Backcasting of Transport Electrification and Efficiency Policies Through Optimal Control

Dr. Vinith Lakshmanan*, Xavier Guichet, and Antonio Sciarretta

IFP Energies nouvelles, France

Short summary

This study presents a backcasting approach applied to the decarbonization of the passenger car fleet in Metropolitan France. Three policy measures are considered, namely, EV purchase incentive, Malus CO_2, and eco-driving (ED) incentives. Through a forecasting model, their impacts are separately evaluated in terms of market shares and emissions.
An optimal control problem is then formulated to determine the combined policy trajectory that minimizes monetary cost and reach a defined CO_2 target. A Pareto front is evaluated, along which costs to achieve lower CO_2 targets increase.
The results suggest that EV incentives should decrease over time and be inversely proportional to the income class, the Malus CO_2 should be kept for a longer time at its maximum value, while the more effective ED incentive should cover as much population as possible.
Keywords: Backcasting, Transport systems, Policy making, Environmental Impacts

1 Introduction

Governance and policies play an important role in shaping transport systems of the future, especially towards decarbonization. Transport modeling and planning encompass various approaches with different objectives. Traditional methods typically follow a "predict-and-provide" paradigm, which assesses the impacts of predefined policy scenarios using transport models (Bibri & Krogstie (2019); ITF (2019)).
More recently, transport planning is shifting towards vision-led approaches such as Backcasting (Robinson (1982); Bibri & Krogstie (2019)). This method first defines a desirable future vision or targets and then works backward to identify the policies necessary to achieve them (International Transport Forum (2025)). It has been mainly deployed qualitatively (Papazikou et al. (2020)), while only a few quantitative studies exist (Gomi et al. (2011); Ashina et al. (2012); Nakamura et al. (2012); Wen et al. (2017)). However, they typically rely on predefined policy combinations or static optimization. Moreover, policies considered are not actionable measures, and the transport models used lacks explicit system dynamics, limiting their ability to capture the temporal evolution of the system.
This study illustrates the backcasting approach using an optimal control framework. The model describes the evolution of the passenger car fleet within a certain region, and is coupled with an environment model to determine its impacts on the CO_2 emissions. It relies on exogenous inputs such as travel demand, among others, and the policy measures as control inputs. Previous studies have examined individual policies, including EV purcahse incentive policy (Lakshmanan et al. (2025)), optimal low-emission zones scheduling (Alami et al. (2025)), and the deployment of shared autonomous vehicles (Héraud et al. (2025)). Building on this line of work, this paper jointly optimizes multi-policy measures, namely, Electric Vehicles (EV) purchase incentive policy, CO_2 malus policy, and Eco-Driving (ED) policy, to achieve a desired target CO_2.
An EV purchase incentive policy is a governmental initiative designed to accelerate EV adoption by subsidizing its purchase cost. An example of one such initiative is the *coup de pouce véhicules particuliers électriques* put in place by the French government in July 2025, providing monetary aid across three income classes (Ministère de l'Économie et des Finances (2025)).
The CO_2 malus is an ecological tax applied to passenger vehicles at the time of purchase, based on their homologated CO_2 emissions (Service Public (2026)). It is implemented to discourage people from buying high emitting vehicles, and increases with increasing emission levels becoming more stringent over time.

The eco-driving (ED) policy encourages drivers to adopt energy-efficient driving behaviors through two main types of guidance: static and dynamic (Tu et al. (2022)). Static guidance includes training delivered via courses or videos, often based on the "Golden Rules" (ECOWILL Project Consortium (2013)), such as maintaining steady speeds, anticipating traffic, shifting gears early, etc. An example is the Quality Alliance Eco-Drive campaign in Switzerland, which attracted over 8,000 participants (Quality Alliance Eco-Drive (2024)). Dynamic guidance provides real-time or post-trip feedback, either through in-trip recommendations via eco-driving advisory systems (EDAS) (Lakshmanan et al. (2024)) or through post-trip analysis using mobile applications (Guillemin et al. (2015)). A comprehensive review of these approaches is provided in Tu et al. (2022).
The remainder of the paper is as follows: Section 2 describes the modeling of the car fleet and environment model, and three policy measures considered. Section 3 describes a forecasting case study with reference scenarios, followed by backcasting illustration in Sect. 4. The concluding remarks are presented in Sect. 5.

2 Modeling

Car Fleet Model

The demand of new vehicles at year t, $N(t)$, is given by the difference between the total vehicle demand, the ratio of the total transport demand $G(t)$ to the mileage $M(t)$, and the sum of the old vehicles disaggregated by vehicle type and age $O_{va}(t)$,

$$N(t) = \frac{G(t)}{M(t)} - \sum_{va} O_{va}(t). \tag{1}$$

The latter is obtained using the age-dependant survival rate η_a and the stock by vehicle type and age $S_{va}(t)$ as

$$O_{va}(t) = \begin{cases} \eta_a S_{v,a-1}(t-1) & \forall a = 1, \ldots, A-1 \\ \eta_A S_{v,A-1}(t-1) + \eta_A S_{vA}(t-1). \end{cases} \tag{2}$$

