A sustainable market niche for hydrogen in the transport sector ? *

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Abstract

We analyze the dynamic replacement of a fleet of polluting vehicles by two competing low-carbon technologies subject to learning-by-doing, in a partial equilibrium setting with a growing carbon price. Learning-by-doing justifies to develop a single technology, in order to reduce costs quickly, while cost convexity justifies diversification. We further introduce horizontal differentiation and perform numerical simulations of the European bus sector with diesel buses being replaced by Battery Electric Buses (BEBs) and/or Fuell Cell Electric Buses (FCEBs). Two strategies are compared: The first strategy is to maximise learning by focusing only on BEB. The second strategy is to develop each technology in its respective market. Based on calibrated parameters, it is shown that diversification dominates and hydrogen mobility has a sustainable niche. The optimal launching date of FCEBs in the bus sector is 2030, that is a social cost of carbon equal to 130€/tCO_2. This diversification solution emits twice less CO_2 than the solution using only BEVs. We further explore the role of three key parameters: the size of the niche market, the level of the absolute cost advantage of FCEV over BEV in that niche, and the learning rate of FCEV.

Keywords: energetic transition; learning by doing; fuel-cell electric vehicles; battery-electric vehicles; competing green technologies

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1 Introduction

Mobility is one of the hard to abate sectors, and in particular, heavy-duty mobility (trucks, buses...) faces several challenges: long range, need for quick refuelling, large payloads. Several technologies are considered to decarbonize heavy-duty transport: battery-electric vehicles (BEVs), fuel cell electric vehicles (FCEVs) using hydrogen as fuel, bioLNG, bioNGV, etc. A key question for policy makers is how many of these technologies will coexist in a carbon neutral transportation system and the pace at which they should be deployed. An efficient allocation of efforts necessitates to anticipate future market shares and the sequencing of the transition. The costs of these low-carbon technologies is expected to decrease along their deployment thanks to learning-by-doing (LBD) which justifies to focus on few technologies to generate a significant volume sufficiently quickly, while differentiation and decreasing return to scale (cost convexity) favors diversification. The purpose of this article is to analyze the choice between one or two low-carbon technologies subject to learning-by-doing to decarbonize a polluting fleet of vehicles, and draw policy recommendations.

In the bus sector BEBs and FECBs are candidate low-carbon technologies. BEBs are currently leading the transition, using a more mature technology with a total cost of ownership (TCO) that is progressively closing the gap with diesel vehicles. Even though there are some concerns about the scarcity of critical material required for batteries, BEBs will play a dominant role in the sector. FCEBs are currently more expensive than BEBs but benefit from a greater range, a shorter charging time, and are more robust to extreme temperature or uneven topographical landscapes. These characteristics give an edge to FCEBs on a niche market. FCEBs costs are expected to decrease along the deployment of the technology if a sustainable niche exists. The question is whether it is worth developing FCEB on this niche.

We develop a dynamic partial equilibrium model inspired by Creti et al. 2018 in which a given number of polluting vehicles should be replaced by non-emitting ones. Two green technologies are available, they are subject to learning-by-doing, and cost convexity. The social cost of carbon (SCC) grows at the discount rate, and the social planner minimizes the overall cost of the fleet including pollution. In a first step, we characterize analytically the optimal deployment path for both technologies. We found preliminary theoretical results on the arbitrage between convexity and learning-by-doing, in accordance with the results highlighted by Bramoullé and Olson 2005. In a second step, we introduce horizontal differentiation and perform numerical simulations based on the European bus sector. There are two market segments: the main market favorable to BEB and a niche market favorable to FCEB. BEBs have a cost penalty on the niche market which is a priori favorable to FCEBs but learning-by-doing might justify to deploy BEBs on both markets.

In the absence of cost convexity, with our hypothesis on costs and differentiation, only two strategies are optimal. The first strategy, called B-B, consists in focusing on BEBs to leverage learning by doing and quickly reduce costs. The second strategy, called B-FC, is to develop each technology in its respective segment, i.e. BEB for the main market and FCEB for the niche market. Each strategy are optimized by choosing the date at which a technology is deployed on each market. Considering the B-FC strategy, due in particular to a higher initial TCO for FCEBs compared with BEBs, the transition to FCEBs on the small segment would take place later than the one of BEBs on the large segment. Using the B-B strategy changes these dates, thus influencing emissions prior to full decarbonization, but

increasing the discounted cash cost since it promotes BEB on the short-distance segment. To provide a numerical application of our model, we consider the mobility segment of buses for the European geographical area. Simulations with parameters calibrated on public reports data and interviews with mobility experts characterize how parameters interact in the choice between the B-B and B-FC strategies.

Based on these calibrated parameters, it is shown that B-FC strategy dominates, i.e hydrogen mobility has a sustainable niche on the small segment of bus mobility. The optimal launching date of FCEBs in the bus sector is 2030, that is a social cost of carbon equal to 130€/tCO_2. The most cost-effective B-FC solution emits twice less CO_2 than the most cost-effective solution using only BEBs. The results also show how three key parameters favor the B-FC strategy: the size of the niche market, the level of the absolute cost advantage of FCEVB over BEB in that niche and the time to TCO parity with diesel for FCEB formalized through the learning-by-doing rate of FCEV. A sensitivity analysis provides some ground to assess the robustness of our conclusion. In all of our scenarios, given the current level of the SCC, electric battery vehicles must be launched immediately in the short-distance segment market.

To our knowledge, the economic literature on induced technical change and the energy transition has mainly focused on the competition between a polluting technology and a green technology. For instance, Grimaud and Rouge 2008 and Acemoglu et al. 2012 construct a endogenous growth model where a final good is produced using inputs from two different sectors: the first sector uses a polluting technology that produces environmental damage, the other uses a clean technology. In the context of a competition between a clean and a dirty technology, the issue is mainly to direct research towards the clean sector in the most efficient way. In practice, for many applications, the clean sector is not homogeneous, and several clean technologies can coexist in the same sector. There may be different alternatives for achieving a given level of abatement in a sector, and an effective abatement strategy must determine how to allocate abatement effort and possibly research and development subsidies between these technologies.

Bramoullé and Olson 2005 analyze the allocation of efforts among two abatement technologies subject to learning-by-doing (LBD) in a dynamic setting. They also stress the tension between learning-by-doing and cost convexity. However, contrary to us they do not explicitly model the output sector and the polluting goods that need be decarbonated. The two technologies they consider do not compete on a given market, but abate on two different markets. Their model is better suited to analyze the competition between carbon capture options than the substitution of a polluting technology by two green technologies. Therefore without cost convexity, two technologies might be jointly deployed in their model. This is not possible with our setting.

Andreassen and Rosendahl 2020 also propose a model of the transportation sector in which two green technologies (hydrogen and battery) can be used, in a static framework. They focuses on indirect network effects due to the interaction between the vehicle fleet and charging/filling station. On the one hand, a representative consumer has a utility dependent on the vehicle itself and the number of stations available for his vehicles, under budget constraints. On the other hand, a firm maximises its profit from the sale of fuel/refill. The authors find that in the presence of an incompatible network, it is optimal to develop

both technologies if they are not too close substitutes for the consumer. In addition, the number of vehicles in each market plays a role in the choice of technology, with the presence of economies of scale. To the best of our knowledge, these articles are among the only examples that mention the possible competition between two green technologies.

Creti et al. 2018 proposed a model to study the optimal exit trajectory of a polluting technology by a green technology. An indicator to determine the optimal date for launching the transition was proposed in the article. Secondary results on the role of convexity, the learning rate, and the impact on the trajectory if the social cost of carbon increases at a different rate from the discount rate are also demonstrated. In this work, we extend the partial equilibrium model developed in Creti et al. 2018 to two low-carbon technologies, competing with different cost advantages on two market segments. We seek to determine the implications of a additional green technology on the optimal deployment of the energy transition in the transport sector. What roles do convexity, learning and negative externalities related to pollution play in the competition between two low-carbon technologies? Moreover, in the case of the bus transport sector, green technologies compete with different cost advantages on two market segments. The learning-by-doing for each technology benefits from the total production on the two segments. This work explores which parameters play the main roles in the different scenarios and on the end-results, i.e. the technologies that are expected to succeed under given conditions. For instance, if the hydrogen market segment is too small or the potential cost reduction of FCEVs not sufficient, inducing a late launching deployment, it could be optimal to deploy BEV on both segments. Characterizing the conditions under which there is a sustainable niche for FCEV is the core issue discussed in the paper.

The paper is organized as followed:

2 The Economic Framework

2.1 From one to two green technologies

The model considers a given market segment of vehicles, for example city buses. Time is continuous going from $t = 0$ to $t = +\infty$. At time t there is an inelastic demand for vehicles N. There are three available technologies: diesel, battery and fuel cell. Diesel is a carbon emitting technology while the other two are assumed to be carbon neutral (green). Denote x_t and y_t the number of battery and fuel cell vehicles respectively at time t so that the number of diesel vehicles writes $N - x_t - y_t$. Units are normalized so that a diesel vehicle emits one unit of CO_2.

The cost of vehicles using the carbon-based technology is constant, and fixed at c_0. The cost function of a green vehicle is a function of the stock of knowledge accumulated at time t and instantaneous production (Goulder and Mathai 2000, Bramoullé and Olson 2005). Let X_t and Y_t respectively stand for the cumulative production of battery and fuel cell vehicles at time t: $X_t = \int_0^t x_u du$ and $Y_t = \int_0^t y_u du$. Denote $C_1(X_t, x_t)$ and $C_2(Y_t, y_t)$ the respective cost functions. These functions are assumed to be non negative, decreasing and convex with respect to cumulative production, and, increasing and convex with respect to instantaneous production.

