—can also generate measurable modal shift, though the evidence suggests these ‘pull’ measures are most effective when combined with ‘push’ disincentives to car use, as illustrated by Germany’s 2022 9-Euro ticket experiment [48], which attracted new users but achieved no lasting shift absent complementary demand-management policies [67,68]. Urban space reallocation—such as Barcelona’s superblocks program, which systematically closes streets to vehicular traffic and redirects them to pedestrian and cycling use—represents a more structurally disruptive intervention that has shown initial improvements in key environmental and health indicators [67]. Land-use planning that reduces car dependence through mixed-use, transit-oriented development also plays an important role over longer time horizons [22]. Taken

together, the literature suggests that achieving the degree of demand reduction implied by the DLS scenario requires a coherent, mutually reinforcing package of regulatory, fiscal, and infrastructural measures, rather than individual instruments in isolation [69].

The present study is subject to several modeling limitations that point to important directions for future work. First, while the model calculates direct tailpipe CO₂ emissions from fuel combustion, it does not currently account for the energy consumption and embedded emissions associated with the manufacturing of new vehicles. The production of passenger vehicles—particularly BEVs, whose batteries are especially energy-intensive to manufacture—constitutes a significant upstream emission source that can amount to 30–60% of the total lifecycle emissions of an electric car [61,70]. Integrating a module for manufacturing energy and material flows into future versions of the model would enable a more comprehensive assessment of the environmental cost of different fleet transition pathways, including the material requirements for batteries highlighted above. Second, the current model focuses exclusively on CO₂ emissions, whereas passenger transport gives rise to a broader range of greenhouse gases and air pollutants whose dynamics differ significantly from CO₂. Third, and relatedly, the study does not address non-exhaust emissions, which are becoming an increasingly important fraction of transport-related particulate pollution as exhaust standards improve. Tire and road wear now accounts for more than 90% of road transport PM emissions in scenarios of high electrification, as exhaust contributions fall below 10% of the total [71,72]; brake wear, tire wear microplastics, and road dust resuspension affect all vehicle types regardless of powertrain. Electric vehicles reduce brake wear through regenerative braking but may generate greater tire wear due to their higher curb weight [73], and the net effect on PM exposures is scenario-dependent.

5. Conclusions

This study has presented and evaluated four scenarios for the evolution of the Spanish passenger transport sector up to 2050 using a system dynamics model that, for the first time, endogenizes modal and technological competition within an integrated assessment framework. Whereas most transport modules of IAMs—including the earlier version of the present model—impose modal and powertrain shares as exogenous trajectories, and least-cost or discrete-choice formulations derive them under assumptions of full rationality and instantaneous market clearing, here shares emerge from pairwise comparisons of relative attractiveness—combining the total cost of ownership, its evolution against the market's price memory, non-pecuniary preferences, and policy effects—damped by fleet-renewal inertia and bounded by structural floors and saturation ceilings. The scenario comparison yields a clear ordering. Under a continuation of current trends, the Baseline delivers only a modest decline in direct CO₂ emissions by 2050, falling far short of Spain's climate commitments. The trajectory implied by current PNIEC targets roughly doubles that reduction, driven primarily by the rapid electrification of the LDV fleet, and the GG+ scenario deepens it further through stronger regulatory standards, more extensive charging infrastructure, and faster fleet renewal. The comparative lesson, however, is that these gains scale with the pace of fleet transformation—and with it the demand for critical minerals and embodied energy, a trade-off that grows monotonically across the technology-centered pathways.

The DLS scenario shows that a fundamentally different approach—combining the technological ambition of GG+ with a substantial reduction in total motorized travel demand through behavioral change—achieves the deepest decarbonization of the four pathways while simultaneously limiting the material throughput required by the transition. It is the only scenario that improves on GG+ in both dimensions at once and the only one approaching levels compatible with the deep decarbonization of the sector by mid-

century, breaking the trade-off that constrains the purely technology-centered pathways. It is also the most demanding to implement, requiring a sustained and coherent package of fiscal, regulatory, and spatial-planning policies capable of reshaping travel habits on a societal scale.

These findings are addressed, first, to the policymakers, transport planners, and government agencies responsible for designing and sequencing decarbonization policy—in Spain and in other car-dependent economies confronting the same structural dilemma—and they carry four direct implications for practice.

These comparisons carry direct implications for policymakers, transport planners, and government agencies. First, the gap between the GG+ and DLS scenarios shows that fleet electrification and stronger regulatory standards, however ambitious, are unlikely on their own to close the distance to Spain's long-term decarbonization targets; demand-side and sufficiency-oriented measures are not an optional complement but a necessary component of any credible pathway. Second, because battery-electric uptake in the model is bounded by charging-infrastructure deployment through the range-anxiety mechanism, planners should treat infrastructure roll-out as a precondition for, rather than a consequence of, purchase incentives: subsidies introduced ahead of adequate charging coverage are likely to under-deliver, while early infrastructure investment compounds through the positive feedback it creates with adoption. Third, the timing of internal-combustion phase-out policies should be set with fleet-renewal inertia explicitly in mind, since vehicles sold before a ban continue to operate and emit for years afterward. Finally, because the underlying model represents these responses endogenously, it can serve as a decision-support tool to test the sequencing and combination of specific instruments before committing them.