The subscripts $a \in \{0, \ldots, 30\}$ and $v \in \{1,2\}$ denote the vehicle age-class and type thermal ($v = 1$), electric ($v = 2$), respectively.
The yearly total sales are split among income classes, $l \in 1, 2, 3$, according to

$$N_l(t) = N(t) \frac{\pi_l \omega_l}{\sum_{l'} \pi_{l'} \omega_{l'}} \tag{3}$$

where π_l and ω_l represent the population percentage and average car ownership distinguished by income class, and are assumed constant over time. The sales by vehicle type in each income class at year t is given by

$$N_{lv}(t) = N_l(t) P_{lv}(t), \tag{4}$$

where $P_{lv}(t)$ is the share of sales by income class and veh-type.
The latter is obtained from a logit expression

$$P_{lv}(t) = \frac{e^{\mu U_{lv}(t)}}{\sum_{v'} e^{\mu U_{lv'}(t)}}, \tag{5}$$

where U_{lv} is the utility function by income class and veh-type, and is given by

$$U_{lv}(t) = (1 - c_v^A(t)) \left(\frac{\bar{i}}{i_l} p^P \left(\frac{C_v^P(t) - u_{lv}^I(t) + u_v^M(t)}{\bar{C}^P(t)} \right) + p^O \left(\frac{C_v^O(t)}{\bar{C}^O(t)} \right) + p^I (1 - c_v^I(t)) \right). \tag{6}$$

The utility function considers $U_{lv}(t)$ different technical-economic characteristics of the vehicles such as purchase costs $C_v^P(t)$, operating costs $C_v^O(t)$(i.e., fuel/energy, maintenance, insurance costs), and the development rate of the refilling (fuel/electricity) infrastructure $c_v^I(t)$ which reflects its availability. The average costs between the two vehicles types are given by $\overline{C}^P(t)$ and $\overline{C}^O(t)$. The socio-economic determinants are introduced through an adoption coefficient $c_v^A(t)$ to better model the penetration of new technologies (McManus & Senter (2009); Struben & Sterman (2008)) such as EVs. The latter is a probability density function based on the Bass model (Bass (1969)).
The parameters p^P, p^O, and p^I, calibrated from observed data, represent the sensitivity of the utility function with respect to purchase cost, operational cost, and development rate of the refilling

infrastructure, respectively. The parameter p^P is scaled with the normalized average income $\bar{i}/i_l$, where i_l represents the average income in each class l and $\bar{i} = \sum_l \pi_l i_l$ represents the weighted average income across all classes. This scaling accounts for heterogeneity in purchasing power across different income classes, implying that lower income classes exhibit greater sensitivity to purchase cost relative to higher income classes. The characteristics of the different income classes considered are detailed in Table 1.

Table 1: Characteristics of the income classes considered.

Income class l	1	2	3
Average annual household income i_l (€)	≤ 27160	21760–41500	≥ 41500
Population percentage $\pi_l(\%)$	60	30	10
Average vehicle ownership per household ω_l (veh)	1.4	1.63	1.7

The evolution of vehicle stock by vehicle type and age, S_{va} at year t, is given by

$$S_{va}(t) = \begin{cases} \sum_l N_{lv}(t) & a = 0 \\ O_{va}(t) & a \geq 1 \end{cases} . \tag{7}$$

Environment Model

Tailpipe CO_2 emissions are described by simple emission factors differentiated by vehicle type and age $\epsilon_{va}(t)$ (g/km), since vehicles produced in a certain year have to comply with the emission regulations in force that year, and emissions reduction as a result of eco-driving. The annual emissions of the stock is given by the equation

$$E(t) = M \left(\sum_a \epsilon_{va}(t)\, S_{va}(t) - x_v(t)\, \epsilon_v(t)\, \Delta\epsilon \right) \tag{8}$$

where $\epsilon_{va}(t)$ represents the emission factor, $M(t)$ represents the annual mileage, ϵ_v is the weighted average of the emission factor

$$\epsilon_v(t) = \frac{\sum_a \epsilon_{va}(t) S_{va}(t)}{\sum_a S_{va}(t)}, \tag{9}$$

$\Delta\epsilon$ represents the percentage of emissions reduction as a result of eco-driving, and $x_v(t)$ represents the number of eco-drivers disaggregated by vehicle type v. This disaggregation is performed proportionally to the stock of each vehicle type and reads

$$x_v(t) = x(t) \frac{S_v(t)}{S(t)}. \tag{10}$$

Consequently, the cumulative emissions of the stock are evaluated as

$$\mathcal{E}(t) = \mathcal{E}(t-1) + E(t). \tag{11}$$

EV Purchase Incentive Policy

The EV purchase incentive policy $u^I_{l2}(t)$ provides a monetary incentive to encourage the purchase of an electric vehicle. This policy is incorporated into the fleet model through the utility function (6) by effectively reducing the purchase price of the vehicle. The incentive is differentiated across income classes l and is assumed to remain fixed over a period of four years to introduce a policy stability . Since the monetary incentive applies only for EVs, we define $u^I_{l1}(t) \equiv 0$. The annual costs associated to the EV purchase incentive policy is given as

$$C^I(t) = \sum_{l2} u^I_{l2}(t) N_2(t) (1 + \tau^s)^{-t}, \tag{12}$$

where τ^s is the discount rate, applied for the state, used to express future expenditures in present year terms.

CO_2 Malus Policy

The CO_2 malus policy $u_v^M(t)$ is an ecological penalty set up to discourage the purchase of high CO_2 emitting vehicles. The amount of the tax depends on the vehicle's tail-pipe CO_2 emissions, and is paid by the customer at the time of registering the vehicle. Consequently, the malus is incorporated in equation (6) as a surcharge to the purchase cost of the vehicle. Since EV tail-pipe emissions are considered zero, we define $u_2^M(t) \equiv 0$. The annual costs associated to the CO_2 malus policy is given as

$$C^M(t) = u_1^M(t) N_1(t)(1+\tau^p)^{-t}, \tag{13}$$

where τ^p is the discount rate, applied to the citizens, used to express future expenditures in present year terms.

