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Fleet Renewal with Electric Vehicles at La Poste

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We provide a decision model for La Poste, the French national postal operator, to address its adoption of electric vehicles (EVs) for mail and parcel distribution. Two competing technologies are available—internal combustion vehicles (ICVs) and EVs. We consider uncertainty about future fuel price and future EV battery costs. Within this framework, we derive the optimal timing of EV adoption and sensitivities to key model parameters. We evaluate the total cost of fleet renewal over a 15-year horizon and the value of flexibility stemming from technology and timing options. This allows us to formulate an optimal strategy for EV adoption for La Poste and to support negotiations with major stakeholders, including energy companies and EV manufacturers.

Key words: equipment replacement; electric vehicles; decision making under uncertainty; real options.

Fleet Renewal and Technology Choice: The Context at La Poste

For postal operators (POs), tangible fixed assets support the core of their businesses; hence, the replacement of deteriorating equipment represents a significant portion of their costs. Together with its stock of buildings and real estate, vehicular fleets represent one of a PO's most important fixed assets. Fleet optimization is therefore an important element of the PO's operational and investment strategy for several reasons. First, it has a direct economic impact on investment, amortization, and operating costs. Second, it impacts the PO's carbon footprint. Therefore, the evaluation of alternative fleet traction systems (e.g., fossil fuel, hybrid, and electric) has become a strategic concern for POs worldwide.

In the light of rising fuel prices and stricter emissions regulations, electric vehicles (EVs) have become a credible alternative to internal combustion vehicles (ICVs), given a promising potential for EV performance improvements and for purchase prices to fall. EVs have a low life-cycle carbon footprint, making them one of the top choices among low-carbon vehicles. This effect is amplified in countries that produce a high percentage of their energy without carbon emissions; for example, nuclear power generates approximately 80 percent of France's total electrical energy. An EV consists of fewer moving parts, components, and systems than an ICV, thereby reducing maintenance costs. Regenerative braking, a standard feature of EVs, makes optimum use of available battery capacity and extends the range of the vehicle, particularly for the start-stop driving style typical of local delivery operations.

The fleet renewal project team included two groups: La Poste senior management and experienced researchers. Management had a mandate from the organization's CEO to develop a plan for introducing EVs. Researchers had strong backgrounds in operations research (OR) modeling, sustainability, and postal economics—skills that proved crucial to fully understanding the issues. Frequent communication and joint project meetings among all team members were a prerequisite for success.

Challenges in the Fleet Renewal Project

Several aspects of the fleet renewal and EV adoption decision make it an interesting research context for applied OR and sustainable energy. These include: the uncertainties in market prices for various sources of energy, including emission credits for carbon leveraging of investments; the problem of infrastructure and support for new technologies; the intangible reputation benefits of sustainable energy investments for POs; the incorporation of technological innovations and learning effects associated with new technologies; and, finally, the nature of strategic partnerships and risk sharing that are needed to achieve the requisite scale of operations to make low-carbon vehicles a feasible alternative for major fleet operators and for the automotive industry. Against this background, this paper provides an analytic framework based on real options theory for evaluating the risks and benefits of transforming postal fleet operations from their current fossil fuel-based traction systems to electric vehicles. The specific context underlying and motivating this research is that of La Poste. However, the analytic framework developed is applicable to other major commercial fleet operators, including other POs.

Within firms, changes associated with technology adoption are often met with inertia or resistance from the employees. Therefore, La Poste undertook a concurrent pilot study using a small fleet of EVs to determine employee attitudes toward these vehicles. As we note below, the postmen responded enthusiastically.

Trade-offs between ICVs and EVs are evident; EVs are more costly to acquire but less costly to operate. Given that these acquisition and operating costs can be expected to change over time, modeling these trade-offs is central to the EV adoption decision. Accordingly, in this paper, we develop a framework to determine and value optimal fleet renewal strategies for La Poste for two technology options (EVs and ICVs), uncertain fuel costs, and an uncertain battery acquisition price. We consider two commitment options for the decision maker: (1) a static policy where decisions for the entire 15-year horizon are made at the present time, and (2) a dynamic policy where decisions are made, given the latest realization of uncertainty, on a quarterly basis. We compare these options to the hypothetical case in which the decision maker has perfect information on future uncertainty realizations, which provides a lower bound on optimal expected-cost performance.

The structure of the paper is as follows. We review the existing literature in the *Searching for a Solution* section. *Decision Model for Fleet Renewal* comprises details about the model development. In *Model Results*, we discuss our findings from the decision model and its limitations. In *Benefits*, we illustrate the total life-cycle cost savings La Poste achieved and the implications of this project for La Poste's sustainability strategy. We conclude in *Lessons Learned*, where we review key success factors of the fleet renewal project.

Searching for a Solution

Initially, we regarded a continuous-time optimal-control approach as an alternative to solving the fleet renewal problem. A good starting point would have been the work by Harrison et al. (1983). However, several limitations became apparent quickly. First, it would have been analytically intractable to include multiple uncertainties in our model. Second, La Poste makes decisions with regard to fleet replacement on a quarterly basis; thus, criteria based on the ultimately selected discrete-time approach provided a better fit for its decision process.

The literature on asset replacement distinguishes between serial and parallel replacement models. Serial replacement refers to the case in which one piece of deteriorating equipment is replaced with a new piece; parallel replacement is concerned with replacement schedules for a group of assets that are economically interdependent because of, for example, capacity demand constraints, capital budgeting restrictions, or economies of scale and fixed costs. Parallel replacement problems are usually more difficult to solve given their inherently combinatorial nature, as Hartman (2000) points out. Jones et al. (1991) analyze a parallel replacement problem in the presence of fixed replacement costs. Rajagopalan (1998) and Chand et al. (2000) discuss dynamic programming algorithms that jointly consider the replacement and capacity expansion problem.

However, treatment of multiple alternatives within parallel replacement is rare in the literature. Karabakal et al. (1994) analyze a parallel replacement problem with multiple alternatives under capital rationing constraints. Keles and Hartman (2004) discuss a bus fleet replacement issue with multiple choices under economies of scale and budgeting constraints, highlighting the importance of considering alternative replacement options that are driven by such factors as environmental regulation. Unfortunately, these problems omit the effects of uncertainty. All of these models are in a deterministic setting.