The social discount rate is denoted r. The social cost of carbon at time t is denoted p_t^{CO2}

and assumed to grow at the rate r, which is efficient in the presence of a carbon budget according to Hotelling's rule.

The objective of the social planner is to minimise the discounted cost for operating the fleet of N vehicles. Let Γ denote this cost.

$$\Gamma = \int_0^{+\infty} e^{-rt}\big[(p_t^{CO2} + c_0)(N - x_t - y_t) + C_1(X_t, x_t) + C_2(Y_t, y_t)\big]dt \tag{1}$$

Under the following constraints:

$$\begin{aligned} \dot{X}_t &= x_t & \dot{Y}_t &= y_t \\ X_0 &= 0 & Y_0 &= 0 \\ x_t &\geq 0 & y_t &\geq 0 \\ x_t + y_t &\leq N \end{aligned}$$

A general proposition holds regarding the phasing of the transition from fossil fuel vehicles to green ones. It is a direct consequence of the increasing total cost of fossil fuel vehicles since p_t^{CO2} goes to infinity with t.

Proposition 1 *Denoting (x_t^*, X_t^*) and (y_t^*, Y_t^*) the optimal productions and stocks along the optimal deployment trajectory, there exist two dates T_{in} and T_{out} such that three deployment phases can be identified:*

Pre-transition phase : *for $0 \leq t \leq T_{in}$ we have $x_t^* = 0$ and $y_t^* = 0$*
Transition phase : *for $T_{in} < t < T_{out}$ we have $0 < x_t^* + y_t^* < N$*
Post-transition phase : *for $t \geq T_{out}$ we have $x_t^* + y_t^* = N$.*

In absence of specific assumptions on the cost functions, an explicit expression of the optimal trajectory cannot be determined analytically. Elements of resolution are given in Appendix A. Still, we know that:

- During the transition phase, between T_{in} and T_{out}, if $x_t > 0$, it satisfies the following equation

  $$C_{1,x}(X_t, x_t) - c_0 = p_t^{CO2} + \int_t^{+\infty} e^{-r(\tau - t)} C_{1,X}(X_\tau, x_\tau) d\tau$$

  and given that the SCC p_t^{CO2} grows at the discount rate, the trajectory $x_{t-T_{in}}$ does not depend on p_t^{CO2}, which extends a result proved in Creti et al. 2018. The same result applies to y_t.

- During the post-transition phase the market share of the two technologies evolves. One technology is progressively replaced by the other, and on the long-run either the two technologies coexist or one of the two technologies prevails. It is theoretically possible that a technology is developed to decarbonize quickly the transportation system and then phased out and replaced by the other technology.

  Along that phase if both technologies are used the first order condition is:

$$C_{1,x}(X_t, x_t) - C_{2,y}(Y_t, y_t) = \int_t^{+\infty} e^{-r(\tau-t)}[C_{1,X}(X_\tau, x_\tau) - C_{2Y}(Y_\tau, y_\tau)]d\tau$$

with $y_\tau = N - x\tau$ and $Y_\tau = Y_{T_{out}} + (\tau - T_{out})N - (X_\tau - X_{T_{out}})$

2.2 Solving a specific case: absence of convexity

Proposition 2 *If the cost function is linear with respect to production ($C_{xx} = 0$), the optimal strategy is to replace all polluting vehicles by low-carbon ones instantaneously, $T_{in} = T_{out}$, with one low-carbon technology, the other is unused.*

This is demonstrated with a generic cost function in the appendix B.

Now, considering the following specific cost functions for low-carbon vehicles:

$$C_1(X_t, x_t) = [\underline{c_1} + (\overline{c_1} - \underline{c_1})e^{-\lambda_1 X_t}]x_t$$
$$C_2(Y_t, y_t) = [\underline{c_2} + (\overline{c_2} - \underline{c_2})e^{-\lambda_2 Y_t}]y_t$$

For $i = 1, 2$, the parameter λ_i represents the learning rate of technology i, and, $\overline{c_i}$ and $\underline{c_i}$ are the short term and long term marginal costs.

As shown in Proposition 2, the transition is instantaneous and involves only one of the two green technologies. The technology chosen minimizes the total discounted cost and is the one with the earlier launching date. Let us denote T_i the date at which technology i replace all polluting vehicles if it is used. We explicit how to determine T_i with our specific cost function. The discounted cost of the post-transition phase is K_i:

$$K_i = \int_0^{+\infty} e^{-rt} C_i(tN, N)dt = \underline{c_i}\frac{N}{r} + (\overline{c_i} - \underline{c_i})\frac{N}{r + \lambda_i N}$$

The total discounted cost is then

$$\Gamma_i = \int_0^{T_i} e^{-rt}(P_t^{CO2} + c_0)Ndt + e^{-rT_i}K_i$$

which is minimized for

$$P_0^{CO2}e^{rT_i} = (rK_i - c_0N)/N$$

Observe from the expression of K_i that $(rK_i - c_0N)/N$ may be seen as a weighted average between two static marginal abatement costs (MACS): one with the short term marginal cost $\overline{c_i}$, and another one with the long term one $\underline{c_i}$, the weights depending on the rate of LBD λ_i and the size of the market N. The higher λ_i and N, the lower $(rK_i - c_0N)/N$ which eventually converge to the standard MAC with the long term marginal cost. On the contrary, if λ_i is null, it coincides with the standard MAC with the short term marginal cost whatever the size of the market.

This example nicely illustrates the trade-off between stationary costs and the speed at which they are reached. It is further discussed in the analysis of Meunier and J.-P. Ponssard 2022 on abatement costs metrics.

2.3 Extensions to be introduced in the simulation

2.3.1 The two green technologies are not perfect substitutes

In many segments battery and fuel cell technologies are not perfectly substitutes. Typically, hydrogen vehicles have a longer range than battery vehicles. Furthermore, uneven topographical landscapes such as mountain, and extreme temperatures also advantage hydrogen technology. This translates into additional costs for the battery vehicles for some usages, either in terms of opportunity cost (the recharging time of the electric vehicle) or in terms of the number of vehicles (to replace a diesel bus operating on a long route, more than one battery vehicle might be needed).

This suggests to introduce some horizontal differentiation: the two green technologies are not perfect substitutes for all types of users. The cost of a technology depends on the characteristics of the agents. To simplify, we assume that there are only two types of users, for a subset of users the cost of BEV is higher than for others. On that segment FCEV might develop. The total number of vehicles N is the sum of N_1 standard users and N_2 peculiar users, with $N_1 > N_2$, and N_2 the possible FCEV niche market.

- **Main market**: for N_1 standard users the cost of FCEV is c_{FCEV} and the cost of BEV is c_{BEV}. With our calibration these agents will allways use BEV.
- **Niche market**: for N_2 peculiar users (i.e. long trips, uneven topography, extreme temperature) the cost of FCEV is c_{FCEV} and the cost of BEV is $c_{BEV} + d$. these users might use FCEV.

There are two strategies to be compared:

- **B-B strategy**: a single technology is used to maximise learning. BEV is used for all users because of its cost advantage and larger market. On the segment N_2 BEV is used which results in a additional cost d per vehicle.
- **FC-B strategy**: the two technologies are used. The N_1 market transitions to battery technology, while the N_2 market transitions to hydrogen technology

The cost of the two strategies can be easily determined and compared. The explicit formula for the cost of the two strategies is given in the appendix C.

2.3.2 Progressive maturity of low-carbon technology

Indeed, the transition from a polluting technology to a green technology does not occur instantaneously. Notably because of the time needed to progressively build the infrastructure of fueling stations and production capacities. Analytically, the introduction of some convexity in the cost functions of green technologies would ensure a progressive deployment.

A possible way to introduce convexity in the model would be to add terms such as $\frac{x_t^2}{2(X_0+b_1X_t)}$ and $\frac{y_t^2}{2(Y_0+b_2Y_t)}$. The strong convexity effect at the beginning of the deployment would progressively vanish as the technology matures. However getting analytical results with this specification appears uneasy, it is left for further research.

In this applied paper we shall follow a much simpler route: a given duration for phase 2 is assumed to occur with a linear growth rate. The impact of several durations can be derived. The addition of a linear transition of exogenous duration in the cost of the two optimal deployment strategies "B-B" and "B-FC" is studied in the Appendix D.

3 Battery-Electric Buses (BEBs) Versus Fuel-Cell Electric Buses (FCEBs): Analysis through Simulation Model

In this part, we use the model developed in part 2, including the imperfect substitution parameters between the two green technologies. In the absence of relevant calibration strategy concerning the convexity of the cost function, we set $C_{i,xx} = 0$. Namely, we take the form of the cost function developed in the previous section: $C_i(X_t, x_t) = [\underline{c_i} + (\overline{c_i} - \underline{c_i})exp(-\lambda_i X_t)]x_t$. As seen in Proposition 2, the optimal transition is therefore instantaneous. The addition of a transition of fixed and exogenous duration will be studied.

We consider the mobility segment of standard buses for the European geographical area (including UK). On this segment, we compare the cost of the B-FC strategy and the B-B strategy, on the main market N_1 (short-distance) and the niche market N_2 (long-distance, intensive use).

3.1 Parameter calibration

The following table gives a value to the different parameters of the model, based on data from public reports and calibration.