Eco-Driving Policy

The number of eco-drivers, x_r, at time t is modeled as a discrete-time first-order linear equation that incorporates training and forgetting effects. The subscript r distinguishes the two training methods, course ($r = 1$) and edas ($r = 2$). The evolution of eco-drivers is given as

$$x_r(t) = (1-\gamma)\, x_r(t-1) + \eta_r n_r(t) \tag{14}$$

where $\gamma \in [0,1]$ represents the forgetting factor, capturing the rate at which drivers lose their eco-driving behavior over time, η_r denotes method's effectiveness, and $n_r(t)$ denotes the number of trained drivers for method r at time t. The total number of trained drivers n at time t depends on fraction $u^{ED}(t)$ of non-eco drivers who are selected for training, and is given by

$$n(t) = u^{ED}(t)\big(D - x(t)\big) \tag{15}$$

where D is maximum number of vehicles concerned, and $x(t) = \sum_r x_r(t)$ is the total eco-drivers at time t. The total trained drivers at time t is further disaggregated by their training methods through the proportion undertaking each method R_r, and reads

$$n_r(t) = R_r n(t). \tag{16}$$

The yearly cost $C_r(t)$ associated with implementing the eco-driving policy for each training method includes a fixed cost c_r^0 and a variable trainee dependent cost c_r^p. The fixed cost includes expenses such as the development of training materials, as well as the design, deployment, and maintenance of edas applications. The variable cost is proportional to the number of drivers trained, $n_r(t)$, and captures the per-trainee expenses, such as instructor time, facility use, or application fees. The total annual cost C^{ED} is therefore given as

$$C^{ED}(t) = \sum_r C_r(t) = (c_{0,r} + c_{p,r} n_r(t))(1+\tau^s)^{-t}. \tag{17}$$

The cost is assumed to be zero when the eco-driving policy is not active, i.e., $C_r(t) = 0$ in the absence of the policy.

3 Study Case

This section describes a case study applied to Metropolitan France. The analysis considers a time horizon from $t_0 = 2022$ to $T = 2050$, with a one year time step. A forecasting analysis is carried out for four reference policy scenarios, namely, Business as Usual, EV purchase incentive policy, CO_2 malus policy, and ED policy. Their impacts are evaluated in terms of emissions, evolution of vehicle sales by technology, and the associated costs over the time horizon. Prior to these analyses, the various exogenous inputs and the calibration of the model parameters are discussed.

Model Parameters and Exogenous Inputs

The parameters and exogenous inputs for the car fleet and environmental model presented in Lakshmanan et al. (2025) are adopted in this study. Moreover, to align the model with since observed data in emissions, total new vehicle sales, and EV market share (Service des Données et Études Statistiques (SDES) (2025)):

- The emission factor ϵ_{10} is offset by 20 gCO_2/km with respect to the values presented in ADEME (2025); CITEPA (2025).
- The parameters of the Bass diffusion model are adjusted to $p = 0.12$ and $q = 0.43$.
- The survival rate η_a decreases with vehicle age at a rate of 0.009 y^{-1}.
- The infrastructure coefficient $c_2^I(t)$ is calibrated to the median charging station deployment scenario presented in Enedis (2026). This coefficient, ranging from 0 to 1, represents an index of perceived charging infrastructure availability, where 0 corresponds to no availability and 1 to optimal coverage.
- The travel demand $G(t)$ and the annual mileage $M(t)$ are taken from Ministère de la Transition Écologique (2019). The former increases gradually from 481 Gvkm in 2022 to 488 Gvkm in 2050, and the latter is a constant set to 12,429 km/y.

Table 2 summarizes the parameters used in the eco-driving model. A fixed ratio R_r of one in ten trainees is assumed to receive training through the course-based method. The forgetting parameter (γ) is calibrated based on the empirical findings from Barla et al. (2017), which indicate that fuel efficiency gains in urban driving conditions are reduced by approximately half within ten months following eco-driving training. An average gain of 10% fuel efficiency, as a result of eco-driving and applied across both training methods, is used in this study. The value is obtained from Lakshmanan & Sciarretta (in press), which reports fuel efficiency improvements ranging from 1% to 16% under real-time traffic conditions using edas. The corresponding reduction in emissions, $\Delta\epsilon$, is assumed to be proportional to the fuel efficiency gains. In addition, we took tentative values for cost and efficiency.

Table 2: Eco-driving model parameters.

Parameter	courses	app
R_r	0.1	0.9
$c_{0,r}$ (k€/y)	30	100
$c_{p,r}$ (€/p)	50	3
η_r	1	0.2
γ	0.58	
$\Delta\epsilon$	0.1	
D	38 Mdrivers	

Forecasting: Reference scenarios

Business-as-usual (BaU) scenario: A business-as-usual (BaU) scenario represents a forecast of future outcomes assuming no new policies or interventions are introduced. In this context, the evolution of vehicle sales and stock, and emissions are obtained by setting $u_{lv}^I \equiv u_v^M \equiv u^{ED}(t) \equiv 0$. Figure 1 (left) shows the evolution of vehicle sales share by type over time. In the absence of any interventions, the forecast of EV sales is monotonically increasing and its market share is projected to reach 41% in 2030 and 81% in 2050. In contrast, the share of thermal vehicles declines monotonically, with a parity point occurring around 2032. Figure 1 (right) shows the corresponding decrease in annual CO_2 emissions. The BaU scenario results in cumulative emissions $\mathcal{E}(T) = 1.177$ Gt.