Beyond this policy audience, the study is addressed to the integrated-assessment and transport-modeling community, for whom the endogenous treatment of modal and technological competition demonstrated here offers a transferable alternative to the exogenous share trajectories still common in the transport modules of most IAMs. For this community, four directions define the next stage of the research. The first is to couple the model with a manufacturing module that captures the embodied energy and critical-material requirements of fleet renewal—the upstream burden that the technology-centered pathways displace rather than avoid. The second is to widen its environmental scope beyond direct CO₂ to other greenhouse gases and to non-exhaust particulate emissions, which come to dominate transport-related air pollution as fleets electrify. The third is to apply the same endogenous framework to the other regions represented in WILIAM, testing whether the primacy of demand-side sufficiency found for Spain holds across different mobility cultures, settlement patterns, and income levels. The fourth is to incorporate the substitution of fossil liquid fuels by low-carbon alternatives—hydrogen, biofuels, and e-fuels—which the present scenarios do not yet contemplate: the entire aircraft fleet continues to run on fossil kerosene, the conventional diesel rail fleet does not transition to alternative fuels, and a share of the light-duty vehicle, bus, and motorcycle fleets remains on fossil liquid fuels. Representing these pathways would extend mitigation to the segments that are hardest to electrify and allow their competition with electrification and demand reduction to be assessed directly.

In the same spirit of candor as the analysis itself, the central message admits little qualification. Technological substitution alone—however rapid the electrification and however strong the regulatory push—is insufficient to bring passenger transport into line with mid-century climate targets. The deepest cuts require a deliberate and sustained reduction in motorized travel demand: a sufficiency-oriented transformation that is socially and politically demanding yet, on the evidence presented here, unavoidable. This is

not a uniquely Spanish finding but a structural feature of car-dependent economies, and confronting it openly is the precondition for any credible decarbonization of the sector.

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Abbreviations

The following abbreviations are used in this manuscript:

BAU	Business-as-Usual
BEV	Battery-Electric Vehicle
CNG	Compressed Natural Gas
CO ₂	Carbon Dioxide
COVID-19	Coronavirus Disease 2019
CPS	Current Policies Scenario
DESIRE	Decent living gaps in Energy and emISSIONS ScEnARios (model name)
DLS	Decent Living Standards
EEA	European Environment Agency
EJ	Exajoule
EMEP	European Monitoring and Evaluation Programme
EU	European Union
EV	Electric Vehicle
FCEV	Fuel-Cell Electric Vehicle
FTT	Future Technology Transformations
GCAM	Global Change Assessment Model
GDP	Gross Domestic Product
GEM-E3T	General Equilibrium Model for Energy–Economy–Environment–Transport
GG	Green Growth
GG-PNIEC	Green Growth scenario aligned with the National Energy and Climate Plan
GG+	Green Growth Plus (enhanced modal-shift scenario)
GHG	Greenhouse Gas
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IEA	International Energy Agency
IES	Institute for Environmental Studies
IMACLIM	Integrated Model for Assessment of the CLIMate
IMAGE	Integrated Model to Assess the Global Environment
IPCC	Intergovernmental Panel on Climate Change

ITDP	Institute for Transportation and Development Policy
LDV	Light-Duty Vehicle
LPG	Liquefied Petroleum Gas
LR	Learning Rate
MARS	Metropolitan Activity Relocation Simulator
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact
PBL	PBL Netherlands Environmental Assessment Agency
PHEV	Plug-in Hybrid Electric Vehicle
PJ	Petajoule
PM	Particulate Matter
PNIEC	Plan Nacional Integrado de Energía y Clima (Spanish National Integrated Energy and Climate Plan)
RFF-CMCC	Resources for the Future—Centro Euro-Mediterraneo sui Cambiamenti Climatici
RMSE	Root-Mean-Square Error
SD	System Dynamics
TCO	Total Cost of Ownership
TIAM-UCL	TIMES Integrated Assessment Model—University College London
TRIMODE	Tri-modal transport model for Europe
UKTCM	United Kingdom Transport Carbon Model
ULEZ	Ultra-Low Emission Zone
WEO	World Energy Outlook
WILIAM	Within Limits Integrated Assessment Model
WITCH	World Induced Technical Change Hybrid model

Appendix A

Table A1. Principal calibrated parameters (light-duty vehicle nest).

