A METHODOLOGY FOR ASSESSING THE POTENTIAL OF ELECTRIC VEHICLES WITH FRENCH COMMERCIAL VANS AS A CASE STUDY

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ABSTRACT

This paper presents a methodology aiming at quantitatively evaluating the competitiveness of electric vehicles with respect to conventional ones, with a focus on small vans. Two main constraints are investigated: range and cost. Based on a statistical distribution of the annual driven mileage, our methodology does not require as much data as a disaggregated study, which goes well with the investigation of business users, as there are generally less data available for them than for households travel patterns. Our method also puts into perspective total cost of ownership computations, as economic and range constraints are strongly linked to battery prices.

Our methodology is then applied to the case of commercial vans in France, today and for a 2021 forecast. Results show that electric vans' competitiveness is likely to grow in the future even in the case of a reduction in public incentives. They also show an important sensitivity to the input parameters, especially diesel prices and incentives. Different business activities are explored, and freight transportation stands out as the one with the highest potential for electric vehicles. The research also shows the mechanical effect of a decrease in battery prices on the broadening of supply in battery sizes, the impact of which was quantified. This suggests that for electric vehicle forecasts to be accurate, several models with different battery sizes should be considered.

Key-words: electric vehicles, light commercial vehicles, total cost of ownership, constraints analysis, freight transportation

INTRODUCTION

As environmental concerns are growing, the use of alternative technologies is an option for a more sustainable transport. In particular, battery electric vehicles raise a growing interest *(1)*. The environmental performance of electric vehicles is promising. Moreover, it brings opportunities in interaction with the energy system and renewable energies *(2–4)*.

Although electric vehicles (EVs) have existed for more than a century, the last decade has witnessed a new interest, driven by the lithium-ion battery technology. Numerous carmakers have brought out several models, and new competitors have entered the market. EVs may finally stopped being a “permanently emerging technology” *(5)*, able to make their way to the mass market, with Norway as a forerunner (but not without significant subsidies) *(6)*. However, the future dominant alternative vehicle technology is still an open question.

Light commercial vehicles (LCVs) seem to be good candidates to be replaced by electric vehicles. Their current environmental impact is high and freight transportation, which represents a significant proportion of road traffic, contributes even more to urban pollution *(7)*. Business users of LCVs differ from private vehicle users, as they attach much more value to functionality, and much less to symbolic and status. LCV users are also less flexible than car users, as they usually have less modal alternatives, especially in urban areas. However, fleets offer interesting possibilities for optimization, by mixing electric and conventional vehicles. An urban use of electric LCVs (eLCVs), by freight companies for instance, seems particularly relevant, since some vehicles drive the same relatively short route every day, they may return to the company’s garage at the end of the day, and companies using eLCVs may benefit from a positive corporate image.

Despite these potential advantages, the sales of eLCVs have remained marginal in Europe, including in countries offering substantial financial incentives. In France for instance, despite a bonus of €6300 for the purchase of an electric vehicle, the market share of eLCVs in 2014 reached only 1.21%. There has been zero growth between the first two quarters of 2014 and 2015 unlike the market for private cars (figures from the CCFA, ‘French Car Sales Federation’). In Norway, eLCV market share is 1.87%, far behind that of passenger cars (figure from the OFV, Norwegian ‘Information Council for the Road Traffic’) .

Different methods have been employed to assess the potential of electric vehicles. According to *(8)*, four key factors impact the choice of a LCV user to purchase an electric car: operational performance, economic performance, regulatory factors, and attitudinal and social factors. In this paper, our methodology will only address operational and economic performances.

Conventional and electric vehicles are not perfectly interchangeable. The transition from one to the other requires addressing several constraints brought by the technology. Low driving range and long charging time are considered in the literature as the most restricting factors for the use of eLCVs *(9)*. Other constraints exist: the difficulty for large LCVs (2.6 to 3.5 ton gross weight) to cope with payload restrictions due to the heaviness of the battery, the lack of after-sale and maintenance services *(8)*. If technical reliability has been a recurring problem in the past, with the newest vehicles, it seems to be less so, as vehicles are no longer trial products but mass-produced *(8)*.