Reference EV Purchase Incentive Policy ($\mathcal{I}$): The reference scenario for the EV purchase incentive policy assumes a constant subsidy of 5 k€ per EV purchase across all three income classes over the period 2026-2050. For the earlier period 2022–2025, the incentive is set at 3 k€ to align with observed EV sales trends. Accordingly, this corresponds to $u_{l2}^I(2022\text{–}2025) = 3000$ and $u_{l2}^I(2026\text{–}2050) = 5000$, for all $l \in [1, 2, 3]$. All other policy instruments are assumed to be inactive, i.e., $u_v^M \equiv 0$ and $P \equiv 0$.

Figure 2 (left) shows the reference incentive policy and its associated discounted annual costs. The latter initially rises with increasing EV sales, but eventually declines as the discount factor reduces the present value of future expenditures. As a result of the EV purchase incentive Policy, the EV market share, shown in Fig. 2 (right), is higher with respect to the BaU, with a projected share of 48% in 2030 and 83% in 2050. Correspondingly, the thermal market share is lower with the parity point advanced to 2030. The $\mathcal{I}$ scenario results in final cumulative emissions $\mathcal{E}(T) = 1.128$ Gt, total cost $C^I = 106.2$ B€, and the abatement costs with respect to BaU as 1.0 k€/tCO_2.

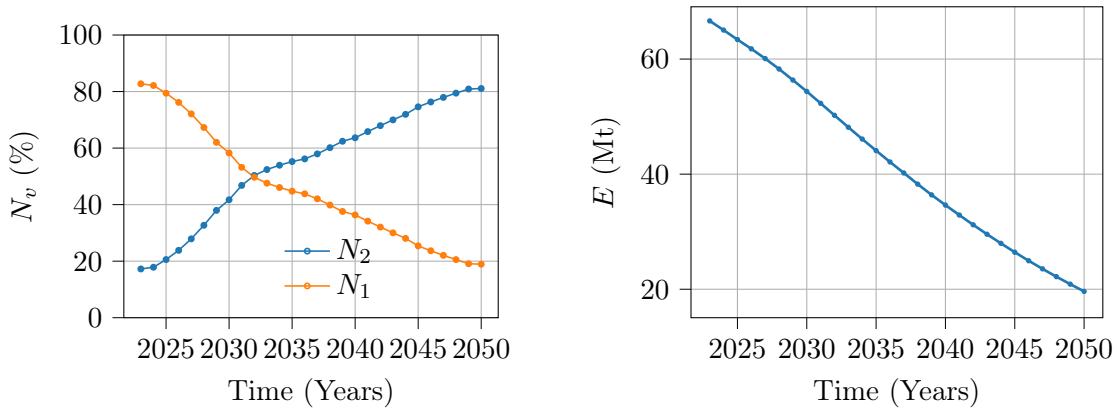


Figure 1: Scenario BaU: Vehicle Sales Percentage N_v and Annual Emissions E for BaU scenario

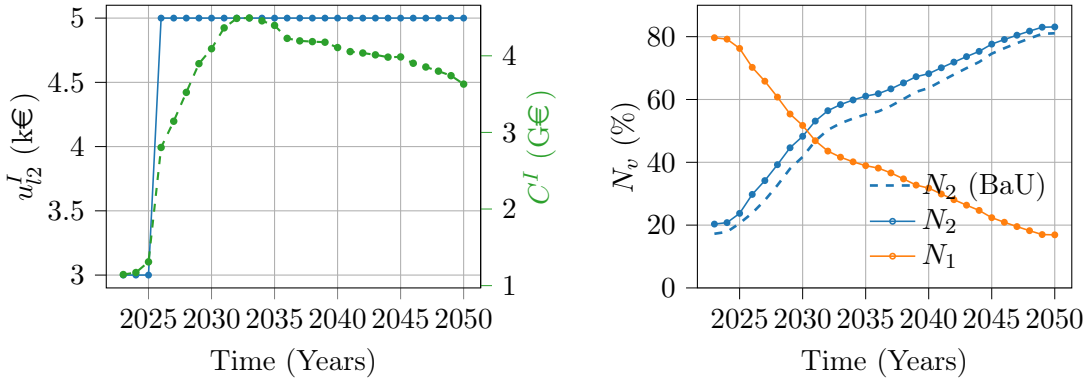


Figure 2: Scenario $\mathcal{I}$: EV Purchase Incentive (left) and Vehicle Sales Percentage (right)

Reference CO_2 Malus Policy ($\mathcal{M}$): The official schedule for the malus policy provides the penalties, in euros, as a function ofof the year of registration and the CO_2 emissions of newly sold vehicles (Service Public (2026)). The average emission factors for newly sold thermal vehicles is used to determine the corresponding malus, and its temporal evolution is the approximated by a linear function, given by