Symbol	Parameter	Range	Value	Units	Role/Interpretation
β^m [LDV]	Weight of the cyclical term	[0, 1]	0.2278	—	Convex weight between TC and TA within the LDV nest (Equation (6))
λ^t	Technological cost sensitivity	[0.1, 50]	50	—	Sigmoid slope inside TA for LDV powertrains (Equation (2), adapted)
τ	Price memory time	[3, 8] years	3.67	years	Retention time of a historical LDV price level (Equation (3), reused at technological level)
ω_t	Seeding parameter	$[1 \times 10^{-5}, 0.005]$	0.005	—	Allows near-zero LDV powertrain shares to emerge (Equation (7))
$S_{m,k}^{\max}$	Saturation ceiling	fixed (structural)	0.8	—	Maximum attainable share of any single LDV powertrain
γ [HEV]	Residual preference	[0, 0.5]	0.50	—	Hybrid eco-label premium (+)
γ [PHEV]	Residual preference	[0, 0.002]	0.002	—	Plug-in hybrid residual (≈ 0)
γ [BEV]	Residual preference	[0, 0.3]	0.30	—	Battery-electric residual (+)
—	Diesel perception intensity	[0, 0.5]	0.50	—	Post-dieselgate stigma amplitude (—)
—	Diesel stigma ramp duration	n/a	4	years	Ramp onset from 2015
$R^{\max}$ [BEV]	Max. recharging anxiety	[0, 0.2]	0.20	—	Range-anxiety amplitude, battery-electric
$R^{\max}$ [FCEV]	Max. refueling anxiety	[0, 1]	0	—	No anxiety penalty (refueling time comparable to ICE)

Table A1. Cont.

Symbol	Parameter	Range	Value	Units	Role/Interpretation
μ [BEV]	Infrastructure saturation midpoint	[0, 1]	0.20	—	Infra. level halving BEV anxiety
μ [FCEV]	Infrastructure saturation midpoint	[0.02, 0.5]	0.1	—	Infra. level halving FCEV anxiety
I_0	Initial infrastructure level	[0, 1]	0.05	—	Base-year (2015) charging-infrastructure level
—	Market charging factor	n/a	0.30	—	Market-induced infrastructure weight (Equation (11))
LR [BEV]	Learning rate	[0, 1)	0.08	—	Per capacity doubling (Equation (6))
LR [PHEV]	Learning rate	[0, 1)	0.06	—	
LR [HEV]	Learning rate	[0, 1)	0.03	—	
LR [FCEV]	Learning rate	[0, 1)	0.12	—	
LR [ICE ¹]	Learning rate	—	0	—	Mature technologies; no learning effect

¹ ICE: gasoline, diesel, LPG, and gas internal-combustion powertrains. n/a: not applicable (no range was applied to these parameters).

Table A2. Mode-dependent parameters.

Mode	α_i (Modal)	β_m (Tech.)	ρ_j (Inertia, Modal)	$\rho_{m,k}$ (Inertia, Tech.)	$S_i^{\min}$
Light-duty vehicles	0	0.2278	0.8	0.5	0.43
Buses	0	0.3	0.464857	0.5	0.12
Two/three-wheelers	1	0.3	0	0.5	0
Urban rail	1	0.3	0	0.5	0
Conventional rail	1	0.3	0.664597	0.5	0
High-speed rail	0.764843	0.3	0	0.5	0
Domestic aviation	1	0.3	0	0.5	0
Intra-EU aviation	1	0.3	0.8	0.5	0
International aviation	0.860875	0.3	0.790328	0.5	0
Maritime	0	0.3	0.8	0.5	0
Non-motorized	1	0.3	0	0.5	0

Note: three additional structural parameters are constant across all modes and are therefore reported here rather than repeated for each row: the modal cost sensitivity $\lambda^m = 15$ (the modal-level counterpart of λ^t in Table A1), the modal seeding parameter $\omega_m = 0.05$, and the modal saturation ceiling $S_j^{\max} = 0.8$. The technological saturation ceiling $S_{m,k}^{\max} = 0.8$ is likewise constant across all modes and is reported once in Table A1 for the LDV nest. $S_i^{\min} = 0$ by default for modes without a declared structural floor. The admissible calibration ranges for the mode-dependent parameters shown above are: $\alpha_i \in [0, 1]$; $\beta_m \in [0, 1]$; ρ_j (modal inertia) $\in [0, 0.8]$; and $\lambda^m = 15$ within a declared range of [0.5, 15]. Unlike the parameters above, $\rho_{m,k}$ (technological inertia) is not itself a free calibrated constant: as detailed in Section 2.2.1, it is derived from a mode-specific structural inertia anchored to fleet turnover and a technology-maturity factor calibrated by family (mature, transitional, emerging), bounded within [0, 0.8]. The value of 0.5 reported here is the resulting point value for the LDV nest and should be read as illustrative of this mechanism rather than as a uniform free parameter.

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