The economical constraint is often measured through a Total Cost of Ownership (TCO) comparison between EVs and conventional vehicles (ICEVs, for Internal Combustion Engine Vehicles). They cover a wide range of vehicles and countries. For commercial vehicles, *(10–12)* have investigated the US case for medium-sized trucks (around 7 ton gross weight). A wide range of different eLCVs, as well as electric quadricycles, were put to test on the Belgian market in *(13)*. TCO computations can be combined with socio-economic evaluations, as in *(14)* for private cars and LCVs in France. Computations aimed at business users can also be found, such as a TCO study for France *(15)*, mainly about conventional LCVs, but with a section about electric vehicles. Tools for businesses willing to calculate TCO within their own operational conditions are available online *(10)*.

Disaggregated studies aimed at evaluating the potential market of electric vehicles represent a second type of approach. These studies are built upon the processing of a comprehensive database, more frequently on private travel behaviors from surveys *(16)* or GPS data *(17)*. The method often uses the Total Cost of Ownership as a measure of economic performance, which is crossed with the constraints of the technology to give a proportion of "*EV-qualifying"* households.

Stated preferences and various discrete choice models are as well commonly used to assess the market for alternative fuels, often including attitudinal factors *(18, 19)*. These market forecast methods, along with agent-based models and diffusion rate and time series models, are comprehensively reviewed in *(20)*.

Based on statistical distributions of the driven distances, and with the help of the TCO and a range constraint, the methodology used in this paper gives an upper bound of the potential market share of electric vans. Methodologies based on statistical distributions of driven distances have already been used in the literature (usually for daily driven distances), to evaluate range constraints *(21)*, energy use *(22)* or EV potential in a similar way than in this paper *(23, 24)*. We investigated the LCV market in France, today and with a projection to 2021.

In the remainder of this paper, we present our model and some methodological specifications in Section 2; we then present assumptions and results when applying the model to the French van market in Section 3; and we discuss the limitations, provide a conclusion and some research perspectives in the final section.

PRESENTATION OF THE MODEL

We focused our efforts on keeping the model simple and allowing thorough sensitivity analyses, rather than aiming at an illusorily high level of precision, given the available data. The model is indeed based on TCO computations, which depends on numerous uncertain or variable parameters.

Total Cost of Ownership Computations

The costs for a business vehicle covers the purchase expenses at year 0 (vehicle, infrastructure), the running costs every year, and the residual values of vehicle and infrastructure at year n. For the sake of simplicity, TCO is linearized with respect to the annual driven distance $\boldsymbol{d}$. For that purpose, the residual value of the vehicle and the running costs are first linearized. This gives:

$$TCO(\boldsymbol{d}) = A + \frac{B_0 + B_1 \cdot \boldsymbol{d}}{(1+r)^n} + \sum_{t=1}^{n} \frac{C_0 + C_1 \cdot \boldsymbol{d}}{(1+r)^t}$$

$$= \left[A + \frac{B_0}{(1+r)^n} + \tilde{n} \cdot C_0\right] + \boldsymbol{d} \cdot \left[\frac{B_1}{(1+r)^n} + \tilde{n} \cdot C_1\right] \quad \text{with } \tilde{n} = \sum_{t=1}^{n} \frac{1}{(1+r)^t}$$

$$= T_0 + T_1 \cdot \boldsymbol{d}$$

Where:

TCO:	Present value of the total cost of ownership
$\boldsymbol{d}$:	Annual driven distance
n:	Study period, in number of years
r :	Real discount rate
A:	Purchase expenses at year 0
$B_0 + B_1 \cdot \boldsymbol{d}$:	Linearization of the residual value with respect to **d**
$C_0 + C_1 \cdot \boldsymbol{d}$:	Linearization of running costs with respect to **d**
$T_0 + T_1 \cdot \boldsymbol{d}$:	Resulting linearized TCO

Linearization of the residual value approximates the decrease of resale value of the vehicle with the increase of the odometer reading ($B_1 < 0$). Linearization of running costs considers the fuel costs per kilometer independent of **d**. The battery costs are included in the running costs, under the assumption of a battery rental business model. The linearization of battery costs with respect to the driven distance is relevant, as battery ageing can be decomposed in calendar ageing and kilometric deterioration.