$$u_2^M(t) = 102.5 \cdot t - 207420 \quad t \in [2023, 2050]. \tag{18}$$

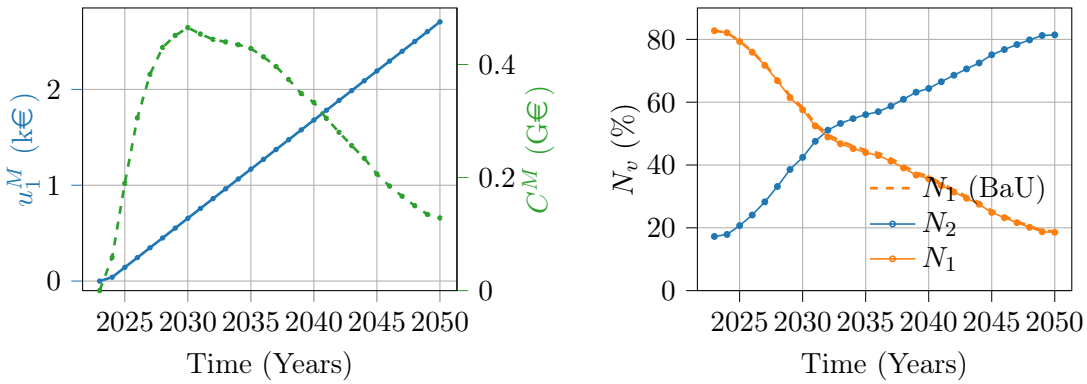


Figure 3: Scenario $\mathcal{M}$: Malus CO_2 (left) and Vehicle Sales Percentage(right)

Figure 3 (left) shows the reference malus policy and its associated discounted annual costs. The

latter initially rises with increasing malus costs, but declines sharply, than the reference incentive policy, after 2030 owing to a stronger discounting factor and reduced sales of thermal vehicles. As a result of the malus policy, the thermal market share, shown in Fig. 3 (right), decreases by 0.7% in 2030 and 0.3% in 2050 with respect to the BaU scenario. Correspondingly, the EV market share is higher with the parity point at 2032. The $\mathcal{M}$ scenario results in final cumulative emissions $\mathcal{E}(T) = 1.172$ Gt, total cost $C^M = 8.4$ B€, and the abatement costs with respect to BaU as 1.3 k€/tCO$_2$.

Reference Eco-Driving Policy (ED): Figure 4 shows the evolution of the number of eco-drivers $x(t)$ (left) and the associated annual emissions $E(t)$ (right) under the eco-driving policy, with a penetration rate ranging from 10% to 100% of the non-eco driving population selected for training. We assume $x_r(t_0) = 0$. For a fixed penetration rate $u^{ED}(t) \equiv u^{ED}$, the number of eco-drivers converge to a steady-state value. Annual emissions of thermal vehicles decrease with increasing penetration rates and its corresponding x_1. While the impact of the ED policy is assessed here in terms of CO_2 emissions, it could also be evaluated in terms of energy savings (in kWh), thereby capturing the benefits for EVs, through x_2, as well. The ED ($u^{ED} = 1$) scenario results in final cumulative emissions $\mathcal{E}(T) = 1.14$ Gt, total cost $C^{ED} = 3.84$ B€, and the abatement costs with respect to BaU as 0.13 k€/tCO$_2$.

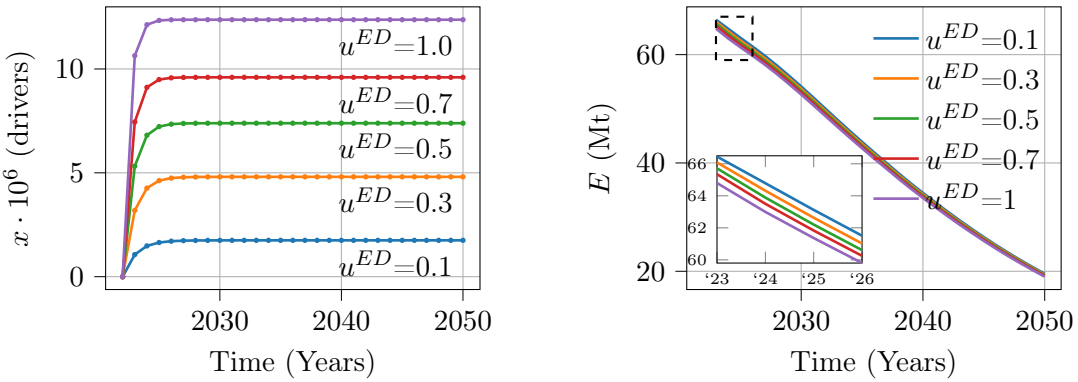


Figure 4: Scenario ED: Eco-drivers x (left) and Annual Emissions E (right)

4 Backcasting

This section illustrates the backcasting approach using an optimal control framework. Rather than prescribing policies ex-ante, like the reference scenarios presented in Sect. 3, the approach determines the combined optimal policy trajectories for EV purchase incentive, CO_2 Malus, and Eco-Driving, required to meet a specified cumulative emissions target while minimizing associated costs.

Optimal Control Problem

$$\begin{aligned} \min_{\mathbf{u}(t)} \quad & J = \sum_{t=t_{opt}}^{T} \boldsymbol{\lambda}^\top \mathbf{C}(t, \mathbf{u}) \\ \text{s.t.} \quad & \text{state equation (7)}, \\ & \mathcal{E}(T) \leq \bar{\mathcal{E}}, \\ & \mathbf{u}(t) \leq \mathbf{u}^{\max}. \end{aligned} \tag{19}$$

where J represents the total cost or budget. The cost vector, the weighting vector, and the control variables entering the system dynamics are defined as