Replacement models in the presence of uncertainty focus mainly on single-replacement problems. Ye (1990) describes a single-replacement model with stochastically increasing operating costs and stochastically deteriorating equipment. Using the possibility of scrapping or selling used equipment, the solution determines the optimal stopping time for replacing equipment in a continuous-time environment. Dobbs (2004) considers a serial replacement model with increasing costs modeled as a geometric Brownian motion and identifies the optimal replacement time. Rajagopalan et al. (1998) provide a dynamic programming algorithm for a capacity expansion and replacement problem in which technological breakthroughs may materialize, but at an uncertain time and magnitude. They model technological evolution as a semi-Markov process. La Poste's issue is different from that discussed by Rajagopalan et al. in that it deals with uncertainties related to both existing (i.e., ICV) and possible replacement (i.e., EV) technologies.

We believe that the following aspects characterize the originality and elegance of our work. First, we provided a solution with very tight bounds to an important large-scale problem. The solution procedure and the results gave clear implementation guidelines and significant profit potential to La Poste's senior management, which proved crucial for gaining management buy-in during the research phase of the project and commitment to subsequent commercialization activities. The model that we developed is grounded in real data, which we derived primarily from the current operations of La Poste's fleet. This enabled us to validate critical elements of the model and the ensuing recommendations. Second, the issue addressed in this project has important strategic ramifications for La Poste and other large commercial fleet operators. As we describe below, the results of this project were instrumental in the creation of a five-year buying consortium to introduce more-profitable and sustainable fleet operations based on EVs. This consortium included several major fleet operators and was led by La Poste.

Decision Model for Fleet Renewal

To appropriately account for the life-cycle costs of the fleet, accurate information on operating and maintenance costs and leasing fees for the available technologies is required. ICV operating costs are primarily fuel (diesel) costs, which we assume to be subject to random fluctuations. We extrapolated maintenance costs from historical data of the existing fleet. The leasing fee for ICVs is assumed to be increasing over time, given the growing pressure for efficiency improvements and the declining residual value of vehicles as cheaper alternatives become available. However, little data on EV life-cycle costs are available. Therefore, we had to rely on available technical reports and expert interviews to come up with appropriate assumptions, as necessary. Electricity consumption impacts operating cost only to a limited extent; thus, we regard the cost of electricity as constant. However, we do analyze the implications of tariff increases for EV adoption. Industry estimates, based on knowledge that EVs have fewer moving parts, allow us to assume maintenance costs to be 30 percent less than comparable costs for ICVs. We derive the shape of the maintenance-cost curve, which increases in a convex shape toward the end of the lease, from empirical estimates of current ICV maintenance costs at La Poste; we also assume that the shape of the curve is the same for both vehicle types.

Because EV purchase prices are high, batteries may be unbundled from the chassis and sold or leased separately. Leasing fees for EVs are assumed to decline over time because of economies of scale and learning effects. At La Poste, vehicles are leased over a six-year period. For private use, battery lifetimes (as measured in terms of minimum remaining capacity of 40 percent) are expected to exceed 8 to 10 years. Thus, we assume that batteries in commercial vehicles have a life of at least six years. We do not consider the salvage value of the battery; we assume the battery is discarded at the end of its use. Hein et al. (2012) derive the residual value of used EV batteries based on a system-dynamics model that indicates that this value will be small, given current battery technology—even in the presence of vehicle-to-grid and battery-to-grid operations. Of course, nonzero salvage values are straightforward to include and would further enhance the value of EV adoption decisions.

Characterization of Uncertain Fuel and Battery Prices

We assume that diesel prices correlate strongly with crude oil prices. Indeed, Girma and Paulson (1999) find a long-term relationship among crude oil, gasoline, and heating oil future prices, thus implying a causal relationship from the products' market to the crude market. Investigation of diesel and oil prices from 1998 to 2008 indicates that the correlation is 0.986, thus further supporting our assumption. Meade (2010) compares the performance of geometric Brownian motion and mean-reverting stochastic processes for longer-term oil price forecasts, and finds that neither yields accurate forecasts beyond a horizon of two years. Therefore, in our case of a 15-year horizon, inaccuracies with respect to oil price forecasts are to be expected. The International Energy Agency argues that the rise of fuel prices because of resource scarcity and emissions regulations is expected to be significant, which might have suggested a model based on jump diffusion. However, no improvement in accuracy was expected because of the long horizon and previous studies for crude oil prices (Pindyck 1999).

Based on the above considerations, we model the fuel price f^t as a discrete Brownian motion with drift. Refer to Equation (1) in the appendix for details. The drift rate and volatility of the fuel price is fitted to historical data from 1999–2010 in France, the country in which La Poste operates.

For EV batteries, multiple variants of battery chemistry are currently under investigation; no clear candidate has emerged yet. However, it seems likely that lithium-ion based technology will be used in the interim. Given several competing battery concepts, forecasting the decline of EV battery prices because of economies of scale, reduced component material cost, and greater efficiency in manufacturing processes is inherently difficult. We model battery price as a discrete-time Ornstein-Uhlenbeck process in which reversion to the mean captures the effect of technological progress. The learning rate, long-term mean, and volatility of battery prices are estimated on the basis of available technical reports. A recent study (Boston Consulting Group 2010) estimates that the price of lithium-ion based car batteries will fall by 65 percent by 2020. The authors assume that 25 percent of battery manufacturing costs are volume independent, which results in a corresponding estimate for the long-run mean of the battery price. However, the learning rate may be subject to uncertainty, the impact of which we consider below. We represent the battery-price process in Equation (2). Furthermore, we assume a negligible correlation between the battery price and the fuel price. This assumption seems plausible if we assume that the number of EVs on the market in the near future (i.e., until about 2025) will be low.

Given the properties of the stochastic processes defined above, the probability that the fuel and battery price take negative realizations is nonzero. However, for realistic values of the parameters, such as those we assume in this paper, this probability is indeed negligible.

