An optimization setup of the decarbonization problem in the transportation sector

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Abstract. This paper proposes an optimization-based formulation of the decarbonization problem for the transportation sector, one of the main sources of CO_2 emissions. An important feature of the proposed approach is that a detailed model is considered i.e., with different transportation modes and compositions of the associated fleets of vehicles. Using real data, this optimization problem is solved numerically under monetary and CO_2 emissions constraints, but also constraints ensuring the feasibility of the transition. The obtained control actions provide insights into the transition from existing transportation modes to more sustainable ones. A discussion is made on the complexity of this problem: the dependency of resolution time on the budget values is in particular numerically assessed.

Keywords: Decarbonization · Non-convex Quadratic Programming · Resource allocation.

1 Introduction

The imperative to mitigate climate change demands effective decarbonization strategies at all governance levels. The European Union has set ambitious Green-House Gas (GHG) reduction targets for 2050, requiring member states to develop comprehensive national and regional strategies[5]. GHG emissions are henceforth measured in CO_2 equivalents and will be referred to as CO_2 emissions. France is adopting a decentralized approach in which each region creates and executes its own decarbonization plan (the so-called "SRADDET"). This decentralization poses significant challenges, especially to find efficient mechanisms in order to incentivize the different regions to make the proper decarbonization efforts.

Research on decarbonization often focuses on global (world) or local (city) scales. Globally, strategies involve international treaties and broad policies targeting sector-wide GHG reduction, with analyses ranging from game theory [1,11] to optimal control [7] and economic impacts [4].

[5] Climate neutrality by 2050, with "Fit for 55" intermediate milestone - with a reduction of at least 55% of net GHG target by 2030.

The transportation sector is central to these efforts, due to its substantial CO_2 emissions impact[6]. Studies on decarbonizing transportation are either macroeconomic model formulations [15,13] or focus on a given aspect, like electric vehicle charging stations [2], or on a specific geographic area [5]. Despite extensive studies, an intermediate-scale approach remains under-explored, even if critical for harmonizing various transportation modes and fleet compositions regionally. Our work aims to fill this gap, providing an optimization model for the private passenger sector, sidestepping the limitations noted in other models [6,8] with notions of Quality of Service (QoS) and congestion, and allowing substitution among all transportation modes. Moreover, it provides insight on the feasibility to meet decarbonization target under monetary constraints.

The main contributions of this paper are: (i) The introduction of a novel generic optimization model, specifically designed to target intermediate levels of analysis within the private passenger sector of a region. This model flexibility allows for adaptation across various geographical scales. (ii) A refined formulation of QoS for passengers within the transportation sector is proposed, enhancing the model realism. (iii) The theoretical aspects of the problem are discussed and reformulated into a form amenable to numerical computation. (iv) The Optimization Problem (OP) is solved using dedicated nonlinear methods, and the results are analyzed across realistic scenarios.

The remainder of this paper is structured as follows: Sec. 2 outlines the transportation model discussed subsequently. Sec. 3 reformulates the OP as a Non-Convex Quadratic Problem (NCQP), facilitating effective resolution within the given context. Sec. 4 presents simulation results that not only highlight potential trade-offs important for regional decarbonization strategy design, but also identify the parameters that most significantly affect resolution time.

2 Problem Formulation

2.1 Decarbonizing transportation under constraints

A tractable decarbonization framework needs to consider a long-term horizon and a discrete-time dynamics in which the *discrete set of sampling times* $\mathcal{T} = \{1, \ldots, T\}$ is typically chosen to represent a period of one or few years[7]. At each time $t \in \mathcal{T}$, the region has a desired *total level of transportation usage* X_t, measured in passenger.km, which represents the transportation of one passenger by a particular mode of transportation over one kilometer. Given this desired transportation usage, the unique decision-maker - referred to hereafter as the "regional planner" or simply "planner", is allocated a *CO_2 emissions budget* $E_t^{\max}$. To achieve this target, the planner employs various decarbonization *levers* while adhering to a *monetary budget* limit of $B_t^{\max}$. Under these constraints, the decarbonization levers have to be activated maximizing the transportation *Quality of Service* (QoS), as introduced in Sec. 2.3.

Two key aspects should be noted: (i) Passenger (or "user") reaction/behaviour is simply modeled as a *mean representative user*. In other words, we do not con-

[6] About one third of French CO_2 emissions in 2023.