$$\mathbf{C}(t) = \begin{bmatrix} C^I(t) \\ C^M(t) \\ C^{ED}(t) \end{bmatrix}, \quad \boldsymbol{\lambda} = \begin{bmatrix} \lambda^I \\ \lambda^M \\ \lambda^{ED} \end{bmatrix}, \text{and} \quad \mathbf{u}(t) = \begin{bmatrix} u^I_{12}(t) \\ u^I_{22}(t) \\ u^I_{32}(t) \\ u^M_1(t) \\ u^{ED}(t) \end{bmatrix},$$

respectively. The optimization start year is set to $t_{opt} = 2026$. For the years $t < t_{opt}$, the control variables are fixed from the reference policies. The associated costs, emissions, and stock evolution for these years are pre-computed and treated as known inputs to the optimization problem. Only for $t \geq t_{\text{opt}}$ are the control variables determined through optimization. Additionally, u^I is forced to stay constant for intervals of four years.
The resulting optimal trajectories are computed using the *trust-constr* algorithm available in the `scipy.optimize` package (Conn et al. (2000)).

Table 3: Backcasting Metaparameters.

Parameter	Value
T	2050
$u^{I,max}$ (€)	30000
$u^{M,max}$ (€)	2700
$u^{ED,max}$	1
λ^I, λ^M, λ^{ED}	1.25, 1, 1.25
τ^s, τ^p (%)	3.2, 8

Results and Discussion

The three policy scenarios are jointly optimized using the meta-parameters listed in Table 3. The maximum EV purchase incentive is set to the lower bound of EV purchase cost (≈ 30 k€). Of course, when this maximum is actually reached, it is an indication that the specific emission target is too ambitious at least for the policies considered. The CO_2 malus is constrained to a maximum of 2.7 k€, corresponding to the upper bound of the reference malus policy. The maximum penetration rate of eco-driving is set to 1. The weighting factors associated with state-funded policies, namely λ^I, and λ^{ED}, are set to 1.25, as recommended in Ministère de la Transition écologique (2022). The discount rate for state-funded policies can range from 2-4 % (Haut-commissariat à la Stratégie et au Plan (2017)), and is set to 3.2% in this study, and the discount rate applied to the citizens is set to 8% (Evans (2004)).
Figure 5 illustrates the Pareto front between cost J and final cumulative emissions $\mathcal{E}$(T). The target cumulative emission $\bar{\mathcal{E}}$ is varied from 1.128 Gt to 0.958 Gt to analyze the total cost J and final cumulative emissions $\mathcal{E}(T)$ sensitivity. Lower emission targets are associated with higher total costs (left-hand side of the Pareto front), while less stringent targets result in lower costs (right-hand side). The curve's steepness towards strict lower emission targets highlights the increasing marginal abatement cost (€/tCO_2), that is, diminishing returns.

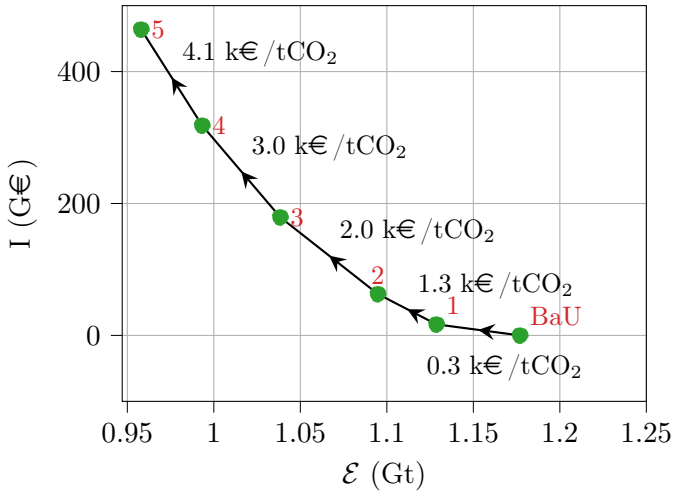


Figure 5: Pareto front : Total cost J vs Cumulative Emissions $\mathcal{E}$

Figure 6 shows the optimal policy trajectories for the points 2 (top left) to 5 (bottom right) on the Pareto front. The optimal EV purchase incentive exhibits three characteristics. Firstly, it varies across the three income classes, with an inversely proportional relationship. Secondly, the stricter

the emissions target, the higher is the incentive and the longer is the distribution period. Finally, the highest incentive is allocated as early as possible and then decreases over time. The optimal CO_2 Malus policy switches between its maximum and minimum values, with increasing duration of maximum malus for stricter emissions targets. The optimal penetration rate for eco-drivers is always set to its maximum value one, with a steady state value of eco-drivers, $x = 12.3{\cdot}10^6$, indicating the ED policy should cover as much population as possible.