Formulating the Decision Model

The model is based on a discrete-time, stochastic dynamic programming formulation with uncertain fuel and battery acquisition prices representing the key underlying uncertainties. The relevant decision criterion is shown to be the expected total cost of ownership (TCO) of individual vehicles, with the expectation taken at the time at which new acquisitions are made. The vehicle-specific TCO measure can be aggregated across the fleet following a superposition principle proved for the present context. Not only does the TCO allow for mathematical tractability, but it also has the benefit of being intuitive for the managers involved in making fleet decisions. The TCO measure also facilitates the integration of model results with internal accounting systems and projected budgetary impacts of fleet operations.

La Poste's goal is to meet the demand for delivery services while minimizing the expected cost of its fleet. Based on discussions with La Poste management, we fixed demand for delivery at 2010 levels. The consequences of varying demand assumptions are easily analyzed. The initial assumption of constant demand for vehicular services was based on the continuing obligation imposed on La Poste to provide delivery services to each address in France each day. Moreover, projected declines in mail volumes are expected to be partially compensated by increased parcel deliveries. Demand can be translated into the total number of replacement vehicles required at a given time. Vehicles are leased for a period of six years. We assume that EVs and ICVs have the same carrying capacity, as is the case for prototype vehicles of both types currently in use or under consideration for adoption.

In keeping with current practice, the fleet operator makes acquisition decisions on a quarterly basis, where an optimal number of EVs and ICVs is chosen at the beginning of each period, subject to demand constraints. Lease contracts cannot be terminated prematurely. Neboian and Spinler (2012) consider the option to breach the leasing contract in the present context.

An immediate cost is incurred because of the acquisition of vehicles. Acquired vehicles entail operating costs until the expiration of the leasing contract. We use six years as the length of a leasing contract in our analysis. We show that the total number of vehicles to be purchased at a particular decision epoch is determined by the acquisition history and demands for new vehicles that materialized until the time when an acquisition decision is made. Lemma 1 and Equation (3) in the appendix provide the details.

La Poste's objective is to determine an acquisition portfolio of vehicles, which minimizes the expected lifetime cost of its total fleet operations. The objective function can then be formalized, as Equation (4) shows.

Model Results

The model allows La Poste to determine the optimal acquisition policy at each quarter and the resulting lifetime costs. Equally important, various sensitivities can be tested; these include the impact of government subsidies, which provide incentives for the acquisition of EVs, and increases in electricity prices, which might occur because of decreasing tax revenue on fuel. Because the battery price has a significant impact on an EV's acquisition price, we must understand the implications if initial expectations about the learning rate driving decreasing battery prices prove to be erroneous; that is, we must consider the case of uncertainty about the learning rate. Finally, we assume that La Poste incurs a fixed cost in the first period in which it switches to EVs; this fixed cost represents the anticipated cost of driver training, infrastructure enhancements, and other one-time switching costs.

Optimal Portfolio of Vehicles

We prove that it is optimal to acquire only one vehicle type—either ICV or EV—in each period. Of course, the optimal acquisition portfolio depends on the evolution of the dynamic programming state variables (i.e., battery price and fuel price). Thus, alternative scenarios for the evolution of battery and fuel prices give rise to alternative optimal paths. These alternative paths can be used indicatively to plan for the optimal closed-loop acquisition trajectory. Alternatively, as we demonstrate below, these alternative scenarios can be used to generate a near-optimal open-loop precommitment strategy.

Acquiring a single vehicle type at each decision epoch is optimal for two reasons. First, we assume that there are no limits to the supply of EVs, even in the technology's current infant state. Below, we discuss further some steps La Poste is taking to assure that minimum volume requirements are not a binding constraint in implementing the optimal acquisition profiles resulting from the framework described in this paper. Second, we do not consider quantity discounts in our model. This leads to cost separability and to the single-vehicle acquisition result shown in Proposition 1. The optimal decision at any point in time is then determined by the minimum of the expected TCO of each vehicle, with the TCO computed using future prices, conditional on the last available fuel and battery price realization.

The Optimal Acquisition Policy and Lower and Upper Bounds

We show that a decomposition principle holds, such that the optimal cost function is a linear combination of discounted expected vehicle cost and acquisition

Type of policy	Total cost (million €)
Replacement with ICVs only	665.03
Static policy with ICVs and EVs	578.71
Dynamic policy with ICVs and EVs	577.45
Replacement with ICVs and EVs under perfect information	577.08
Expected total value of EVs under dynamic policy	87.58
Expected total value of the dynamic policy	1.26

Table 1: The availability of EVs yields significant cost savings over the entire planning horizon, whereas the dynamic policy entails little additional benefit over the static policy.

cost at each stage. The optimal policy can then be shown to be a dynamic policy in which the optimal vehicle type is determined based on the last realizations of uncertainties in each period. However, obtaining upper and lower bounds for the optimal policy is of interest. A lower bound on the total cost can be derived based on the expected value of perfect information, whereas an upper bound is a static policy in which acquisition decisions are based on the information available at the beginning of the planning horizon (i.e., 2010).

The different policies entail lifetime costs of the fleet (see Table 1). This comparison yields a number of interesting insights. First, the real option value of being able to switch to EVs (€87.58 million) is significant. Second, although the dynamic policy is optimal, the narrow bounds provided by the static and perfect information policies suggest that precommitment to the static policy entails only small cost penalties. The low value of the dynamic policy (€1.26 million) surprised the research team; thus, it warranted further investigation, as we discuss in the next section.

Optimal Timing of EV Acquisition

Figure 1(a) illustrates the evolution of the expected TCO of the two vehicle types, EVs and ICVs, over time. Because fuel prices have a positive drift, although battery prices are expected to decline, as outlined above, the two intersect at about quarter 21 (i.e., in the second quarter of 2015). At this point, the probability of adoption for EVs switches to 100 percent for the static policy and reaches 50 percent for the dynamic and perfect information policies, as Figure 1(b) indicates. The expected unit cost, illustrated in Figure 1(c), is initially driven by the increase in ICV operating costs; however, subsequent to quarter 21, the unit costs decrease as EVs are adopted. Figure 1(d) helps to explain why the incremental value of the dynamic policy over the static precommitment policy is so small; only where the two TCO curves for EVs and ICVs are close to each other (i.e., around the breakeven point in quarter 21), the dynamic policy is superior to the static policy because the flexibility to revise an earlier decision has value at this point. However, because of the positive drift for fuel prices and negative drift for battery prices, this time interval is short relative to the decision horizon; thus, flexibility can be exploited only to a very limited extent.