[7] Public targets granularity e.g., 4 years for French "Stratégie Nationale Bas-Carbone".

sider a variety of particular reactions to the decisions of the regional planner. (ii) The CO_2 emissions and monetary budgets are here taken as exogenous parameters.

2.2 Usage, vehicles and decarbonization decision-making modeling

Our model is based on three main ingredients, that are described in the following paragraphs : the *modal usage*, the *fleet of vehicles* and the *infrastructure*.

Modal Usage modeling. In addition to the aggregation over users mentioned in Subsec. 2.1, transportation usage representation is aggregated over both space (within the region) and time (over the considered time step)[8].

Let $\mathcal{K} = \{0, 1, \cdots, K\}$ be the set of transportation *modes*. The mode $k = 0$ represents the sobriety which corresponds to reduced or avoided travels, encapsulating passengers.km that are in fact not spent. The modes $k = 1, \cdots, K$ represent the conventional means of transportation (car, train, bus, etc.). The primary transportation service metric is x_t^k, the transportation usage of mode k at time t, measured in passengers.km. For a more convenient writing, we introduce the *modal share* of mode k at t, $\tilde{x}_t^k$, defined by

$$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \qquad x_t^k = \tilde{x}_t^k X_t, \ \left(\tilde{x}_t^k\right)_{k \in \mathcal{K}} \in \Delta^{K+1}, \tag{1}$$

with Δ^{K+1} denoting the K-dimensional simplex.

A first transportation decarbonization lever is now introduced: the *modal switch*, with variable $\beta_t^{k,l}$, the proportion of mode k replaced by mode l at time t, inducing the following dynamics for the modal shares:

$$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \qquad \tilde{x}_{t+1}^k = \tilde{x}_t^k - \sum_{l \in \mathcal{K}} \beta_t^{k,l} + \sum_{l \in \mathcal{K}} \beta_t^{l,k}. \tag{2}$$

It is imposed that for all $k \in \mathcal{K}$, $\beta_t^{k,k} = 0$ at any time t. This shift variable $\beta_t^{k,l}$ corresponds to the facilitation "process" (subsidies, communication, etc.) so that users are incentivized to switch from k to l.

Practical limitations impose to consider lower and upper bounds on modal switch, as well as on induced modal usage.

$$\forall k, l \in \mathcal{K}, \forall t \in \mathcal{T}, \qquad 0 \leq \beta_t^{k,l} \leq \overline{\beta}_t^{k,l}, \ 0 \leq \underline{x}_t^k \leq x_t^k \leq \overline{x}_t^k. \tag{3}$$

In particular, these bounds allow: (i) Excluding "impossible" travels e.g., long-distance walking commute. (ii) Integrating only modal usage changes that correspond to a gradual transition, without abrupt shift (as new usages adoption is typically associated to a progressive diffusion process [14]).

After introducing modal usage, the vehicle fleet is now described.

Vehicle Fleet Dynamics. Each mode k is associated to a set $\mathcal{I}_k$ of *vehicle types* aggregated as a fleet. For example, electric or gasoline cars (resp. trains) types compose the fleet of the car (resp. train) mode. We introduce this distinction to access the different CO_2 emissions factors of the different types of vehicle. The

[8] Considering specificities of different seasons, days of weeks, times of days (resp. geographical locations) are indeed too complex to be integrated in the optimization setting described hereafter.

number of vehicles of type i at time t is denoted by the variable v_t^i. To accommodate the needs of different transportation modes, there must be a sufficient total number of vehicles - aggregated over the types. Mathematically:

$$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \qquad x_t^k \leq \sum_{i \in \mathcal{I}^k} d^i r^i v_t^i, \tag{4}$$

with the parameters d^i and r^i being the average distance traveled with a vehicle of type i over the step time and the average occupancy rate of the vehicles in this fleet.