	BEV	FCEV
Current cost $\overline{c}$ (€/km)	3.8	5
Minimal cost $\underline{c}$ (€/km)	3.4	3.4
Learning rate λ	0.00001	0.00010
Mean penalty for BEBs on the niche market d (€/km)	0.3	
Cost of diesel vehicles (c_0) (€/km)	3.5	
Tank-to-wheels emissions of diesel buses (gC02/km)	820	
Social cost of carbon in 2020 (SCC) (€/tC02)	88	
Social cost of carbon in 2020 per diesel km (p_0) (€/km)	0.07	
Social cost of local pollution per diesel km (p_{loc}) (€/km)	0.07	
Market size N (volume of vehicles)	28500	
Niche market relative size θ (% of N)	10 %	
Discount rate r	0.045	

Table 1: Estimated parameters of battery and hydrogen technology in the model

The calibration of parameters of Table 1 is explained below.

3.1.1 Cost of vehicles and learning rates

We focus on the bus sector and neglect the impact of other mobility on bus market prices. The cost of vehicles corresponds to the total cost of ownership (TCO) of the buses for the different technologies considered. TCO takes into account fixed capital, maintenance, personnel costs, and the cost of fuel or charge. Fuel and charge costs take into account the costs of charging infrastructures but don't include fuel taxes on diesel, which are reflected in the social price of carbon. The TCOs of low-carbon vehicles are assessed in 2020 for each

technology, based on data from Meunier, Moulin, and J. Ponssard 2019, from public reports (French Transport Department taskforce and Ministère de la Transition Ecologique) and internal experts interviews with the different entities of ENGIE. These data are summarized in Table 2. $c_0, \underline{c_{BEB}}, \underline{c_{FCEB}}$ are respectively calibrated using 2021 TCO values of diesel buses, BEBs, and FCEBs.

	Diesel Bus	FCEB	BEB
Fixed capital (€/km)	**0.3**	**0.9**	**0.7**
Corresponding purchase price (€)	260 000	650 000	500 000
km/year	50 000	50 000	50 000
life duration (years)	15	15	15
Maintenance (€/km)	**0.3**	**0.4**	**0.2**
Personnel costs (€/km)	**2.7**	**2.7**	**2.7**
Fuel/Charge (no tax) (€/km)	**0.2**	**1.0**	**0.2**
Unit price (€/L, kgH2 or kWh)	0.5	10.0	0.1
Consumption (L, kgH2 or kWh per 100km)	46.0	10.0	150.0
TCO (€/km)	**3.5**	**5.0**	**3.8**

Table 2: TCO analysis of FCEB, BEB, Diesel bus in 2020

We assume, based on technical reports on TCO projections (Ballard 2020), that BEBs and FCEBs can reach the same target minimal cost $\underline{c}$ after a sufficient learning stock. This minimum cost is estimated to be slightly lower than the current TCO of diesel vehicles, i.e $\underline{c} = 3.4$ €/km.

The critical parameter λ_i describes the rate of cost reduction depending on the stock, from the current cost $\overline{c_i}$ to the minimal cost $\underline{c_i}$. From a benchmark of different sources, we find that BEBs reach cost parity with diesel buses in 2025 and FCEBs reach cost parity with diesel buses in 2035. We therefore assume that cost parity with diesel for BEBs is reached after producing BEBs on the N_1 market during 5 years, while cost parity with diesel for FCEBs is reached after producing FCEBs on the N_2 market during 15 years.

Based on these assumptions, we estimate for each technology i a value of λ_i, such as:

$$\lambda_i = ln(\frac{\overline{c_i} - \underline{c_i}}{c_0 - \underline{c_i}})/\overline{X_i}$$

with $\overline{X_i}$ the bus stock of technology i to build to achieve cost parity with diesel buses. Sensitivity analysis on the critical parameter λ_i will be carried out in the results part.

3.1.2 Pollution cost of vehicles

ADEME and Scania 2018 estimate the tank-to-wheel emissions of current diesel city buses at 82 $kgCO_2$/100km. The pollution cost corresponds to the social cost of carbon, defined as the additional cost to society of emitting an unit of carbon. Quinet 2014 proposes to set the social price of carbon, for a discount rate of 4.5%, at 88€t in 2020, 250€t in 2030, 775€tCO_2 in 2050. To compare with current carbon legislation, the value of the carbon tax on fuels is approximately two times lower in 2020. (Source: Carbon taxation, Ministry of Ecological

Transition). Based on tank-to-wheels emissions, life duration and the distance traveled per year for each technology, the social cost of carbon leads to an additional cost of 0.07€km per diesel buses in 2020.

According to our methodology, we only take into account direct CO_2 emissions, so that FCEBs and BEBs do not emit greenhouse gases. For information, the social cost of carbon leads to an additional cost of 0.007€km for BEB and of 0.02€/km for FCEBs with French electric mix in 2020, consideringg the life cycle assessment of low-carbon buses ADEME 2018. Thus, we can consider that the cost of carbon is negligible for low-carbon vehicles compared to their TCO, considering only the first years of transition. This calculation validates our methodology, even if low-carbon mobility is not carbon-free from well-to-wheel.

In addition, Meunier and J. Ponssard 2020 proposed to integrate the cost of local pollution (NOx and PM 2.5 emissions) generated by diesel vehicles in the assessment of abatement cost for deploying low-carbon fleets. The Quinet report gives value to the 'local' social cost for diesel buses, depending on the area concerned (urban, suburban) and the corresponding density of inhabitants. Ponssard and Meunier (2019) proposes to increase the pollution cost of diesel buses by 0.27 €km for dense urban areas. We supposed, based on data from Commissariat général au développement durable 2020 that 25% of bus transport is located in dense urban area, which leads to an increase in average TCO of diesel bus of 0.07€km. This value is considered to be fixed over time.

3.1.3 Market size parameters

Bus market size European Automobile Manufacturers' Association (ACEA) 2021 estimates the number of medium and heavy bus registrations in the European Union to be 28,500 in the year 2020 . It is assumed that these registrations correspond to the number of buses built for the European market, and that this number of buses remains stable over time.

Potential size of the hydrogen niche in the bus sector Roland Berger 2015 expects the size of the hydrogen market for the bus sector to be around 9% in 2025. It is assumed that this share is representative of the size of the market that hydrogen buses could occupy, i.e the long-distance and intensive-in-use market niche of the bus sector.

3.1.4 Penalty on the niche market for BEBs

According to ADEME 2018, BEBs currently offer an average range of 200 km for a standard bus. The range of hydrogen vehicles is between 300 and 500 km depending on the pressure in the hydrogen tanks and their size. For simplicity, it is assumed that 9 % of the bus market needs a range of 400km. To travel this distance with a BEB, different charging strategy are available. We evaluate the additional cost of the different charging options on the TCO:

- The most expensive option is to own a second BEB to make the same journey that a single FCEB could travel in a day. The penalty would then be equal to the CAPEX cost of a second BEB. For simplicity, we take the average CAPEX of BEB between 2020 and 2030, i.e. 0.5 €/km. This assumption is very simplistic as it ignores that learning would be done on these additional buses. This solution will only be chosen if

other solutions to increase the reach of BEBs are not viable. This penalty can therefore be seen as an upper bound.

- The other two main options that allow BEBs to be used over long distances would be to either increase the size of the batteries in buses, or the installation of ultra-fast charging stations, allowing electric buses to recharge in 15-30 min at regular intervals (opportunity charging). Transport & Environnement 2018 estimates that the additional cost of installing fast charging network for an electric bus in "opportunity charging" would be 0.2€/km. This option is now considered the most viable for increasing the range of BEBs. However, it requires a dense network of fast-charging stations, which will take a long time to install. According to the same study, increasing the size of the batteries to charge them at night would increase the TCO of buses by a slightly greater amount. In addition, increasing the size of the batteries reduces the space available for passengers. The penalty of 0.15€/km can therefore be considered as a lower bound.

For our standard scenario, we choose the average penalty between these two bounds, i.e. 0.3€/km.

3.1.5 Other parameters

Discount rate We use a discount rate of 4.5%, as chosen in the Quinet 2014 report.

3.2 Key results

3.2.1 Baseline scenario results and sensitiviy analysis

Table 3 presents some key indicators obtained by simulating the model with the calibrated parameters. These key indicators are: the most cost-effective strategy between B-FC and B-B, the cost difference in % between the two strategies (considering only cash production costs without SCC), the difference in direct CO_2 emissions between the strategies, then for each strategy, the launching date T_1 (respectively T_2) on N_1 (resp. N_2) of the low-carbon technologies, then the marginal cost after 5 years of learning of the different technologies.

Several sensitivity analysis are conducted. In addition to a variation on the parameters of interest, the effect of taking into account local pollution (0.07€/km malus for diesel buses) is studied, as well as the impact of a lower estimation of the social cost of carbon in 2020.