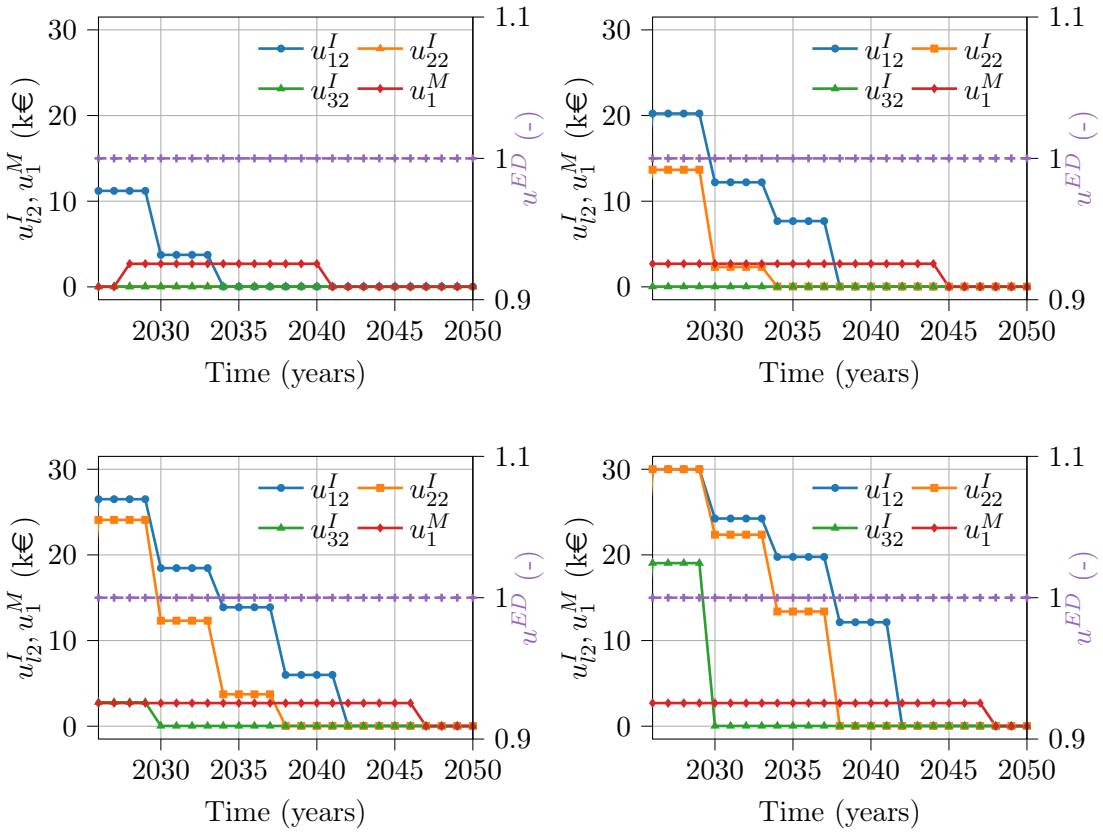


Figure 6: Optimal policy trajectories for points 2-5 in the Pareto front: 2 (top left), 3 (top right), 4 (bottom left), and 5 (bottom right).

5 Conclusions

The study illustrates how the backcasting approach in transport systems can be cast and solved as an optimal control problem, even in the presence of multiple policy measures to coordinate. The problem formulation provided a rigorous framework for cost/benefit analysis for the measures considered, resulting in a Pareto front with varying CO_2 abatement costs.
In summary these results suggested that the optimal policy combination aims to: accelerate the early introduction of EVs into the market, deter thermal vehicles purchase, and promote eco-driving.
Future work will be directed at integrating more national-level policies, oriented to the demand reduction and the modal shift (e.g., favoring active modes, shared mobility) and extending the modeling framework accordingly.

Acknowledgements

This research benefited from state aid managed by the *Agence Nationale de la Recherche (ANR)*, under France 2030, within the project FORBAC bearing the reference ANR-23-PEMO-0002.

References

ADEME. (2025). Évolution du taux de CO_2 – car labelling. https://carlabelling.ademe.fr/chiffrescles/r/evolutionTauxCo2.

Alami, A., Lakshmanan, V., & Sciarretta, A. (2025). Optimal low emission zones scheduling as an example of transport policy backcasting. In 2025 9th international conference on models and technologies for intelligent transportation systems (mt-its) (p. 1-6). doi: 10.1109/MT-ITS68460.2025.11223602

Ashina, S., Fujino, J., Masui, T., Ehara, T., & Hibino, G. (2012). A roadmap towards a low-carbon society in japan using backcasting methodology: Feasible pathways for achieving an 80% reduction in co2 emissions by 2050. Energy Policy, 41, 584–598. doi: 10.1016/j.enpol.2011.10.053

Barla, P., Gilbert-Gonthier, M., Lopez Castro, M. A., & Miranda-Moreno, L. (2017). Eco-driving training and fuel consumption: Impact, heterogeneity and sustainability. Energy Economics, 62, 187-194. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140988317300051 doi: https://doi.org/10.1016/j.eneco.2016.12.018

Bass, F. M. (1969). A new-product growth model for consumer durables. Management Science, 15(1), 215–227.

Bibri, S. E., & Krogstie, J. (2019). A scholarly backcasting approach to a novel model for smart sustainable cities of the future: strategic problem orientation. City, Territory and Architecture, 6(3), 1–27. doi: 10.1186/s40410-019-0102-3

CITEPA. (2025). Secten – Émissions de gaz à effet de serre et de polluants atmosphériques en France. https://www.citepa.org/fr/secten.

Conn, A. R., Gould, N. I., & Toint, P. L. (2000). Trust region methods (Vol. 1). SIAM. doi: 10.1137/1.9780898719857

ECOWILL Project Consortium. (2013). Eco-driving, short-duration training for licensed drivers and integration into driving education for learner drivers: Experiences and results from the ecowill project (Project Report). ECOWILL (Ecodriving Widespread Implementation for Learner and Licensed Drivers). (Available at:www.cieca.eu)

Enedis. (2026). Trajectoire du nombre de points de charge ouverts au public en france. Retrieved from https://opendata.enedis.fr/datasets/trajectoire-du-nombre-de-points-de-charge-accessibles-au-public (Dernière mise à jour : 20 janvier 2026)

Evans, D. (2004). A social discount rate for france. Applied Economics Letters, 11(13), 803–808. doi: 10.1080/1350485042000254638

Gomi, K., Ochi, Y., & Matsuoka, Y. (2011). A systematic quantitative backcasting on low-carbon society policy in case of kyoto city. Technological Forecasting and Social Change, 78(5), 852–871. doi: 10.1016/j.techfore.2011.01.005

Guillemin, F., Grondin, O., Moulin, P., & Dib, W. (2015). An innovative eco-driving coaching solution: Geco. In Proceedings of the its world congress.