Regardless of their usage, vehicle fleets undergo dynamic changes through natural turnover, driven by vehicle lifespan and decay. New vehicles of type $i \in \mathcal{I}^k$, added to the fleet during time t, can either be introduced, with variable θ_t^i, or replaced with another vehicle $j \in \mathcal{I}^k$ reaching its end of life, with variable $\nu_t^{j,i}$. These variables, θ_t^i and $\nu_t^{j,i}$, which govern the purchase or replacement of vehicles, are key levers used by the regional planner. Representing the total number of vehicles of fleet i at the end of t, w_t^i is obtained by summing the two previous quantities:

$$\forall k \in \mathcal{K}, \forall i \in \mathcal{I}^k, \forall t \in \mathcal{T}, \qquad w_t^i = \theta_t^i + \sum_{j \in \mathcal{I}^k} \nu_t^{j,i}. \tag{5}$$

Note that the main reason to distinguish newly introduced vehicles and replaced ones is monetary, as these two quantities have a different impact on the budget expressed in (10). Also, it is assumed that vehicles are used until their end-of-life, of duration τ^i, which is assumed to be a deterministic parameter. This simplification: (i) Allows the regional planner to measure all emissions generated by the usage of vehicles over their lifetime. (ii) Leads to a tractable model. (iii) Can induce an optimality loss compared to a model where vehicles could exit or be replaced before their end-of-life. Assessing this optimality loss is left as a future perspective. Altogether, the vehicle fleets dynamics expresses:

$$\forall k \in \mathcal{K}, \forall i \in \mathcal{I}^k, \forall t \in \mathcal{T}, \qquad v_{t+1}^i = v_t^i - w_{t-\tau^i}^i + w_t^i, \tag{6}$$

$$\forall k \in \mathcal{K}, \forall i \in \mathcal{I}^k, \forall t \in \mathcal{T}, \qquad 0 \leq \theta_t^i, \quad 0 \leq \sum_{j \in \mathcal{I}^k} \nu_t^{i,j} \leq w_{t-\tau^i}^i \,. \tag{7}$$

After detailing the transportation model's usage and vehicle fleet dimensions, the infrastructure is described next.

Infrastructure: At time t and for each transportation mode $k \in \mathcal{K}$, y_t^k is the variable representing the number of kilometers that the fleet k of vehicles can travel, measured in vehicles.km. For simplicity, it is assumed that infrastructures are independent between the different modes. For example, cars and buses do not drive on the "same roads". Both fleet and infrastructure states are related through:

$$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \qquad \sum_{i \in \mathcal{I}^k} d^i v_t^i \leq y_t^k. \tag{8}$$

Infrastructures are subject to natural decay from usage and environmental factors, necessitating regular renewal. Investments can be made to counterbalance this effect. The variable μ_t^k represents the expansion of the infrastructure of transportation mode k at time t (another political lever). The dynamics of infrastructure is then given by:

$$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \qquad y_{t+1}^k = \delta^k y_t^k + \mu_t^k,\ 0 \leq \mu_t^k \leq \overline{\mu}_t^k, \tag{9}$$

where $0 < \delta^k \leq 1$ stands for the depreciation rate of infrastructure of mode k. The right hand side of constraint (9) accounts for the operational constraints limiting the capacity increase of an infrastructure, as building time.

The decisions previously presented concerning modal usage, vehicle fleets and infrastructures are associated to monetary and emissions budget constraints; they are gathered in the following section.

The decisions regarding modal usage, vehicle fleets, and infrastructure, constrained by monetary and emissions budgets, are presented in the next section.

Emissions and monetary budgets. Let describe the exogenously set monetary costs: (i) $c_{t,\text{switch}}^{k,l}$ represents the cost of incentivizing users' transition from transportation mode k to l e.g., with subsidies for public transportation subscriptions to make the switch from private vehicles more affordable and c_t^{sob} the cost of maintaining one kilometer of sobriety; (ii) $c_{t,\text{buy}}^i$ (resp. $c_{t,\text{conv}}^{i,j}$) are the costs of adding (resp. replacing) one vehicle to the fleet; and (iii) $c_{t,\text{inv}}^k$ are the costs of infrastructure investments.

All these costs provide the monetary budget constraint: $\forall t \in \mathcal{T}$,

$$\sum_{k \in \mathcal{K}} \left[c_{t,\text{inv}}^k \mu_t^k + \sum_{l \in \mathcal{K}} c_{t,\text{switch}}^{k,l} \beta_t^{k,l} X_t + \sum_{i \in \mathcal{I}^k} \left[c_{t,\text{buy}}^i \theta_t^i + \sum_{j \in \mathcal{I}^k} c_{t,\text{conv}}^{i,j} \nu_t^{i,j} \right] \right] + x_t^0 c_t^{\text{sob}} \leq B_t^{\max}. \tag{10}$$

Moreover, the CO_2 emissions budget constraint, is directly expressed by the vehicle fleets state and the respective emissions factors of the different vehicle types e^i:

$$\forall t \in \mathcal{T}, \qquad \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}^k} d^i e^i v_t^i \leq E_t^{\max}. \tag{11}$$

In addition to the different constraints introduced previously, the following section describes the objective of the regional planner; it completes the considered -transportation sector decarbonization - OP definition.