Representing the Annual Driven Distance by a Statistical Distribution

A statistical distribution is then fitted to the annual driven distance of LCV business users. Data stems from the "Survey on the uses of light commercial vehicles" conducted in 2010-2011 by the SOeS, the French environment ministry's statistics service. Light Commercial Vehicles are defined as vehicles of the N1 category according to the European general classification of vehicle categories.

The survey is vehicle-based and declarative, answers are provided by the users of the vehicles. Freight activities have been oversampled on purpose, to have a more accurate representation of this specific use (which engages 17% of all LCVs). The same has been applied for recent vehicles, as they run a great deal. A statistical adjustment was conducted on the database by the SOeS, by a marginal calibration, relying on several variables (fuel type, vehicle gross weight, vehicle main use and vehicle age) to define 32 strata.

The model is applied on subsets of the database. Vehicles of under 2.5 ton gross weight

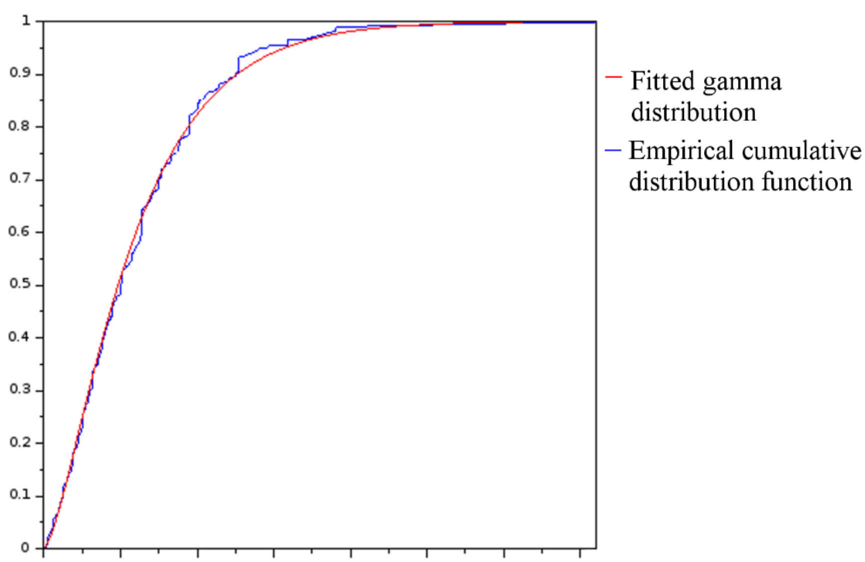

FIGURE 1 Fitted gamma distribution over the empirical cumulative distribution function (whole dataset)

(small vans) were extracted from the database, as they represent the market segment with the broadest range of electric vehicles commercially available today. Vehicles that are only driven for private purposes have been removed. To be more representative of the market, as it is likely that buyers of new EVs would be among buyers of new conventional vans, only vehicles bought in 2009 and after have been taken into account. The final subset of the database consists of 2357 vehicles, operating all over France.

After having tested several distributions, the distribution which fits observations the best is the two-parameter gamma law $\mathbf{\Gamma}(k, \theta)$, with k the shape parameter and θ the scale parameter (see Figure 1).

Defining the market share estimate

The aim of the methodology is to estimate the proportion of EV-qualifying vehicles, or equivalently the probability that a random vehicle is EV-qualifying. For this study, the definition of EV-qualifying vehicle implies (i) that the TCO is favorable for eLCVs, and (ii) that the daily driven distance is less than the range of the electric vehicle. Investigating daily driven distances only in average fails to address the variability of trip lengths, but data about daily use is lacking. However, an ex post correction aims at rectifying this shortcoming.