Scenario	**Winning Strategy**	**Strategies**	**Cash cost** (BN. €)	**CO_2 emission** (M. teqCO_2)	T_1	T_2
Baseline	B-FC	B-B	370,9	39,7	0,0	23,2
		B-FC	370,8	19,7	0,0	11.5
Sensitivity on niche market size (baseline $\theta = 10\%$)						
$\theta = 20\%$	B-FC	B-B	378,5	79	0,0	23,2
		B-FC	373,4	0	0,0	0
$\theta = 5\%$	B-B	B-B	367,0	19.8	0,0	23,2
		B-FC	367,1	26,5	0,0	30,9
Sensitivity on FCEB learning rate (baseline $\lambda_{FCEB} = 0.0001$)						
$\lambda_{FCEB} = 0.00014$ (cost parity in 2030)	B-FC	B-B	370,9	39.7	0,0	23,2
		B-FC	370,7	0,0	0,0	0,0
$\lambda_{FCEB} = 0.00006$ (cost parity in 2040)	B-B	B-B	370,9	39.7	0,0	23,2
		B-FC	370,9	42.0	0,0	24,6
Sensitivity on penalty for BEBs on long-distance (baseline $d = 0.3$)						
$d = 0.2$ €/km	B-B	B-B	370,7	15,3	0,0	8.9
		B-FC	370.9	19.7	0.0	11.5
$d = 0.5$ €/km	B-FC	B-B	370,9	66,0	0,0	38.6
		B-FC	370.9	19.7	0.0	11.5
Sensitivity analysis on negative externalities (baseline: $p_0 = 0.07$)						
adding local pollution	B-FC	B-B	374.0	14.9	0,0	8.5
		B-FC	373.1	0.0	0.0	0.0
(SCC)/ 2	B-FC	B-B	367.7	153.7	0,0	89.9
		B-FC	367.7	133.7	0.0	78.2

Table 3: Key indicators on B-FC and B-B strategies for the baseline scenario, with sensitivity analysis on model parameters.
Reading the first line: the winning strategy is "Battery-fuel cell". With the B-B strategy: the cash cost (total discounted costs without emission costs) is 370.8 BN. €, 19.7 M. teqCO2 are emitted, the optimal launching date of BEBs on N_1 is 2020 (2020 + 0), the optimal launching date of FCEBs on N_2 is 2031 (2020 + 11). For the B-B-strategy: the cash cost (total discounted costs without emission costs) is 370.8 BN. €, 19.7 M. teqCO2 are emitted, the optimal launching date of BEBs on N_1 is 2020 (2020 + 0), the optimal launching date of BEBs on N_2 is 2043 (2020 + 10).

The analysis of this table shows that the existence of a hydrogen niche is relatively robust to sensitivity analyses. A significant reduction in θ, λ_{FCEB} and d would be required for the B-B strategy to be dominant over B-FC. Moreover, in all scenarios, BEBs must be deployed immediately on the main market segment N_1. Considering the baseline scenario, launching FCEBs in 2030 is more cost-effective than waiting 2040 to launch BEBs in the main market. This means that the B-FC strategy is dominant in the base case. At T_1, the launching date of BEBs on the main market N_1, the social cost of carbon equals 88 €/teqCO2. At T_2, the launching date of FCEBs on the niche market N_2, the social cost of carbon equals 130 €/teqCO2.

The comparison between both strategies shows that the cash cost comparison, ignoring CO_2 emission costs, is very negligible in most scenarios. We are in a situation with a flat optimum, where discounted cash cost are not very sensitive to the choice of strategy. However, the impact of the strategy on the optimal transition date, and therefore on total emissions, is greater. In the baseline scenario, the most cost-effective B-FC strategy emits more than twice less direct CO_2 emissions than the most cost-effective B-B strategy. It can be said that at the cost of additional CO_2 emissions, the losing strategy can approach the cash cost of the winning strategy.

Table 3 helps to disentangle complex interaction effects, particularly concerning launching dates. According to our simulations, the relative size of the niche market has a great impact on T_2, the optimal launching date in the niche market N_2, for B-FC strategy, but not for B-B strategy. A decrease in the discount rate r increases T_2 for strategy B-B, but decreases T_2 for strategy B-FC. As shown in Creti et al. 2018, additional negative externalities or increase in the social cost of carbone shifts optimal starting dates towards 0. The impact of λ and d will be studied in more detail in 3.2.2.

Nevertheless, the sustainability of a hydrogen market niche is threatened if the learning rate is smaller than expected. Moreover, if fast-charging stations are generalized, d will tend to the lower bound $d = 0.2$, which would compromised the existence of an hydrogen market niche. These results have public policy implications which will be discussed in Section 4. In the next part we focus on the joint evolution of two critical parameters in the determination of an optimal strategy, i.e. the learning rate of FCEB λ_{H2} and the penalty d.

3.2.2 Impact of the learning rate on the equilibrium penalty

From this paragraph, we note d^* the penalty that equalizes the cost of the B-B strategy and the B-FC strategy. Figure 1 shows the evolution of the equilibrium penalty as a function of FCEB's learning rate. Indeed, it is interesting to observe the joint evolution of these two parameters, because it is likely that the d penalty also depends on the technical progress induced on the technologies, thus on the learning rates λ_{BEB} and λ_{FCEB}. The range of BEBs may also depend on the learning rate of technologies. According to our simulations, the lower the learning rate of FCEBs, the more dominant the B-strategy will be : only a strong long-distance penalty for BEBs could make the construction of FCEBs in its market niche cost-competitive. On the contrary, if the learning rate of hydrogen technology is high, the deployment of hydrogen in its niche no longer requires a high penalty to be competitive. Thus, for the calibrated learning rate value, $\lambda_{FCEB} = 0.0001$, B-FC strategy is dominant if $d > 0.21$, i.e. approximately the penalty that would correspond to the installation of

ultra-fast charging stations for buses.

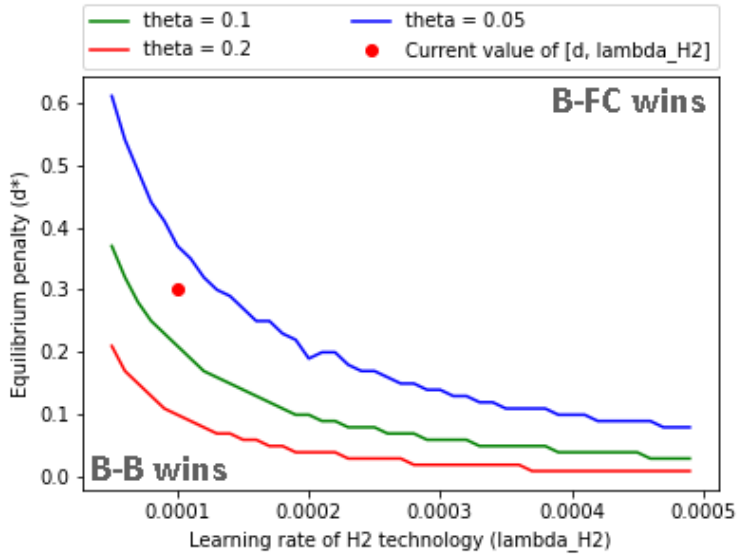

Figure 1: Evolution of d*, penalty ensuring indifference between both strategies, as a function of the learning rate of the hydrogen technology: sensitivity analysis on the niche market size

We observe the effect of the size of the niche market on the impact of the learning rate on the equilibrium penalty. An increase in the size of the niche to 20% of the total market increases the number of scenarios where the B-FC strategy is competitive. For $\lambda_{FCEB} = 0.0001$, the B-FC strategy would be dominant if $d > 0.12$, that is, even if fast-charging installations for BEBs are deployed. On the contrary, if the size market is smaller than expected (5%), B-FC is dominant if $d > 0.4$, that is the mean penalty considered. The total size of the bus market affects this trade-off in the same way. If the bus market is expanding, the B-FC strategy is more often dominant, because the hydrogen market niche is large enough for the costs of the hydrogen technology to decrease. On the contrary, if sobriety constraints are introduced into the model and reduce the bus market size, the volume of FCEBs built in the hydrogen market niche would be too low to expect a significant cost reduction, and the B-B strategy will prevail.

3.2.3 Impact of the transition duration on the optimal strategy

In this previous section, we have imposed the convexity of the cost functions to be equal to 0. This allows to obtain explicit formulas of the two optimal strategies, and to compare their costs. The transition from a carbon technology to a low-carbon technology on the N_1 and N_2 markets is therefore instantaneous. This modeling approach is not representative of the economic reality of the energy transition. We study the impact of the addition of an exogenous transition duration on the trade-off between both strategies B-B and B-FC. To simplify, an exogenous duration of 10 years is imposed for both strategies. This transition is linear. Schemas and cost formulas for strategies with exogenous linear transition are detailed in the appendix D.

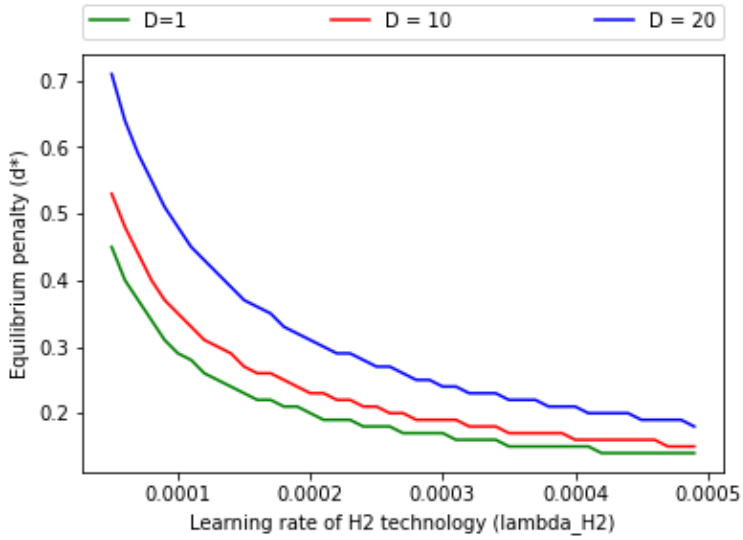

Figure 2: Evolution of d*, penalty ensuring indifference between both strategies, as a function of the learning rate of the FCEB technology: sensitivity analysis for transition duration of 1, 10 and 20 years

We compare the evolution of d^*, the penalty ensuring cost equality between both strategies, depending on λ_{H2}, for 3 different transition duration: 1 years, 10 years ans 20 years of transition are needed for the main market N_1 and the niche market N_2 to use low-carbon technologies.