Government Subsidies and EV Adoption

The small hump that we can observe in the charts (see Figures 1(a), 1(b), and 1(d)) at quarter 12 is because of a government incentive of €5,000 for EV adoption, which expires in 2013. We observe from Figure 2 that this government subsidy has little impact on the EV acquisition decision for La Poste because the subsidy amount is insufficient to bridge the gap between ICV and EV TCO, which persists until roughly quarter 17, as we can extrapolate from Figure 1(a). The subsidy is provided too early in the technology life cycle—a period during which battery prices are prohibitively high.

The Impact of a Deterministic Drift in Electricity Prices

In the base-case model, we assume that electricity prices are deterministic and exhibit no drift. Figure 3(a) illustrates the impact of a positive or negative deterministic drift on the adoption probability under the dynamic policy. We observe that a small negative or positive drift has limited impact on the adoption probability, whereas a larger positive drift delays adoption until battery prices have decreased sufficiently. The total fleet cost (see Figure 3(b)) increases up to a point at which EVs cease to be competitive. We can also observe that the incremental value of the dynamic policy over the static policy increases for larger electricity price slopes; however, it remains a small fraction of the total cost.

The Sensitivity to Model Risk

We observe above that the static policy is a viable decision policy for the given problem parameters.

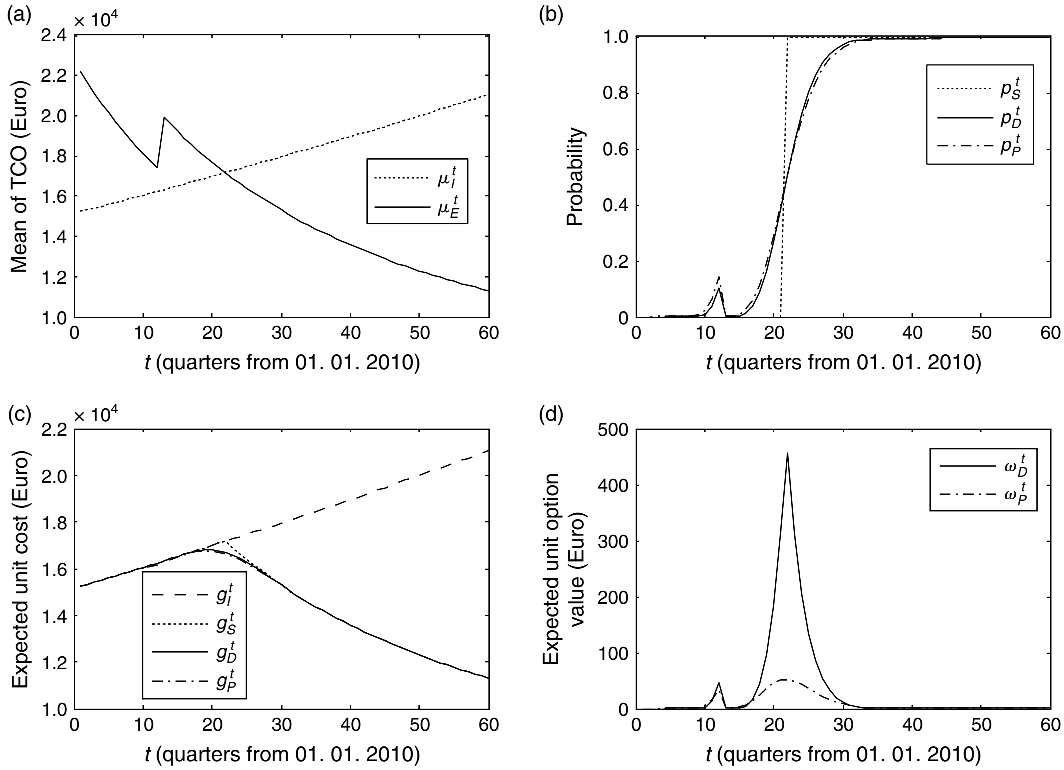

Figure 1: (a) The expected TCO of EVs (index E) decreases over time, whereas ICV TCO (index I) exhibits an increasing trend. (b) The acquisition probabilities for the static (S), the dynamic (D), and the hypothetical perfect information (P) policies increase markedly around the break-even point of the TCOs of the two technologies. (c) The expected unit costs exhibit a downward trend once EVs are adopted; if only ICVs (I) are available, we can observe an upward trend. (d) The value of the dynamic (D) policy is highest where the two TCO curves for EVs and ICVs are close to each other.

However, we also need to investigate how sensitive the static policy is to model risk, in particular to an incorrectly specified battery learning rate. A standard measure for risk, appropriate for our purposes, is the expected downside risk (EDR). Eppen et al. (1989) define it as the expectation of profits below a prespecified target profit level. To compute the EDR, which stems from an incorrectly specified battery price (see Equation (16) in the appendix for the definition), we use a simulation approach in which we generate a set of 10,000 realizations for the fuel price and two battery price processes; one is the base case and the other is an alternative scenario representing a potential departure from the base case because of uncertainty.

We make two further assumptions in our study of EDR. The first assumption is that the decision maker knows the range of possible values for the learning rate. Such information could be obtained from existing technical reports or through expert interviews. The second is that the static policy may offer additional fixed savings resulting from reduced administrative expenses, volume discounts, or benefits from a contractual relationship with the vehicle supplier. We assume that such planning reliability given by the static policy yields a total benefit in present value terms of $Q^0 = €10$ million, which corresponds to less than 2 percent of the expected total cost of the fleet in the base case.