2.3 Quality of Service (QoS) with congestion

Transitioning to a decarbonized transportation sector - constrained by monetary and emissions budgets, the maximization of users QoS is crucial to ensure policy adoption. Here, the transportation QoS is defined as follows:

$$\text{QoS}(x, y, v) = \sum_{k \in \mathcal{K} \setminus \{0\}} q^k x^k \Big(1 - \sum_{i \in \mathcal{I}^k} \frac{d^i v^i}{y^k} \Big) - q^0 x^0, \tag{12}$$

where $q^k > 0$ is a weight parameterized to translate user preference for mode k - emphasizing comfort, accessibility and affinity. Remember that index $k = 0$ is to represent the sobriety fictive mode, with a specific treatment regarding QoS. This formulation also considers the impact of traffic congestion with the

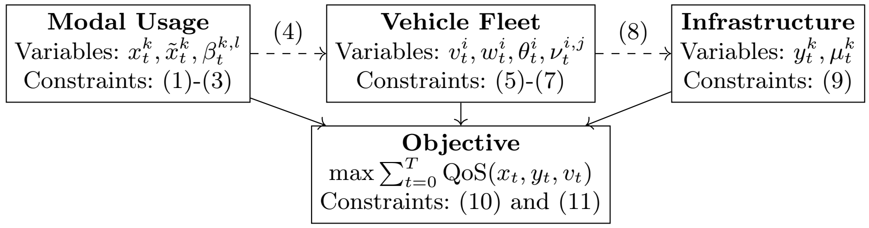


Fig. 1. Summary of the transportation sector OP (variables and constraints). All quantities not shown in the diagram are exogenous parameters and are assumed to be known.

multiplication factor $1 - \left(\sum_{i\in\mathcal{I}^k} d^i v^i\right)/y^k$: the closer the distance covered in mode k, $\sum_{i\in\mathcal{I}^k} d^i v^i$, to the associated infrastructure capacity y^k, the lower is this term. Then, the QoS of a mode deteriorates when its fleet is too large for its infrastructure [10].

2.4 Optimization Problem Formulation

The regional transportation planner's optimization model aims to maximize QoS over a planning horizon. It is constrained by monetary and emissions budgets, and assumes perfect knowledge of all parameter trajectories. This involves strategic decisions concerning modal usage, vehicle fleet management, and infrastructure investment. The obtained OP is as follows:

$$\max \quad \sum_{t\in\mathcal{T}} \mathrm{QoS}(x_t, y_t, v_t)$$

$$\text{s. t. } \textbf{Modal usage: } (1)\text{-}(3),\ \textbf{Vehicle fleets: } (4)\text{-}(7),\ \textbf{Infrastructure: } (8)\text{-}(9),$$
$$\textbf{Monetary and CO}_2 \textbf{ emissions budgets: } (10) \text{ and } (11).$$

3 Mathematical Discussion

Our optimization problem is a continuous non-linear and non-convex problem, which makes it nontrivial to solve. Indeed, this problem is a fractional problem : all the constraints are linear, and the congestion term in the QoS formulation (12) makes the objective function fractional and non-convex. This problem can be reformulated as a Non-Convex Quadratic Program (NCQP). We need to introduce intermediate variables p_t^k, and add the quadratic constraints $p_t^k y_t^k = \sum_{i\in\mathcal{I}^k} v_t^i d^i$ for all $k \in \mathcal{K}$ and $t \in \mathcal{T}$. Then, by replacing the fraction by p_t^k in the objective, the QoS function becomes linear.