For a fixed value of λ_{H2}, the addition of a transition period increased the equilibrium penalty value d^*. It means that a higher penalty is necessary to make the launch of a hydrogen market niche profitable for all values of FCEBs learning rates. Delaying the transition or extending its duration would therefore disadvantage the deployment of hydrogen in the transport sector. The policy implications of these sensitivity analyzes are left for future research.

4 Going further to evaluate the two strategies

The simulation model discusses two strategies, a first one based on battery vehicles only (B-B) and a second one based on both battery and fuel-cell vehicles (B-FC), to decarbonize a market involving two segments, a main segment (N_1) in which battery vehicles have a large absolute cost advantage and a niche segment (N_2) in which fuel cell vehicles have only a potential cost advantage.

The optimal strategy balances the amount of emissions prior the full decarbonization of the sector with the total discounted cash cost for the transition. Regarding the B-FC strategy, due in particular to a higher initial TCO for FCEV compared to BEV, the transition to FCEV on the segment N_2 would take place later than the one of BEV on N_1. Using the B-B strategy changes these dates thus influences the emissions prior the full decarbonization but increases the discounted cash cost since it delivers BEV on N_2.

The simulation characterizes how the parameters interact in the choice between the B-B and B-FC strategies. Based on our calibration of the model it is shown that the B-FC strategy dominates. The results also show how three key parameters favor the B-FC strategy: the size of the niche market ($\theta = N_2/N_1$), the level of the absolute cost advantage of FCEB over BEB in that niche (d) and the time to TCO parity with diesel for FCEB formalized through the learning-by-doing rate of FCEB (λ_{FC}). A sensitivity analysis provides some ground to assess the robustness of our conclusion. This suggests that further attention should be given on the drivers of these three parameters.

The size of the niche market for FCEV over BEV could be refined through a detailed segmentation of the transport sector. Some studies do explore this question. For instance, Hydrogen Council 2021 provides the potential market shares of FCEV relative to BEV depending on two criteria: ranges and weight. The question of the absolute cost advantage in each segment is more difficult but it could be quantified more specifically through interviews with industry experts.

Concerning the calibration of the learning-by-doing rate of FCEV, the current calibration strategy does not take into account the diffusion of learning that takes place between the different mobility segments. One more realistic approach would be to decomposed the TCO into components, such as the fuel cell itself, the tank and to precise on which market segments the respective cost component is shared. Each technology uses a certain number of components, the cost of which can be reduced according to their respective production volume. These components are often common to the different light and heavy-duty mobility sectors. For example, fuel-cell components could be used by a hydrogen bus, a hydrogen truck or a hydrogen utility vehicle. The production volume, and therefore the experience gained in building a component, will therefore be common to the different mobility sectors. Thus, the costs of the battery of a BEB will be impacted by the cumulative production volume of the battery-electric car. Here also some studies address this question. For instance, E4Tech 2021 provides detailed information for the cost evolution of fuel cells components, and the breakdown of component costs by type of fuel cell-electric vehicle. However, this approach requires a large amount of data that we do not yet have.

Special attention should be given to the cost of fuel which in our calibration integrates two components: the production cost as such and the cost of infrastructure. For the former one could start with projections of the electricity price which impacts both BEV and FCEV fuel cost. The infrastructure cost for both technologies significantly differ. For BEV it should be segmented in terms of public and private parkings, commercial sites, highways.. with relevant power for each segment. For FCEV the cost depends on the total demand in each cluster coming not only from mobility but also from industry. There is a long way from our simple model to such a global one which would be similar to existing sector models. We think that it would worthwhile to undertake such a task to put down more realistic roots in sector models and evaluate the impacts of public policies.

5 Conclusion

Contributions of the paper are twofold. Firstly, it clarifies the impacts of learning-by-doing, convexity and horizontal differentiation on the optimal transition path when several green competing technologies are available to decarbonize a given mobility segment. Secondly the analysis is applied to the case of fuel-cell electric and battery electric buses to decarbonize the European park of diesel buses. Based on available data, the existence of a sustainable niche for FCEB is validated.

Our model can be extended in several directions. It would be possible to include other competing low-carbon technologies in the model, namely bioLNG and bioNGV. The model could be adapted to model a competition other than BEB vs FCEB, either between other low-carbon technologies (for example BioLNG VS hydrogen) or on a another type of mobility (truck, trains, boats...). However a more relevant extension would be to encompass all mobility segments into a larger sector model so as to link the market niches in these segments with the learning rates in the respective common cost components (fuel cells, tanks, monitoring systems). Additionally, a more detailed study of the environmental impacts of the different low-carbon technologies must be carried out. In particular, the issue of indirect emissions from low-carbon vehicles needs to be addressed. In our model, if both low-carbon technologies still emit indirect CO2 emissions, the increase of the social cost of carbon at the discount rate makes the discounted cost of the transition non-finite. If only one low-carbon technology still emits CO2 emissions in the long run, in the long run it will inevitably be evicted. The addition of a carbon capture parameter could allow these indirect emissions to be introduced into the model.

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A Proof of proposition 1

Phase decomposition

See Creti et al. (2017)

Post-transition phase (phase 3)

In the third phase, vehicles with polluting technologies are no longer produced, so the competition is only between two low-carbon technologies ($x_t^* + y_t^* = N$) that saturate the market. The objective function to be minimised can then be expressed in this way.

$$\Gamma_2 = \int_{T_{out}}^{+\infty} e^{-rt}\big[(C_1(X_t, x_t) + C_2(Y_t, y_t)\big]dt$$

subject to

$$\begin{aligned} \dot{X}_t &= x_t & \dot{Y}_t &= y_t \\ x_t &\geq 0 & y_t &\geq 0 \\ x_t + y_t &= N \end{aligned}$$

By inserting the last constraint into the objective function, the problem can be reduced to a problem with one control variable and one state variable.

$$\begin{aligned} \Gamma_2 &= e^{-rT_{out}} \int_0^{+\infty} e^{-rt}\big[(C_1(X_t, x_t) + C_2(Y_{T_2} + \int_{T_{out}}^{t} (N - x_u)du, N - x_t)\big]dt \\ &= e^{-rT_{out}} \int_0^{+\infty} e^{-rt}\big[(C_1(X_t, x_t) + C_2(Y_{T_{out}} + tN - (X_t - X_{T_{out}}), N - x_t)\big]dt \\ &\text{subject to } \dot{X}_t = x_t, x_t \geq 0, X(0) = X_{T_{out}}, x(0) = x_{T_{out}} \end{aligned}$$

We put $C_2(\tilde{X}_t, \tilde{x}_t) = C_2(Y_{T_{OUT}} + tN - (X_t - X_{T_{out}}), N - x_t)$, where $Y_{T_{OUT}}$ corresponds to the stock of knowledge of the second technology accumulated during the transition phase.

The Hamiltonian and Lagrangian of the optimization problem are:

$$\begin{aligned} \mathcal{H}(t) &= C_1(X_t, x_t) + C_2(\tilde{X}_t, \tilde{x}_t) + \lambda_t x_t \\ \mathcal{L}(t) &= C_1(X_t, x_t) + C_2(\tilde{X}_t, \tilde{x}_t) + \lambda_t x_t + \theta x_t \end{aligned}$$

The optimality conditions of the problem are:

$$\begin{cases} C_{1,x}(X_t, x_t) - C_{2,x}(\tilde{X}_t, \tilde{x}_t) + \lambda_t + \theta = 0 \\ \dot{\lambda}_t - r\lambda_t = -C_{1,X}(X_t, x_t) + C_{2,X}(\tilde{X}_t, \tilde{x}_t) \end{cases}$$

If we suppose that $x_t > 0$, then $\theta = 0$. The optimality conditions of the optimisation problem in phase 3 become:

$$\begin{cases} C_{1,x}(X_t, x_t) - C_{2,x}(\tilde{X}_t, \tilde{x}_t) + \lambda_t = 0 \\ \dot{\lambda}_t - r\lambda_t = -C_{1,X}(X_t, x_t) + C_{2,X}(\tilde{X}_t, \tilde{x}_t) \end{cases}$$

Deriving the first optimality condition with respect to time,

$$\dot{\lambda}_t = -\dot{X}_t C_{1,xX}(X_t, x_t) - \dot{x}_t C_{1,xx}(X_t, x_t) + (N - \dot{X}_t) C_{2,xX}(\tilde{X}_t, \tilde{x}_t) - \dot{x}_t (C_{2,xx}(\tilde{X}_t, \tilde{x}_t))$$
$$\lambda_t = -C_{1,x}(X_t, x_t) + C_{2,x}(\tilde{X}_t, \tilde{x}_t)$$

Using the expressions for λ_i and $\dot{\lambda}_i$ in the second optimality condition, we find:

$$\ddot{X}_t(-C_{2,xx}(\tilde{X}_t, \tilde{x}_t) - C_{1,xx}(X_t, x_t)) + \dot{X}_t(-C_{2,xX}(\tilde{X}_t, \tilde{x}_t) - C_{1,xX}(X_t, x_t))$$
$$- r(-C_{1,x}(X_t, x_t) + C_{2,x}(\tilde{X}_t, \tilde{x}_t)) = -C_{1,X}(X_t, x_t) + C_{2,X}(\tilde{X}_t, \tilde{x}_t) - N C_{2,xX}(\tilde{X}_t, \tilde{x}_t)$$

Transition phase (phase 2)

Phase 2 corresponds to the transition phase between one carbon technology and two low-carbon technologies ($0 < x_t + y_t < N$). During this phase, the technologies are deployed without saturating the market, and are not mutually constrained. We note T_{in} the beginning of this transition phase, such that $\forall t > T_{in}, x_t + y_t > 0$.