Unfortunately, no data on the possibility of installing charging stations at the companies' premises could be found. So, the estimate tends to overestimate the potential market share of LCVs as it does not account for all constraints and results must be interpreted in the light of the investigated population, especially the nature of the activity.

We define φ as the probability for a random vehicle to be EV-qualifying, depending of a set of parameters π. If a random vehicle $v(D)$, represented by its driven distance D distributed according to the $\mathbf{\Gamma}$(k,θ) law, mathematical definition of φ is:

$$\begin{aligned}
\varphi &= \gamma \cdot \Pr(\{\mathrm{v}(D) \text{ is EV} - \text{qualifying}\}) \\
&= \gamma \cdot \Pr(\{TCO_{EV}(D) \leq TCO_{ICEV}(D)\} \cap \{D < d_{max}\}) \\
&= \begin{cases} \gamma \cdot \max\left(0, \mathbf{\Gamma}(d_{max}; \mathrm{k}, \theta) - \mathbf{\Gamma}\left(-\frac{\Delta T_0}{\Delta T_1}; \mathrm{k}, \theta\right)\right), & if\ \Delta T_1 > 0 \\ \gamma \cdot \frac{sgn(\Delta T_0) + 1}{2} \cdot \mathbf{\Gamma}(d_{max}; \mathrm{k}, \theta), & if\ \Delta T_1 = 0 \\ \gamma \cdot \mathbf{\Gamma}\left(\min\left(-\frac{\Delta T_0}{\Delta T_1}, d_{max}\right); \mathrm{k}, \theta\right), & if\ \Delta T_1 < 0 \end{cases}
\end{aligned}$$

Where:

γ:	Ex post correction ($\gamma \in [0,1]$)
EV and $ICEV$ indexes:	Referring to electric and international combustion engine (i.e. conventional) vehicles respectively
d_{max}:	Electric vehicle range
ΔT_i:	$T_{i,ICEV} - T_{i,EV}$, $i \in \{0,1\}$, with previous notations

Thereafter, "before correction" will mean "with γ =1". Figure 2 gives a graphical representation of φ.