However, the problem remains inherently non-convex, presenting challenges in finding optimal solutions efficiently, even more if the horizon is far (T big). We then use a non-linear solver conducting Spacial Branch and Bound (SBB) or Outer Approximation approaches. Recall that SBB is an algorithm of global optimization used to solve Non Linear Problem (NLP) and Mixed-Integer NLP [9]. At each iteration, a local optimal point is found by solving an NLP as a black-box. Since NLP is, in general, an NP-hard problem in itself [12], finding the global optimum of our non-convex problem is also NP-hard. In the computations

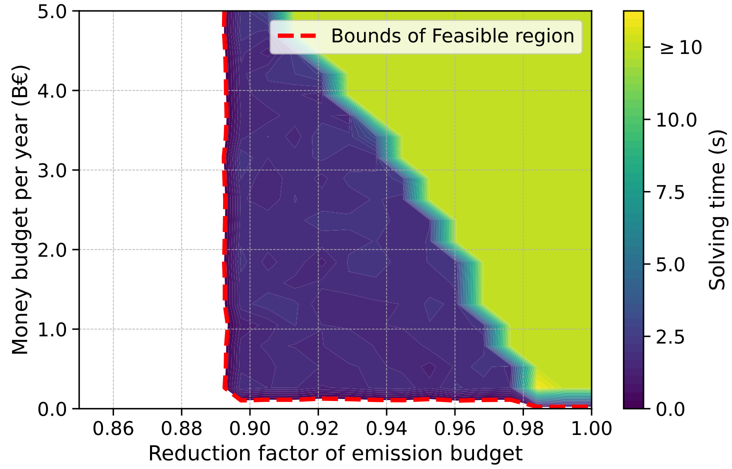


Fig. 2. Computation times and feasibility with parameters as in Sec. 4, x-axis corresponds to the reduction factor applied each year after the first year (e.g., 0.90 corresponds to a 10% decrease.). *Constrained budget lead to small resolution time.*

of Sec. 4, solving our model with a SBB takes longer with higher monetary and emissions budgets due to a larger set of feasible solutions. In contrast, tighter budgets allow for quicker optimal solutions. Fig. 3 illustrates this, with colors indicating the time taken to solve, with a 10 seconds threshold.

4 Simulation

4.1 Methodology

The code is available at [3]. Simulations use latest data available for the Bretagne region in France. Vehicle usage data and lifespan parameters, v_t^i and τ, are taken from French government transportation statistics [16], while initial modal shares, x_0^k, rely on recent surveys by CEREMA [17]. Emissions factors e^i, are based on data from ADEME's environmental database [18], and cost parameters, $c_{\cdot\cdot\cdot}^{i,j}$, are obtained from socio-economic studies by the French Ministry of Ecology [19]. These values are assumed to be constant over time; however, there are financial uncertainties and challenges in accurately determining user preferences q^k parameters. This issue could potentially be addressed through robust optimization techniques[9]. Here, assuming constant costs is already conservative.

The Gurobi Solver is employed to solve the OP, chosen for its ability to handle NCQP and to guarantee optimality[10] of the solution by using SBB techniques.

4.2 Optimal Trajectory with Emission and Monetary Budgets

The monetary budget $B_t^{\max}$ is constant over time, while emissions budgets $E_t^{\max}$ decrease by 10% annually, starting from 10% above the initial emissions level.

[9] Introducing an uncertainty set for QoS parameters and setting conservative financial and emission budgets to handle worst-case scenarios.

[10] Up to a precision of the gap between the lower and upper bounds of the objective.

Table 1. Budget Usage and Monetary Distribution for Low and High Budget Scenarios

	Low Budget Scenario		High Budget Scenario	
	Budget	Used (%)	Budget	Used (%)
Emissions (Mteq.CO_2)	36.04	33.79 (93.8%)	36.04	33.5 (93.1%)
Monetary (M€)	800	800 (100%)	8000	8000 (100%)
	Allocation between levers			
Sobriety	48.16%		1.66%	
Modes	23.14%		1.35%	
Vehicles	7.86%		85.14%	
Infrastructures	20.84%		11.85%	

The modal categories $\mathcal{K}$ = {Sobriety, Car, Tramway, Bus, Walking, Biking, Train} include a diversified vehicle fleet for "Car" mode, comprising Diesel, Electric, and Gasoline types $\mathcal{I}^{\text{Car}} = \{\text{Diesel}, \text{Electric}, \text{Gasoline}\}$. QoS coefficients q^k reflect the preference hierarchy among the modes, based on initial shares: car (1.5), tramway (1.2), bus (1), walking (0.5), biking (0.9), and train (1.2), balancing speed and comfort to mirror realistic preferences. Subsidy costs and baseline data are sourced from previously mentioned references. Mode shifts β are capped at 5%, and investments per mode k at time t cannot exceed 10% of infrastructure at time $t-1$. Tab. 1 details emissions and monetary allocations across different budget levels (low and high). Fig. 3(a) and Fig. 3(b) depict modal share evolution under varying budgets, while Fig. 3(c) and 3(d) display the respective fleet compositions.