The objective function to be minimised is then expressed in this way.

$$\Gamma_1 = \int_{T_{in}}^{T_{out}} e^{-rt} \big[(p_t^{CO2} + c_0)(N - x_t - y_t) + C_1(X_t, x_t) + C_2(Y_t, y_t) \big] dt \tag{2}$$

Under the following constraints:

$$\begin{aligned} \dot{X}_t &= x_t & \dot{Y}_t &= y_t \\ X_0 &= 0 & Y_0 &= 0 \\ x_t &\geq 0 & y_t &\geq 0 \\ x_t + y_t &\leq N \end{aligned}$$

The Hamiltonian and Lagrangian of the problem are:

$$\mathcal{H}(t) = (p_t^{CO2} + c_0)(N - x_t - y_t) + C_1(X_t, x_t) + C_2(Y_t, y_t) + \lambda_{1,t} x_t + \lambda_{2,t} y_t$$
$$\mathcal{L}(t) = (p_t^{CO2} + c_0)(N - x_t - y_t) + C_1(X_t, x_t) + C_2(Y_t, y_t) + \lambda_{1,t} x_t + \lambda_{2,t} y_t$$
$$+ \theta_{1,t} x_t + \theta_{2,t} y_t + \delta_t (N - x_t - y_t)$$

In the transition phase, we are sure that $x_t + y_t < N$, so $\delta_t = 0$. Let T_1, such that $\forall t > T_1, x_t > 0$ and T_2, such that $\forall t > T_2, y_t > 0$. We have $T_{in} = min(T_1, T_2)$. We first assume that $t > T_1$, so $\theta_{1,t} = 0$, and we express the optimality conditions related to the first technology. Then we suppose that $t > T_2$, so $\theta_{2,t} = 0$, and we express the conditions of optimality related to the second technology.

Once it is assumed that $x_t > 0$ and $y_t > 0$, we can derive the optimality conditions during the transition phase of both technology.

$$\frac{\partial \mathcal{L}}{\partial x_t} = 0 \qquad \frac{\partial \mathcal{L}}{\partial y_t} = 0$$
$$-\frac{\partial \mathcal{L}}{\partial X_t} = \dot{\lambda_{1,t}} - r\lambda_{1,t} \qquad -\frac{\partial \mathcal{L}}{\partial Y_t} = \dot{\lambda_{2,t}} - r\lambda_{2,t}$$
$$\frac{\partial \mathcal{L}}{\partial \lambda_{1,t}} = x_i \qquad \frac{\partial \mathcal{L}}{\partial \lambda_{2,t}} = y_i$$

Rewriting this conditions

$$\begin{aligned} C_{1,x}(x_t, X_t) - c_0 &= p_t^{CO2} + \lambda_{1,t} \\ C_{2,y}(y_t, Y_t) - c_0 &= p_t^{CO2} + \lambda_{2,t} \\ \dot{\lambda_{1,t}} - r\lambda_{1,t} &= -C_{1,X}(X_t, x_t) \\ \dot{\lambda_{2,t}} - r\lambda_{2,t} &= -C_{2,Y}(Y_t, y_t) \end{aligned}$$

Deriving the first two equations with respect to time, we have:

$$\begin{aligned} \dot{\lambda_{1,t}} &= C_{1,xx}\ddot{X}_t + C_{1,xX}\dot{X}_t - \dot{p_t^{CO2}} = C_{1,xx}\ddot{X}_t + C_{1,xX}\dot{X}_t - r * p_t^{CO2} \\ \dot{\lambda_{2,t}} &= C_{2,yy}\ddot{Y}_t + C_{2,yY}\dot{Y}_t - \dot{p_t^{CO2}} = C_{2,yy}\ddot{Y}_t + C_{2,yY}\dot{Y}_t - r * p_t^{CO2} \\ \lambda_{1,t} &= C_{1,x}(x_t, X_t) - c_0 - p_t^{CO2} \\ \lambda_{2,t} &= C_{2,x}(y_t, Y_t) - c_0 - p_t^{CO2} \end{aligned}$$

Using the expressions for λ_i and $\dot{\lambda}_i$ in the second optimality condition, we find:

$$\begin{cases} C_{1,xx}\ddot{X}_t + C_{1,xX}\dot{X}_t - rC_{1,x} - C_{1,X} + rc_0 & = 0 \text{ for } t > T_1 \\ C_{2,yy}\ddot{Y}_t + C_{2,yY}\dot{Y}_t - rC_{2,y} - C_{2,Y} + rc_0 & = 0 \text{ for } t > T_2 \end{cases}$$

Pre-transition phase (phase 1)

In phase 1, the energy transition has not started yet: N vehicles use carbon technology, so $x_t = y_t = 0, \forall t \in [0, min(T_1, T_2)]$. We need to determine the end date of phase 1, i.e. the start date of the transition, i.e. T_1 or T_2. This is done by determining the total cost of the transition.

- The cost of a fleet of polluting cars, deployed over $t \in [0, T_{OUT}]$, is

$$\int_0^{T_{OUT}} e^{-rt}(c_0 + p_t^{CO2})N dt$$

- The cost of deployment is the cost of producing carbon-neutral vehicles in place of carbon cars. This deployment takes place over D years, during which time $\overline{X}$ carbon-neutral vehicles are produced.

The cost of deploying technology 1 is

$$I((\xi_\tau), \tau \in [0, D_1]) = \int_0^{D_1} e^{-r\tau}[C_1(\overline{X_\tau}, \xi_\tau) - c_0\xi_\tau]d\tau$$
$$\text{where } \overline{X_\tau} = \int_0^{\tau} \xi_u du$$

The cost of deploying technology 2 is

$$I((\eta_\tau), \tau \in [0, D_2]) = \int_0^{D_2} e^{-r\tau}[C_2(\overline{Y_\tau}, \eta_\tau) - c_0\eta_\tau]d\tau$$
$$\text{where } \overline{Y_\tau} = \int_0^{\tau} \eta_u du$$

- Finally, in the post-transition phase, only low-carbon vehicles are built. The cost of the transition is :

$$\Omega(\overline{X}, \overline{Y}) = \int_0^{+\infty} e^{-rt}\big[(C_1(\overline{X} + \int_0^t x_{2,\tau}d\tau, x_{2,t}) + C_2(\overline{Y} + \int_0^t y_{2,\tau}d\tau, y_{2,t})\big]dt$$
$$\text{where } \overline{X} = \int_0^{D_1} \xi_t dt, \overline{Y} = \int_0^{D_2} \eta_t dt$$

Finally, discounting these different costs gives the following total cost:

$$\Gamma(T_1, T_2, T_{out}, \overline{X}, \overline{Y}, D_1, D_2, \xi, \eta) = \int_0^{T_{out}} e^{-rt}(c_0 + p_t^{CO2})Ndt +$$
$$e^{-rT_1}I(\xi) + e^{-rT_2}I(\eta) - p_0 * (\overline{Y} + \overline{X}) + e^{-rT_{out}}\Omega(\overline{X}, \overline{Y})$$

To obtain the optimal date for launching the transition for each of the two technologies, we would like to derive this total cost with respect to the respective launching date of the different technologies, and determine the conditions under which this derivative is null.

$$\frac{\partial\Gamma(T_1, T_2, T_{out}, \overline{X}, \overline{Y}, D_1, D_2, \xi, \eta)}{\partial T_1} = e^{-rT_{out}}[\frac{\partial T_{out}}{\partial T_1}(p_{T_{out}}^{CO2}N + c_0N) - re^{-rD_1}I(\xi) - \frac{\partial T_{out}}{\partial T_1}r\Omega(\overline{X}, \overline{Y})] = 0$$
$$\frac{\partial\Gamma(T_1, T_2, T_{out}, \overline{X}, \overline{Y}, D_1, D_2, \xi, \eta)}{\partial T_2} = e^{-rT_{out}}[\frac{\partial T_{out}}{\partial T_2}(p_{T_{out}}^{CO2}N + c_0N) - re^{-rD_2}I(\xi) - \frac{\partial T_{out}}{\partial T_2}r\Omega(\overline{X}, \overline{Y})] = 0$$

However, the end date of the transition T_{OUT} depends simultaneously on T_1 and T_2: it is the date t where $x_t + y_t = N$. The duration of the transition for low-carbon technology 1 is D_1, i.e. the duration between T_1 and T_{out}. This duration also depends on the transition of technology 2, D_2, and therefore on T_2. It therefore seems difficult, at this stage of our reflection, to determine the two optimal launching dates in an analytical and simultaneous manner. However, it is possible to determine this launch date numerically, by choosing the launching dates that minimise the total cost of the transition.

B Proof of proposition 2

Immediacy of transition Given a technology i, whose cost function is $C_i(X, x)$. It is assumed that the function is not convex, so $C_{i,xx} = 0$. As we know that $C_i(X, 0) = 0$, we have $C_i X(X, x) = C_i X, x(X, x)x$.