From Figure 4(a), we observe that over a broad range of realized battery learning rates, the static policy with fixed savings, policy SQ, yields a benefit over the dynamic policy. For high learning rates (i.e., greater than 0.1), the dynamic policy is superior

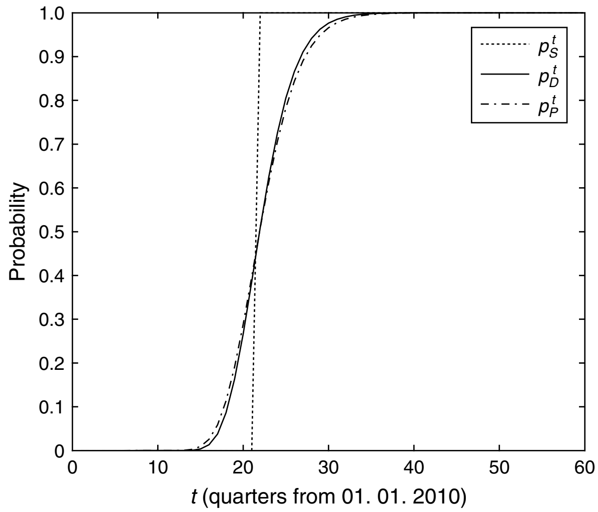

Figure 2: If the governmental subsidy is removed, we observe only a slight impact on the adoption probabilities under the various policies.

because it allows earlier EV adoption in response to lower-than-expected battery prices. For low learning rates, the dynamic policy once again is advantageous because it allows the postponement of EV adoption.

Figure 4(b) illustrates that the dynamic policy is very robust against incorrectly specified battery learning rates because the EDR is flat across a broad range of realized battery learning rates. As for the static policy, the fixed savings do not contribute to the reduction of EDR as significantly as to the improvement of the expected EV value. This is because the fixed savings, which cause a shift of the distribution function to the right, are relatively small compared to the expected EV value. Furthermore, the EDR of the static policy grows exponentially as the value of the learning rate falls below 0.025. These results illustrate the usual trade-off between potential expected project savings (in this case, arising from a static precommitment strategy) and EDR (Froot et al. 1994). Moreover, the EDR framework provides important information for strategic risk management in the form of project savings from precommitment and the associated incremental EDR, under various scenarios on underlying model parameters, including the model risk associated with battery price learning rate. The result for decision making at La Poste is that the static policy has been adopted because the EDR risk is tolerable.

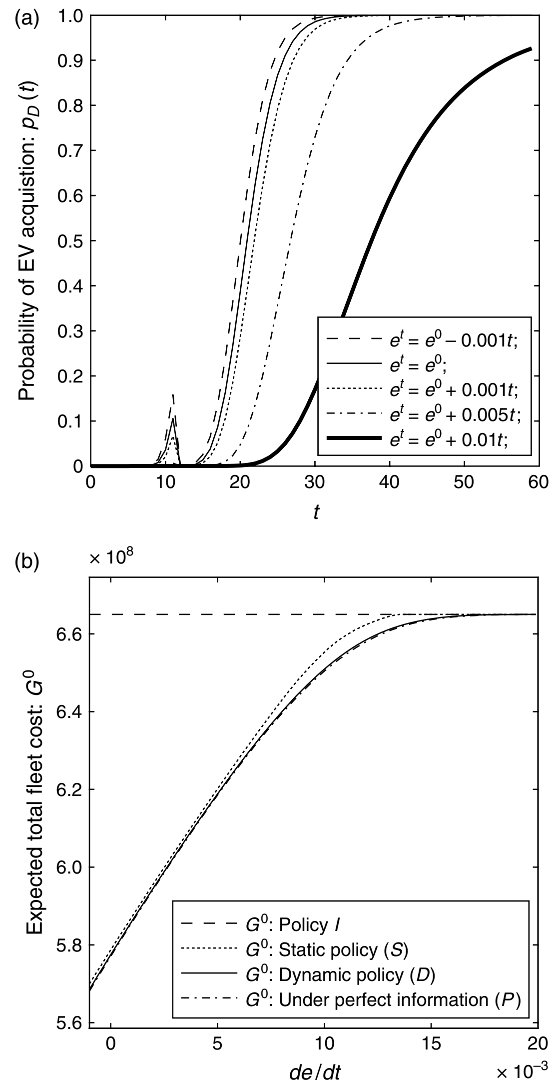

Figure 3: An increase in electricity prices shifts the probability of EV adoption to later times, as Figure 3(a) shows for the dynamic policy. Figure 3(b) shows that this entails an increase of total fleet cost, which eventually approaches the limit of the ICV-only policy. The notation used in the graphs is explained in Table 2.

The Impact of a Fixed Cost on EV Adoption

As we discussed in the beginning of this paper, La Poste will incur fixed switching costs associated with its EV adoption. Therefore, we consider the impact of such switching costs on the probability of EV adoption. In Figure 5, we observe that low values of fixed switching costs (i.e., less than €10 million) have little impact on adoption probability. As the switching costs increase, the benefit of

Symbol	Definition
a_i^t	Discounted total cost of leasing and maintenance for a single vehicle
a_e^t	Discounted total cost of leasing an EV chassis and maintenance of an EV
B^t	Price of a battery pack realized at time t
d^t	Demand, or the required stock of vehicles between t and $t+1$
e^t	Average electricity price over the period $t-1$ to t per unit of energy
de/dt	Drift in electricity prices
$EDR_{D,S,SQ}$	Expected downside risk for the dynamic, static, or static policy with fixed savings Q
EV	Electric vehicle
f^t	Average fuel price per unit volume over the period $t-1$ to t, realized at time t
$\bar{\Gamma}^0_{D,S,SQ}$	Total EV value under dynamic, static, or static policy with fixed savings Q
ICV	Internal combustion vehicle
k_e	Electricity consumption of an EV over a single period
k_i	Fuel consumption of an ICV over a single period
l	Length of the leasing contract, which is equal for both vehicle types
λ	Learning rate leading to battery price reduction
μ_f^t	Mean fuel price at time t
PO	Postal operator
ρ	Discount factor per period
t	Time index
T	Time index of the last acquisition decision
TCO	Total cost of ownership
$\xi^t = \{f^t, B^t\}$	Set of uncertainty realizations at time t
$\mu^t_{I,E}$	Expected ownership cost of an ICV or EV at time t
$g^t_{I,S,D,P}$	Expected optimal ownership cost under ICV-only, static, dynamic, or policy with perfect information
$p^t_{S,D,P}$	Probability of EV acquisition under static, dynamic, or policy with perfect information
$\omega^t_{D,P}$	Expected option value to wait under dynamic or policy with perfect information
G^0	Expected fleet cost
$p_I(t)$	Probability to invest in EV infrastructure
K	Fixed cost of EV infrastructure

Table 2: The table lists the symbols and acronyms used in the mathematical model.