Haut-commissariat à la Stratégie et au Plan. (2017, mars). Le taux d'actualisation dans l'évaluation des projets d'investissement public. https://www.strategie-plan.gouv.fr/le-taux-dactualisation-dans-levaluation-des-projets-dinvestissement-public. (Colloque sous la présidence de Roger Guesnerie, publié le 29/03/2017)

Héraud, T., Lakshmanan, V., & Sciarretta, A. (2025). Developing a dynamic mobility model for backcasting applications: A case study with shared autonomous vehicles. Retrieved from https://arxiv.org/abs/2509.17928

International Transport Forum. (2025). Developing future transport scenarios: Insights and best practices from national authorities (Tech. Rep.). Paris: OECD Publishing.

ITF. (2019). Understanding consumer vehicle choice: A new car fleet model for france (Tech. Rep.). OECD Publishing, Paris.

Lakshmanan, V. K., Guichet, X., & Sciarretta, A. (2025). Backcasting policies in transport systems as an optimal control problem : An example with electric vehicle purchase incentives. IFAC-PapersOnLine, 59(5), 181-186. Retrieved from https://www.sciencedirect.com/science/article/pii/S2405896325004550 (11th IFAC Symposium on Advances in Automotive Control AAC 2025) doi: https://doi.org/10.1016/j.ifacol.2025.07.102

Lakshmanan, V. K., Lemaire, O., & Sciarretta, A. (2024). Practical implementation and experimental validation of an optimal control based eco-driving system. In 2024 ieee 63rd conference on decision and control (cdc) (p. 3233-3238). doi: 10.1109/CDC56724.2024.10886002

Lakshmanan, V. K., & Sciarretta, A. (in press). Experimental validation of predictive optimal control based eco-driving. Control Engineering Practice. (Accepted for publication, Article No. 106932)

McManus, W., & Senter, R. (2009). Market models for predicting phev adoption and diffusion. (Final Report)

Ministère de la Transition Écologique. (2019). Ii - scénario de référence (Government Report / Technical Document). Ministère de la Transition Écologique, France. Retrieved from https://www.ecologie.gouv.fr/sites/default/files/documents/II%20-%20Sc%C3%A9nario%20de%20r%C3%A9f%C3%A9rence.pdf

Ministère de la Transition écologique. (2022). Méthode pour la réalisation des bilans d'émissions de gaz à effet de serre (beges) – version 5. Retrieved from https://www.ecologie.gouv.fr/sites/default/files/documents/V.5.pdf (Accessed: 2026-03-27)

Ministère de l'Économie et des Finances. (2025). Achat d'un véhicule électrique : pouvez-vous bénéficier de la prime « coup de pouce » véhicules particuliers électriques ? https://www.economie.gouv.fr/particuliers/voyager-et-se-deplacer/achat-dun-vehicule-electrique-pouvez-vous-beneficier-de-la-prime-coup-de-pouce-vehicules-particuliers-electriques. (Accessed: 30 March 2026)

Nakamura, K., Hayashi, Y., & Kato, H. (2012). A backcasting approach to designing low-carbon urban transport systems for asian developing cities: Application to bangkok. In Transportation research board 91st annual meeting. Washington, DC: Transportation Research Board.

Papazikou, E., et al. (2020). Detailed list of sub-use cases, applicable forecasting methodologies and necessary output variables (Tech. Rep.). Deliverable D4.4 of the H2020 project LEVITATE.

Quality Alliance Eco-Drive. (2024). Quality alliance eco-drive — rapport annuel 2024. https://www.ecodrive.ch/media/filer_public/68/b4/68b400ac-d921-478e-a793-0629a77a462f/eco_jb_2024_fr.pdf. (Accessed: YYYY-MM-DD)

Robinson, J. (1982). Energy backcasting—a proposed method of policy analysis. Energy Policy, 12(4), 337–344. doi: 10.1016/0301-4215(82)90048-9

Service des Données et Études Statistiques (SDES). (2025). Données sur le parc automobile français au 1er janvier 2025. https://www.statistiques.developpement-durable.gouv.fr/donnees-sur-le-parc-automobile-francais-au-1er-janvier-2025. (Accessed: 30 March 2026)

Service Public. (2026). Taxe sur les émissions de co2 des véhicules de tourisme (malus co2). Retrieved from https://www.service-public.gouv.fr/particuliers/vosdroits/F35947 (Vérifié le 21 février 2026)

Struben, J., & Sterman, J. (2008). Transition challenges for alternative fuel vehicle and transportation systems. Environment and Planning B, 35(6), 1070–1097.

Tu, R., Xu, J., Li, T., & Chen, H. (2022). Effective and acceptable eco-driving guidance for human-driving vehicles: A review. International Journal of Environmental Research and Public Health, 19(12), 7310. doi: 10.3390/ijerph19127310

Wen, Z.-g., Di, J.-h., Yu, X.-w., & Zhang, X. (2017). Analyses of CO_2 mitigation roadmap in China's power industry: Using a backcasting model. Applied Energy, 205, 644–653.