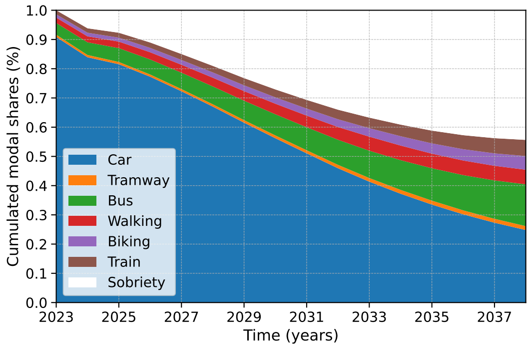
Monetary constraints significantly impact transportation choices, promoting sobriety due to its lower cost despite a reduction in QoS. Under tight budget, Fig. 3(a) illustrates a marked decline in traditional car usage, offset by increases in bus, walking, biking, and train modes, which are more cost-effective and less polluting (due to the need for financing cars). Consequently, the car fleet size is reduced by a third over 15 years, with a notable decrease in gasoline vehicles, which emit more than diesel, and a slight increase in electric vehicles.

In contrast, the high budget scenario shows minimal sobriety, as seen in Fig. 3(b) with only marginal reductions in car usage. Cars offer higher service quality, but fleet modernization to reduce emissions is expensive. Therefore, a high budget is necessary to maintain private car usage — through infrastructure investment and a shift to electric vehicles — while meeting decarbonization goals, as depicted in Fig. 3(d), where the fleet transitions entirely from diesel and gasoline to electric, maintaining a stable total vehicle count.

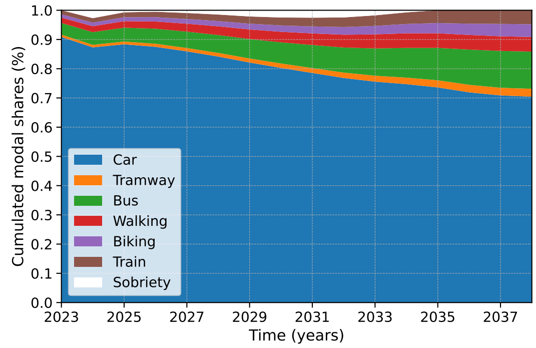
The differences in budget allocation are highlighted in Tab. 1. Despite a tenfold difference in available funds, the entire budget is utilized in both scenarios. In the low-budget scenario, funds mainly compensate for reduced usage and support modal shifts. In contrast, the high-budget scenario focuses on transitioning cars from high to low emissions and enhancing infrastructure to improve QoS.

5 Conclusion

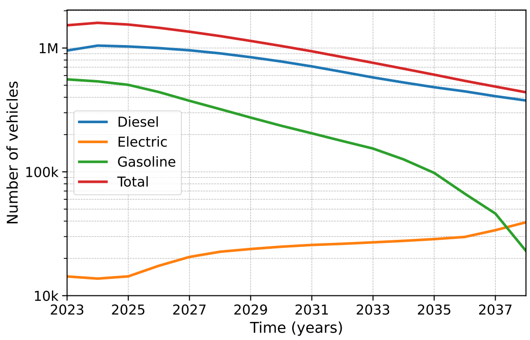
This study presents an optimization model tailored for the private passenger transportation sector at an intermediate scale, typically the one of a region. The



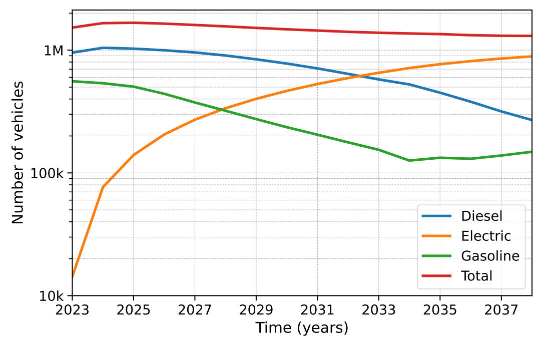
(a) Low budget: modal shares



(b) High budget: modal shares



(c) Low budget: vehicle fleet



(d) High budget: vehicle fleet

Fig. 3. Comparison of optimal solution of the two scenarios of Tab. 1.

development of this model involved a significant modeling work, including the formulation of assumptions and relationships essential for capturing the complexities of the transportation sector. By reformulating the optimization problem as a Non-Convex Quadratic Problem, the model effectively balances CO_2 emissions and monetary budget constraints. It provides actionable insights for regional policy planners with an introduced metric of congestion - of vehicles on transportation infrastructure.