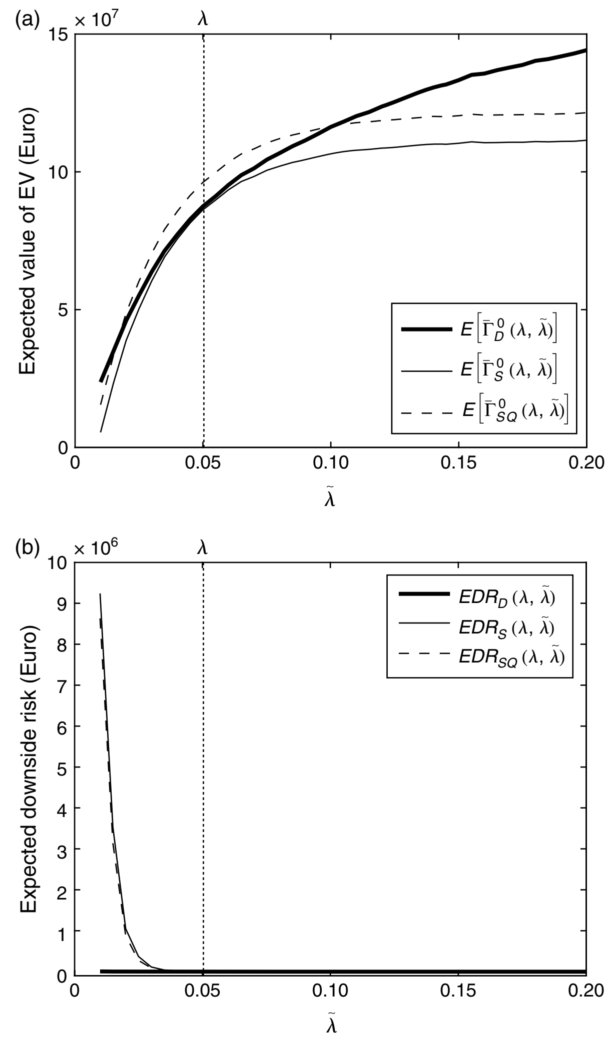

Figure 4: (a) The expected value of an EV decreases strongly if the learning rate for battery production has been over-estimated. The static policy with fixed savings of $Q^0 =$ €10 million (SQ) usually outperforms the dynamic policy. (b) The expected downside risk increases sharply for learning rates below 0.025 (i.e., about half the value of the initially assumed learning rate). However, the dynamic policy is unaffected.

government subsidies becomes even less significant and EV adoption is shifted to later times, (i.e., beyond quarter 26). Note that for very high switching costs, the possibility exists that no EVs will be adopted.

Limitations of the Model

One current general concern is that the limited range of EV batteries is typically less than 150 kilometers (km) (Boston Consulting Group 2010). The per-vehicle distance driven at La Poste shows a distribution of approximately 50 to 250 km. This suggests that it cannot serve all its regions using current technology. However, given the gradual adoption of EVs and La Poste's initial focus on densely populated areas, this is not a major concern. Indeed, vehicles with a range of 150 km would easily cover more than 95 percent of existing La Poste routes.

Benefits

The model generated in this research project was built in a spreadsheet and Matlab-based environment,

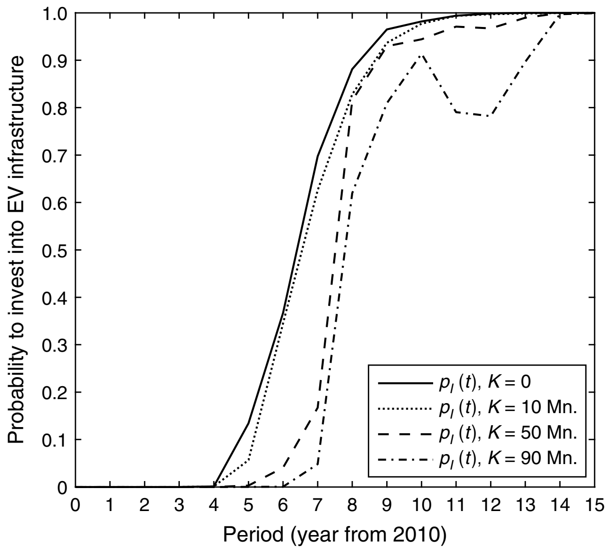

Figure 5: A one-time investment cost K has little impact on the EV adoption probability as long as this cost is less than approximately €10 million. For larger values, we can observe a gradual shift of EV adoption to later times.

which provided a number of significant advantages. First, management could alter model parameters to gain an understanding of the relevant EV drivers and trade-offs. It also allowed the research team to test the results for further sensitivities, such as the impact of alternative electricity tariffs, direct subsidies of various types for EVs, and other scenario variables, which have been debated as public policy options on EV introduction. Second, this combination allows for fast and reliable computation and simulation, which we required for exploration of multiple scenarios. Third, spreadsheet-based decision models were in common use at La Poste; thus, managers and research personnel outside of the core team were able to explore the implications of the model without requiring special training.

For La Poste, the results of the model, the corresponding sensitivity analyses, and the corresponding simulation results have been instrumental in defining the company's EV acquisition strategy and quantifying its effects. This strategy was crafted in 2010 and has led, inter alia, to the establishment of a buying consortium to solicit bids from qualified automotive manufacturers in France. This consortium, which was established after a feasibility study under the management of the La Poste's CEO and which the company spearheaded, includes several major fleet operators in France. It will act to coordinate standardized design features for EVs purchased by consortium members and to assure an order of sufficient size for the winning suppliers (of both autos and batteries); thus, it will act as a major stepping stone to achieving minimum production volumes.