Assume that there is a transition period (phase 2) for technology i, starting on date T_1 and ending at date T_{out}, with $T_1 \leq T_{out}$. Then, we resort by reductio ad absurdum, assuming $T_1 < T_{out}$. Using the framework of the Phase 2 deployment demonstration in A, we have

$$p_t^{\dot{CO2}} = C_{Xx}\dot{X}_t + C_{xx}\ddot{X}_t - \dot{\lambda}_t = C_{Xx}x_t - r\lambda_t - C_X$$

As we have $C_{i,X} = C_{i,Xx}x$, we conclude that $p_t^{\dot{CO2}} = -r\lambda_t$. This is impossible, because $p_t^{\dot{CO2}} > 0$ (the price of CO_2 is increasing) and $\lambda_t > 0$. Therefore, we have a contradicition, and $T_1 = T_{out}$. The transition is therefore instantaneous, and the number of vehicles built suddenly increases on the date $T_1 = T_{out}$.

Focus on one technology As $C_{xx} = 0$, we can rewrite the cost function $C_i(x, X) = \gamma_i(X)x$, with $\gamma_{1,X}(X) < 0$.

The total discounted cost once the carbon-based technology is phased out is:

$$\Omega(X_0, Y_0) = \int_0^{+\infty} e^{-rt}[\gamma_1(X).x + \gamma_2(tN - X)(N - x)]dt$$

We resort by reductio ad absurdum, assuming that two technologies are deployed in phase 3, i. e $0 < x_t < N$. Then, along the optimal deployment path, the first order condition of the optimal control problem gives $\gamma_1(X) = \gamma_2(tN - X)$. Then

$$\Omega^*(X_0, Y_0) = \int_0^{+\infty} e^{-rt}\gamma_1(X_t^*)Ndt > \int_0^{+\infty} e^{-rt}\gamma_1(tN)N, \text{ as } X_t < tN \text{ and } \gamma_1(X) > \gamma_1(tN)$$

As (x_t^*, X_t^*) should be the solution that minimises the cost $\Omega(X_0, Y_0)$, we conclude $x_t = 0$ or $x_t = N$ during phase 3. Then, the optimal solution is to focus on only one technology.

Winning technology If the transition date is instantaneous, and only one technology is chosen for the transition, then there are only two choices of optimal trajectories.

$$\Gamma_1 = \int_0^{T_1} e^{-rt}[(p_t^{CO2} + c_0)N]dt + e^{-rT_1}\int_0^{+\infty} e^{-rt}C_1(tN, N)dt$$
$$\Gamma_2 = \int_0^{T_2} e^{-rt}[(p_t^{CO2} + c_0)N]dt + e^{-rT_2}\int_0^{+\infty} e^{-rt}C_2(tN, N)dt$$

Therefore, we have $\Gamma^* = min(\Gamma_1, \Gamma_2)$. If the technology i is chosen, then we derive Γ_i with respect to T_{out} to find the optimal starting and ending date.

C Cost of both strategies without transition

- The strategy B-B is to maximise learning by focusing on a single technology, in this case the cheapest and the one with the largest market, the battery. BEVs are built on both market N_1 and N_2. On the N_2 market, there is an additional cost d for BEB, for example because of using battery on long-distance. The cost of this strategy is:

$$\Gamma_{BB} = \int_0^{T1} e^{-rt}(c_0 + p_0 e^{rt})(N_1 + N_2)dt \tag{1}$$

$$+ \int_{T1}^{T2} e^{-rt}(c_0 + p_0 e^{rt})N_2 dt + \int_{T_1}^{T_2} e^{-rt} C_{BEV}(N_1, N_1(t - T_1))dt \tag{2}$$

$$+ \int_{T_2}^{+\infty} e^{-rt}[C_{BEV}(N_1 + N_2, N_1(T_2 - T_1) + (N_1 + N_2)(t - T_2)) + dN_2]dt \tag{3}$$

$$= p_0 T_1(N_1 + N_2) + \frac{c_0}{r}(N_1 + N_2)[1 - e^{-rT_1}]$$

$$+ p_0 N_2(T_2 - T_1) + \frac{c_0 N_2}{r}(e^{-rT_1} - e^{-rT_2})$$

$$- \frac{1}{r}e^{-rT_2}\underline{c_1}N_1 - \frac{(\overline{c_1} - \underline{c_1})N_1}{r + \lambda_1 N_1}e^{-T_2[r+\lambda_1 N_1]+\lambda_1 N_1 T_1}$$

$$+ \frac{1}{r}e^{-rT_1}\underline{c_1}N_1 + \frac{(\overline{c_1} - \underline{c_1})N_1}{r + \lambda_1 N_1}e^{-T_1 r}$$

$$+ \frac{1}{r}e^{-rT_2}\underline{c_1}(N_1 + N_2) + \frac{(\overline{c_1} - \underline{c_1})(N_1 + N_2)}{r + \lambda_1(N_1 + N_2)}e^{-T2[r+\lambda_1 N_1]+\lambda_1 N_1 T_1} + \frac{1}{r}e^{-rT_2}dN_2$$

There is no analytical solution to find optimal starting date T_1 and T_2. The problem is solved numerically, using package SciPy on Python.

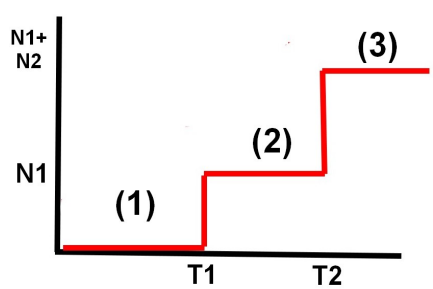

Figure 3: Schema of the evolution of the BEB fleet over time with BB-strategy

- The second strategy B-FC is to develop each technology in its respective market: BEVs are deployed on the main market (N_1), FCEVs are deployed on the niche market (N_2).

$$
\begin{aligned}
&\Gamma_{mix} = \Gamma_{BEV}(N_1) + \Gamma_{FCEV}(N_2) \\
&= \int_0^{T1} e^{-rt}(c_0 + p_0 e^{rt})N_1 dt + e^{-rT_1}\int_0^{+\infty} e^{-rt}C_{BEV}(N_1, N_1 t)dt \\
&+ \int_0^{T2} e^{-rt}(c_0 + p_0 e^{rt})N_2 dt + e^{-rT_2}\int_0^{+\infty} e^{-rt}C_{FCEV}(N_2, N_2 t)dt \\
&= p_0 T_1 N_1 + \frac{c_0}{r}N_1(1 - e^{-rT_1}) + e^{-rT_1}[\frac{1}{r}\underline{c_1}N_1 + (\overline{c_1} - \underline{c_1})\frac{N_1}{r + \lambda_1 N_1}] \\
&+ p_0 T_2 N_2 + \frac{c_0}{r}N_2(1 - e^{-rT_2}) + e^{-rT_2}[\frac{1}{r}\underline{c_2}N_2 + (\overline{c_2} - \underline{c_2})\frac{N_2}{r + \lambda_2 N_2}]
\end{aligned}
$$

There is an analytical solution to find optimal starting date T_1 and T_2.

$$
\begin{aligned}
&\mathbf{T_{1,mix}} : \frac{\partial \Gamma_{mix}}{\partial T_1} = p_0 N_1 - re^{-rT_1}[\frac{(\underline{c_1} - c_0)N_1}{r} + (\overline{c_1} - \underline{c_1})\frac{N_1}{r + \lambda_1 N_1}] = 0 \\
&\mathbf{T_{2,mix}} : \frac{\partial \Gamma_{mix}}{\partial T_2} = p_0 N_2 - re^{-rT_2}[\frac{(\underline{c_2} - c_0)N_2}{r} + (\overline{c_2} - \underline{c_2})\frac{N_2}{r + \lambda_2 N_2}] = 0 \\
&T_{1,mix} = \frac{1}{r}ln(\frac{rK_1}{p_0 N_1}), \text{ with } K_1 = \frac{N_1(\underline{c_1} - c_0)}{r} + (\overline{c_1} - \underline{c_1})\frac{N_1}{r + \lambda_1 N_1} \\
&T_{2,mix} = \frac{1}{r}ln(\frac{rK_2}{p_0 N_2}), \text{ with } K_2 = \frac{N_2(\underline{c_2} - c_0)}{r} + (\overline{c_2} - \underline{c_2})\frac{N_2}{r + \lambda_2 N_2}
\end{aligned}
$$

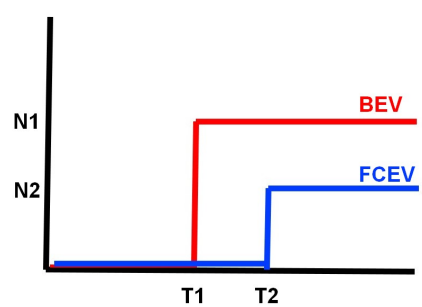

Figure 4: Schema of the evolution of the BEB and FCEB fleet over time with B-FC strategy

D Cost of both strategies with fixed linear transition

It is assumed that the duration of the transition D is the same for both technologies.