The proposed model has been reformulated to be numerically tractable on real instances; the resolution being faster for small budget upper bounds. This observation on computation times is particularly interesting for the next stage of this research work, enhancing this model into a bi-level problem. This bi-level framework will include an upper-level decision-maker (e.g., a State) that optimizes both emissions and monetary budgets (imposed to the lower-level agent considered here). Indeed, this upper level agent will naturally tend to set budget values at low values. This enhancement will allow to capture the dynamics between different levels of decision-making, regional versus national, and provide deeper insights on optimal decarbonization strategies at a national scale.

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References

1. Bahn, O., Haurie, A.: A class of games with coupled constraints to model international ghg emission agreements. International Game Theory Review **10**(04) (2008)
2. Bouguerra, S., Bhar Layeb, S.: Determining optimal deployment of E.V. charging stations: Case of Tunis City, Tunisia. Case Studies on Transport Policy **7**(3) (2019)
3. Couthures, A.: AnthonyCouthures/Private-Transport-Sector-Optimization-Model: Zenodo (Jun 2024). `https://doi.org/10.5281/zenodo.12205178`
4. Hänsel, M.C., Drupp, M.A., Johansson, D.J.A., Nesje, F., Azar, C., Freeman, M.C., Groom, B., Sterner, T.: Climate economics support for the UN climate targets. Nature Climate Change **10**(8) (2020)
5. Jiang, J., Zhang, D., Meng, Q., Liu, Y.: Regional multimodal logistics network design considering demand uncertainty and CO2 emission reduction target: A system-optimization approach. Journal of Cleaner Production **248** (2020)
6. Kany, M.S., Mathiesen, B.V., Skov, I.R., Korberg, A.D., Thellufsen, J.Z., Lund, H., Sorknæs, P., Chang, M.: Energy efficient decarbonisation strategy for the Danish transport sector by 2045. Smart Energy **5** (2022)
7. Kellett, C.M., Weller, S.R., Faulwasser, T., Grüne, L., Semmler, W.: Feedback, dynamics, and optimal control in climate eco. Annual Reviews in Control **47** (2019)
8. Li, C., Liu, P., Li, Z.: A Long-Term Decarbonisation Modelling and Optimisation Approach for Transport Sector Planning Considering Modal Shift and Infrastructure Construction: A Case Study of China. Processes **10**(7) (2022)
9. Liberti, L.: Introduction to global optimization. Ecole Polytechnique (2008)
10. Maerivoet, S., De Moor, B.: Transp. Planning and Traffic Flow Models (2005)
11. Mroué, B., Couthures, A., Lasaulce, S., Morărescu, I.C.: A Quadratic Static Game Model for Assessing the Impact of Climate Change. In: Complex Networks & Their Applications XII. Springer Nature Switzerland, Cham (2024)
12. Pardalos, P.M., Schnitger, G.: Checking local optimality in constrained quadratic programming is NP-hard. Operations Research Letters **7**(1) (1988)
13. Pietzcker, R., Longden, T., Chen, W., Fu, S., Kriegler, E., Kyle, P., Luderer, G.: Long-Term Transport Energy Demand and Climate Policy: Alternative Visions on Transport Decarbonization in Energy Economy Models (2013)
14. Rogers, E.M., Singhal, A., Quinlan, M.M.: Diffusion of Innovations. In: An Integrated Approach to Communication Theory and Research. Routledge (2008)
15. Zhang, R., Hanaoka, T.: Cross-cutting scenarios and strategies for designing decarb. pathways in the transport sector. Nature Communications **13**(1) (2022)
16. Ministry of Sustainable Development, “Transportation statistics and analyses”, `https://www.statistiques.developpement-durable.gouv.fr`.
17. CEREMA, “EMC2: Enquêtes en cours”, `https://www.cerema.fr`
18. ADEME, “Base Carbone”, `https://base-empreinte.ademe.fr`.
19. Ministry of Ecology, “Socio-economic costs of transportation”, (December 2020).
20. Burtin, A., Marteau, F., Nogues, P., Turboult, F. Vers la neutralité carbone en région à l’horizon 2050: l’exemple de PACA. (2019). La Revue de l’Energie N°644.