La Poste has already begun the direct exploration of the risks and benefits associated with EV adoption. Since the beginning of 2011, the company has operated 250 electric vehicles, which the postmen have accepted enthusiastically; the vehicles are easy to drive, have strong acceleration, make no noise, connect easily to the electrical network, and give the postmen a general sense of having entered into a more sustainable world. These 250 EVs (which are but a fraction of the over 40,000 vehicles that La Poste operates currently) were acquired partly to provide accurate figures to ground the assumptions of the model described above, and to support strategic purchasing and operations decisions. For this small prototype fleet, the activity of each EV is monitored using sensors and key metrics (e.g., speed, temperature, electricity consumption, and coordinates provided through the global positioning system) are gathered continually. Some important lessons are already emerging. For example, first-line management must understand that EV adoption implies a fundamental change in the underlying economic model of fleet operations. This change has turned out to be much more significant than we expected at the beginning of this project. Accustomed to a vehicle with costs driven mainly by the car's use (e.g., fuel and maintenance), drivers sought to reduce the total route length. By contrast, EV optimization objectives shifted to the global link between routes, the collection and delivery tasks to be performed, and vehicle characteristics. EV use is less costly; however, the initial acquisition price of these vehicles is currently more costly; therefore, they must run a maximum of kilometers at the limit of their battery capacity. Moreover, ICV drivers were trained to economize on fuel because of the cost shown directly at the pump when they refilled the tanks. With EVs, the fundamental performance metric is not fuel cost (i.e., electricity consumption in recharging batteries), but rather the average daily kilometers logged per vehicle to minimize overall fleet acquisition costs. These figures are less visual and more complex for the postmen to understand. In short, the decision modeled here has implications that go well beyond the investment decision that was the initial focus of this project.

Much has yet to be learned about new operating and management paradigms that will also have to shift if, as expected, La Poste undertakes major EV purchases. As of 2012, La Poste has successfully completed a complex dialogue with several EV manufacturers about the TCO of EVs; the negotiations were enlightened by the study described in this paper. In October 2011, La Poste signed a contract for delivery of an additional 10,000 EVs. The first vehicles associated with this contract are now in operation. The responsibility of the EV project organization is shifting to the operational teams (i.e., the business-as-usual teams). The next challenge is to prepare the infrastructure for the refilling of these 10,000 vehicles: 10,000 plugs, wires, specific meters, and interfaces with electricity suppliers for optimization of the refilling cost, which also includes determining the best time slots for refilling during periods of vehicle inactivity.

In addition to the direct decisions noted above on its EV strategy, La Poste has launched a new business venture, Greenovia, to explore and harvest opportunities from assisting other fleet operators in acquiring and operating EV fleets and in improving the efficiency and sustainability of their urban transport operations. These collaborative initiatives, which leverage the modelling environment developed in this research, are expected to provide profit opportunities for La Poste and to promote sustainable fleet operations across major commercial fleet operators in France. To increase its presence as a sustainable operator in urban logistics, La Poste is undertaking additional research based on the use of low-pollution EVs. Given the importance of postal operators worldwide in parcel and logistics operations at the local level, this research could provide important new business opportunities for postal operators based on their established competence in commercial fleet operations.

Lessons Learned

The key lesson that La Poste learned was that risks associated with the decision process to enter an era of EVs for postal delivery could be modeled, tested, and controlled. The sense of strategic control and the ability to validate model findings were fundamental in its ultimate decision to initiate plans for EV adoption, beginning with the decision to establish a buying consortium. The success of the project hinged first on the frequent interaction among the team members, which allowed data gathering and model refinements, and second on the ability of the La Poste team members to communicate model results and ramifications to decision makers at La Poste. OR played a key role in this large-scale project because it allowed the definition and the subsequent testing of relevant decision policies. However, that the outcomes and policies generated through OR were understandable and plausible to the management team was equally important. This project has been an important standard bearer in La Poste's ongoing research on sustainable postal operations and has been extended to the study of sustainable urban logistics, an area in which EVs are an important enabler.

Appendix. Mathematical Details

The relevant uncertainties for our decision model are future fuel prices for ICVs and future battery prices for EVs. The fuel price process is modeled as a Brownian motion with drift:

$$f^t = f^{t-1} + \mu_f + \sigma_f \cdot z_f, \tag{1}$$

where $z_f \sim \mathcal{N}(0,1)$, μ_f is the drift rate, and σ_f is the standard deviation of the fuel price. The battery price is given as an Ornstein-Uhlenbeck process:

$$B^t = \mu_B(1-\exp(-\lambda)) + B^{t-1}\exp(-\lambda) + \sigma_B\sqrt{\frac{1-\exp(-2\lambda)}{2\lambda}} \cdot z_B, \tag{2}$$

where $z_B \sim \mathcal{N}(0,1)$, σ_B is the standard deviation, λ is the learning rate, and μ_B is the average battery price in the long run.

Lemma 1. *The total number of vehicles to be acquired at time t is defined by the acquisition history $n^{-(l-1)}, \ldots, n^{-1}$ and the demand $d^0, \ldots, d^t$.*

$$n^t = \begin{cases} 0, & t > T \\ d^t - d^{t-1} + n^{t-l}, & 0 < t \le T \\ d^0 - \sum_{\tau=1}^{l-1} n^{-\tau}, & t = 0 \end{cases}. \tag{3}$$

Proofs are contained in Neboian et al. (2011).

La Poste's objective function is to minimize its expected fleet cost over the relevant decision horizon:

$$G^t(f^t, B^t) = \min_{n_e^t\ge 0,\, n_i^t\ge 0} \big\{ n_e^t(a_e^t + B^t) + n_i^t a_i^t + \rho \mathbb{E}_{\xi^{t+1}\mid \xi^t} \cdot [s_e^{t+1}k_e e^{t+1} + s_i^{t+1}k_i f^{t+1} + G^{t+1}(f^{t+1}, B^{t+1})]\big\}. \quad (4)$$

In the above equation, the terms $s_e^{t+1} = \sum_{\tau=t-l+1}^{t} n_e{}^{\tau}$ and $s_i^{t+1} = \sum_{\tau=t-l+1}^{t} n_i^{\tau}$ represent the number of vehicles in the fleet between t and $t+1$ (indices e and i represent EVs and ICVs, respectively). The terms k_e and k_i represent electricity and fuel consumption over one period, respectively, and e^t is the cost of electricity at time t. The discount factor ρ is set such that it reflects the cost of capital at La Poste. The parameter a_e^t represents the discounted total cost of leasing an EV chassis and maintenance of an EV for a single vehicle when this vehicle is acquired at time t.