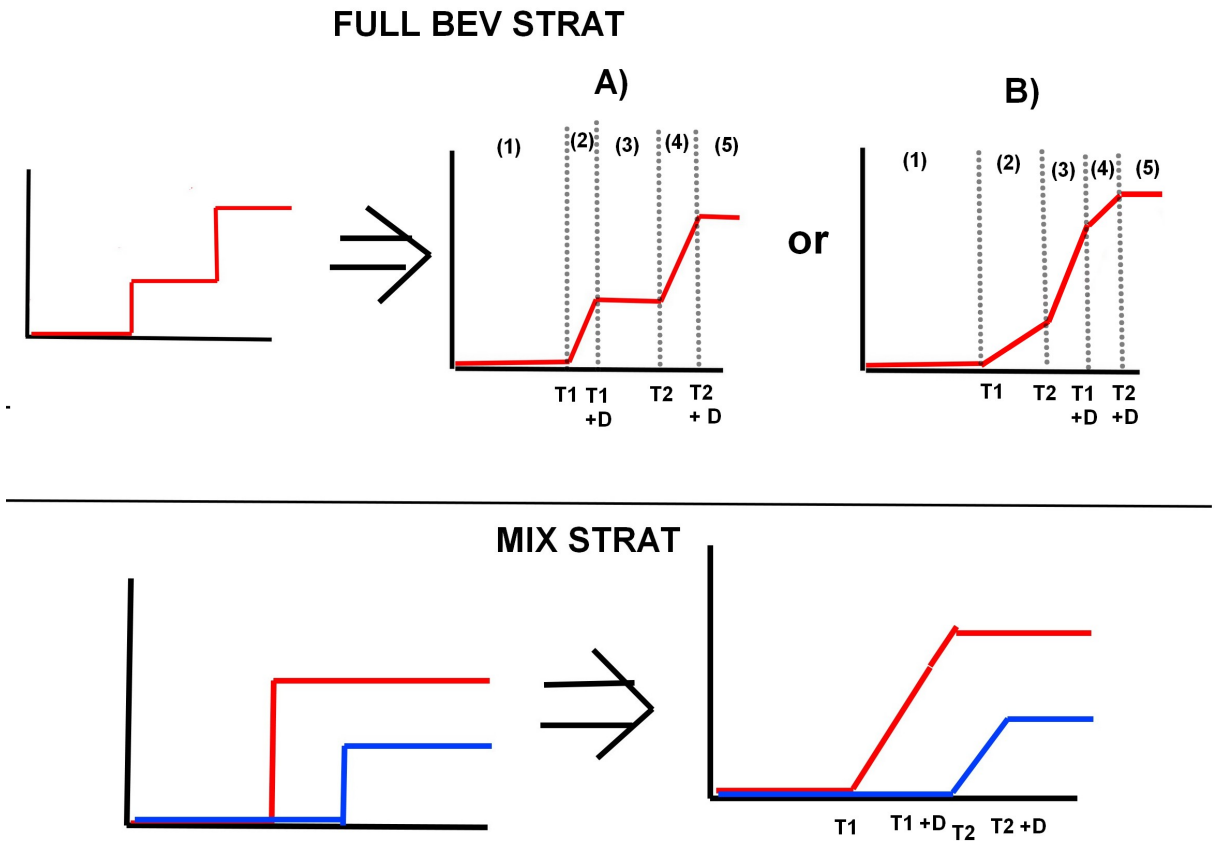

Figure 5: Schema of the evolution of the BEB and FCEB fleet over time with B-B and B-FC strategy, adding a linear transition duration

D.1 B-FC strategy with transition

- Cost of diesel:

$$\textbf{(N1 market)}: \int_0^{T_1} e^{-rt}[c_0 + e^{rt}p_0]N_1 + \int_{T_1}^{T_1+D} e^{-rt}[c_0 + e^{rt}p_0]\frac{N_1(D-t+T_1)}{D}$$

$$\textbf{(N2 market)}: \int_0^{T_2} e^{-rt}[c_0 + e^{rt}p_0]N_2 + \int_{T_2}^{T_2+D} e^{-rt}[c_0 + e^{rt}p_0]\frac{N_2(D-t+T_2)}{D}$$

- Cost of BEV:

$$\textbf{(During transition)}: \int_{T_1}^{T_1+D} e^{-rt}C_{BEV}[\frac{N_1(t-T_1)}{D}, \int_0^{t-T_1} \frac{N_1 u}{D}du]$$

$$= e^{-rT_1}\int_0^{D} e^{-rt}C_{BEV}[\frac{N_1 t}{D}, \frac{N_1 t^2}{2D}]$$

$$\textbf{(After transition)}: \int_{T_1+D}^{+\infty} e^{-rt}C_{BEV}[N_1, \frac{N_1 D}{2} + N_1 t]$$

- Cost of FCEV:

$$\textbf{(During transition)} : e^{-rT_2}\int_0^D e^{-rt}C_{FCEV}[\frac{N_2 t}{D}, \frac{N_2 t^2}{2D}]$$
$$\textbf{(After transition)} : \int_{T_2+D}^{+\infty} e^{-rt}C_{FCEV}[N_2, \frac{N_2 D}{2} + N_2 t]$$

D.2 B-B strategy with transition

D.2.1 A) $T_1 + D < T_2$

- Cost of diesel

$$\begin{aligned}
&\int_0^{T_1} e^{-rt}(c_0 + p_0 e^{rt})(N_1 + N_2)dt + && \mathbf{1}\\
&+ \int_{T_1}^{T_1+D} e^{-rt}(c_0 + p_0 e^{rt})(N_2 + \frac{N_1(D - t + T_1)}{D})dt && \mathbf{2}\\
&+ \int_{T_1+D}^{T_2} e^{-rt}(c_0 + p_0 e^{rt})N_2 dt && \mathbf{3}\\
&+ \int_{T_2}^{T_2+D} e^{-rt}(c_0 + p_0 e^{rt})\frac{N_2(D - t + T_2)}{D}dt && \mathbf{4}\\
&+ 0 && \mathbf{5}
\end{aligned}$$

- Cost of BEVs

$$\begin{aligned}
&0 && \mathbf{1}\\
&+ \int_{T_1}^{T_1+D} e^{-rt}C_1[\frac{N_1}{D}(t - T_1), \int_0^{t-T_1} \frac{N_1}{D}udu]dt \left[= \int_{T_1}^{T_1+D} e^{-rt}C_1[\frac{N_1}{D}(t - T_1), \frac{N_1}{2D}(t - T_1)^2]dt) \right] && \mathbf{2}\\
&+ \int_{T_1+D}^{T_2} e^{-rt}C_1[N_1, \frac{N_1 D}{2} + N_1(t - T_1 - D)]dt && \mathbf{3}\\
&+ \int_{T_2}^{T_2+D} e^{-rt}(C_1[N_1 + \frac{N_2(t - T_2)}{D}, \frac{N_1 D}{2} + (T_2 - T_1 - D)N_1 + \frac{N_2(t - T_2)^2}{2D}] + \frac{dN_2(t - T_2)}{D})dt && \mathbf{4}\\
&+ \int_{T_2+D}^{+\infty} e^{-rt}(C_1[N_1 + N_2, \frac{N_1 D}{2} + (T_2 - T_1 - D)N_1 + \frac{N_2 D}{2} + (N_1 + N_2)(t - T_2 - D)] + dN_2)dt && \mathbf{5}
\end{aligned}$$

D.2.2 B) $T_1 + D > T_2$

- Cost of diesel

$$
\begin{aligned}
&\int_0^{T_1} e^{-rt}(c_0 + p_0 e^{rt})(N_1 + N_2)dt + && \mathbf{1}\\
&+ \int_{T_1}^{T_2} e^{-rt}(c_0 + p_0 e^{rt})(N_2 + \frac{N_1(D - t + T_1)}{D})dt && \mathbf{2}\\
&+ \int_{T_2}^{T_1+D} e^{-rt}(c_0 + p_0 e^{rt})(\frac{N_2}{D}(D - t + T_2) + \frac{N_1}{D}(D - t + T_1))dt && \mathbf{3}\\
&+ \int_{T_1+D}^{T_2+D} e^{-rt}(c_0 + p_0 e^{rt})\frac{N_2(D - t + T_2)}{D}dt && \mathbf{4}\\
&+ 0 && \mathbf{5}
\end{aligned}
$$

- Cost of BEVs

$$
\begin{aligned}
&0 && \mathbf{1}\\
&+ \int_{T_1}^{T_2} e^{-rt} C_1[\frac{N_1}{D}(t - T_1), \frac{N_1}{2D}(t - T_1)^2]dt) && \mathbf{2}\\
&+ \int_{T_2}^{T_1+D} e^{-rt} C_1[\frac{N_1}{D}(t - T_1) + \frac{N_2}{D}(t - T_2), \int_0^{T_2-T_1} \frac{N_1}{D}udu + \int_{T_2-T_1}^{t-T_1} \frac{N_1}{D}udu + \int_0^{t-T_2} \frac{N_2}{D}udu]\\
&+ \frac{dN_2(t - T_2)}{D}dt && \mathbf{3}\\
&+ \int_{T_1+D}^{T_2+D} e^{-rt}(C_1[N_1 + \frac{N_2}{D}(t - T_2), \frac{N_1 D}{2} + \int_0^{T_1+D-T_2} \frac{N_2}{D}udu + \int_{T_1-T_2+D}^{t-T_2} \frac{N_2}{D}udu]\\
&+ \frac{dN_2(t - T_2)}{D})dt && \mathbf{4}\\
&+ \int_{T_2+D}^{+\infty} e^{-rt}(C_1[N_1 + N_2, \frac{N_1 D}{2} + \frac{N_2 D}{2} + (N_1 + N_2)(t - T_2 - D)] + dN_2)dt && \mathbf{5}
\end{aligned}
$$

For B-B and B-FC with transition, there is no analytical solution to find optimal starting date T_1 and T_2. The problem is solved numerically, using package SciPy on Python. For B-B strategy, first we optimize T_1 and T_2 with A and B formula, then we choose between A and B the strategy that minimises the total discounted cost.