Proposition 1. *It is optimal to acquire only one vehicle type in each period. The optimal decision is determined by the minimum of a vehicle's expected TCO based on the last available fuel and battery price realization.*

In Proposition 1, the total discounted fleet cost at time $t=0$ can be shown to be given by the following expression; Neboian et al. (2011) provides details of this and the subsequent derivations.

$$G^0(f^0, B^0) = \sum_{t=0}^{T} (\rho)^t n^t \mathbb{E}_{\xi^t\mid\xi^0}[\min\{E^t, I^t\}] + E_R^0 + I_R^0, \quad (5)$$

where E^t, I^t represent the TCO for each vehicle type at time t:

$$E^t = a_e^t + B^t + k_e \sum_{\tau=1}^{l} (\rho)^{\tau} e^{t+\tau}, \quad (6)$$

$$I^t = a_i^t + k_i \sum_{\tau=1}^{l} (\rho)^{\tau} (f^t + \tau\mu_f). \quad (7)$$

The above solution is referred to as a closed-loop or dynamic policy. The optimal cost function (5) is a linear combination of discounted expected optimal vehicle costs and the acquisition volume at each stage. E_R^0 and I_R^0 represent the remaining operating costs of vehicle acquisitions before $t=0$. Because E_R^0 and I_R^0 are not influenced by decisions made at $t \ge 0$, it is convenient to derive a reduced form of optimal cost function (5), where we omit these parameters for simplicity. We denote the corresponding optimal cost function as $G_D^0(f^0, B^0)$:

$$G_D^0(f^0, B^0) = \sum_{t=0}^{T} (\rho)^t n^t g_D(t), \quad (8)$$

where the function $g_D(t)$ represents the expected optimal cost per vehicle acquired at time t under the dynamic policy:

$$g_D(t) = \mathbb{E}_{\xi^t\mid\xi^0}[\min\{E^t, I^t\}]. \quad (9)$$

Under a dynamic policy, the fleet operator makes decisions pertaining to the current period only. We define $p_D(t) = \Pr(E^t \le I^t)$ as the probability of acquiring an EV at time t. It can be shown that E^t and I^t are distributed normally. Respective mean values are defined as μ_E^t and μ_I^t, and the standard deviation is defined as σ_E^t and σ_I^t, respectively. Furthermore, we denote the difference between the expected TCOs of an EV and an ICV at time t as C^t, which is also normally distributed. The corresponding mean and variance are then $\mu_C^t = \mu_E^t - \mu_I^t$ and $(\sigma_C^t)^2 = (\sigma_E^t)^2 + (\sigma_I^t)^2$.

The probability of EV acquisition under dynamic policy is given by

$$p_D(t) = \Phi\left(-\frac{\mu_C^t}{\sigma_C^t}\right). \quad (10)$$

The second approach to solve the problem evaluates decisions at time $t=0$ for the entire horizon; therefore, we refer to it as the open-loop or static policy (subscript S). The minimum discounted fleet cost in this policy is denoted by $G_S^0(f^0, B^0)$:

$$G_S^0(f^0, B^0) = \sum_{t=0}^{T} (\rho)^t n^t g_S(t). \quad (11)$$

The static solution ignores the effects of uncertainty (i.e., all random variables are replaced by their expected values). The optimal cost per vehicle under the static policy is given by

$$g_S(t) = \min\{\mu_I^t, \mu_E^t\}, \quad (12)$$

and the probability of EV acquisition under static policy follows as

$$p_S(t) = \begin{cases} 1 & \text{if } \mu_C^t < 0 \\ 0 & \text{if } \mu_C^t > 0 \\ 0.5 & \text{if } \mu_C^t = 0 \end{cases}.$$

For the hypothetical case of perfect information, we obtain the unit optimal cost under perfect information as

$$g_P(t) = \mu_I^t + \mu_C^t \cdot p_P(t) - \varphi\left(\frac{\mu_C^t}{\sqrt{(\sigma_C^t)^2 + (\sigma_p)^2}}\right)\sqrt{(\sigma_C^t)^2 + (\sigma_p)^2}. \quad (13)$$

The probability of EV acquisition under perfect information is given by

$$p_P(t) = \Phi\left(-\frac{\mu_C^t}{\sqrt{(\sigma_C^t)^2 + (\sigma_p)^2}}\right), \quad (14)$$

where $(\sigma_p)^2 = (k_i\sigma_f)^2 \sum_{i=1}^{l} (\sum_{\tau=i}^{l} \rho^{\tau})^2$.

In Neboian et al. (2011), we derive closed-form expressions for the option value of EVs as an option to switch to the new technology.

The static solution provides an upper bound to the dynamic solution, because we can observe from the following expression for the unit option value of the dynamic policy $\omega_D(t)$:

$$\begin{aligned}\omega_D(t) &= g_S(t) - g_D(t)\\ &= \min\{\mu_C^t, 0\} - \mu_C^t p_D(t) + \sigma_C^t \varphi\left(\frac{\mu_C^t}{\sigma_C^t}\right) \geq 0. \qquad (15)\end{aligned}$$

The EDR, which we refer to in *The Sensitivity to Model Risk* section, is defined as follows:

$$EDR_{D,S}(\lambda, \tilde{\lambda}) = -\mathbb{E}[\min\{\bar{\Gamma}^0_{D,S}(\lambda, \tilde{\lambda}), 0\}], \qquad (16)$$

where the indices D and S correspond to a dynamic or static policy, respectively, and the random variable $\bar{\Gamma}^0_{D,S}(\lambda, \tilde{\lambda})$ represents the total EV value as a function of estimated battery production learning λ and realized learning $\tilde{\lambda}$.

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