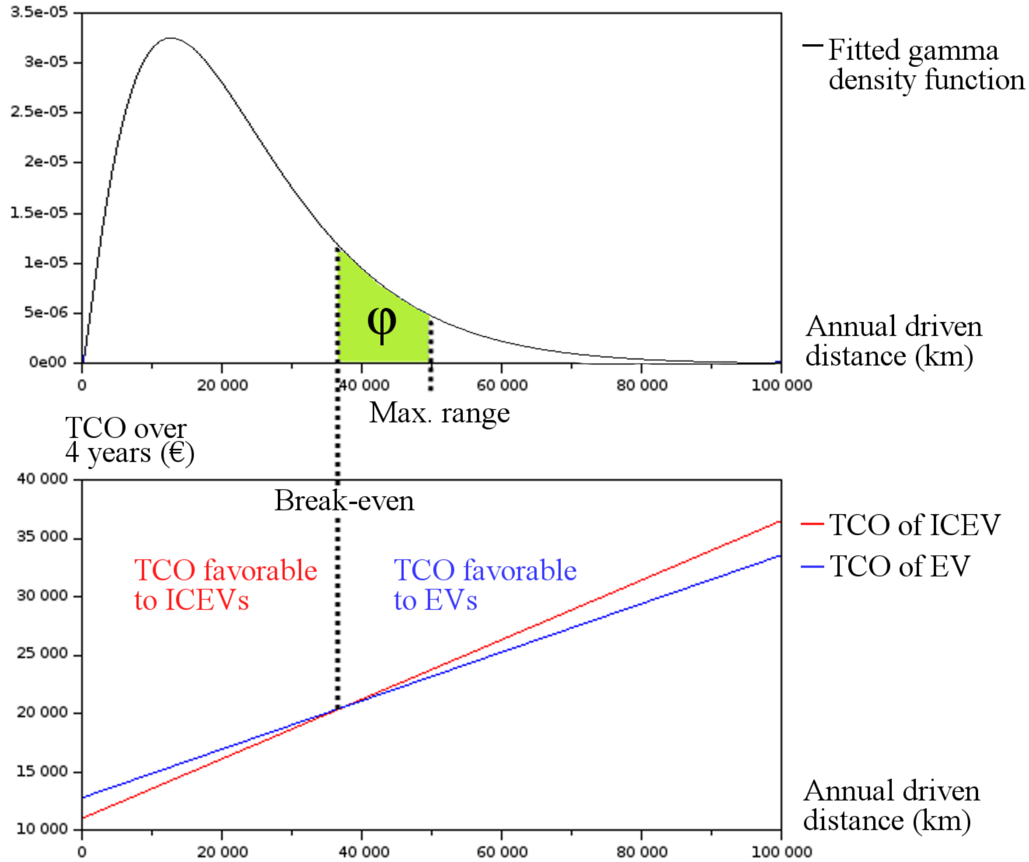

FIGURE 2 The green surface represents the market share estimate φ (before correction) on a specific example

The large number of parameters makes a single estimate difficult to interpret, especially for future projections. For a parameter set π distributed over a space $\prod$ of possibilities, we therefore define:

$$\bar{\varphi} = E_{\pi}(\varphi)$$

In practice, this expectation is computed by computing φ with a large amount of random parameter sets π (independent and identically distributed). As a result of the law of large numbers, the empirical means uniformly converges to $\bar{\varphi}$.

Variance-based global sensitivity analyses are performed, using Sobol's sensitivity indexes *(25)*. They assess the impact of the input parameters' variability on the result's variability. We will refer to φ (and by extension $\bar{\varphi}$) as a market share estimate, for the sake of clarity. This expression might be a bit abusive as it assumes a perfectly rational behavior of business users, and disregards the lack of exhaustiveness.

TABLE 1 Numerical Assumptions for the Case Study on Commercial Vans in France

Parameter:	ICEV 2016	ICEV 2020	EV 2016	EV 2020
Study Period (years)	4			
Discount rate (%)	7			
Purchase price (€)	17450	17450 to 18450	21850	21850 to 20850
Incentives (€)	0	0	-6300	-4000 to -2000
Battery Size (kWh)	n.a.	n.a.	22 kWh	40kWh
Battery Rental (€/year)	n.a.	n.a.	$512 + d \cdot 0.01794$	$377 + d \cdot 0.01321$ to $433 + d \cdot 0.01517$
Infrastructure (€)	n.a.	n.a.	1500 to 3000 amortized on 8 years + 200€/year of maintenance	
Mean consumptions (L/100km, kWh/100km)	5.76 to 8.14		15.75 to 26.4	
Residual Value (%)	$48.3 - \mathrm{d} \cdot 1.369 \cdot 10^{-4}$		$38.6 - \mathrm{d} \cdot 1.093 \cdot 10^{-4}$ to $48.3 - \mathrm{d} \cdot 1.369 \cdot 10^{-4}$	
Number of working days	229 to 254 business days			
Fuel prices (€/L, €/kWh)	1.02 to 1.09	1.13 to 1.50	0.0954 to 0.1016	0.10989 to 0.14540

n.a. is for not applicable. d is the annual driven distance in kilometers.

APPLICATION OF THE METHODOLOGY TO THE CASE OF FRENCH COMMERCIAL VANS: ASSUMPTIONS AND RESULTS

Numerical Assumptions

Results depend on a wide range of numerical parameters, which define the space $\prod$ of possibilities. Table 1 shows all the numerical values taken for the implementation and thereafter is a short explanation of sources and assumptions. When a parameter is considered uncertain or variable, a range is given instead of a single value. These variables are considered independently (unless stated otherwise) and uniformly distributed over the interval.

Purchase prices are for a Renault Kangoo Express Confort dCi 90 model (ICEV) and a Renault Kangoo Z.E. Confort model (EV). They are among the most sold LCVs in their respective segment in France and in Western Europe (source: CCFA). ICEV price increase in 2021 accounts for possibly more demanding air-pollution treatment devices, whereas EV price decrease (excluding batteries) accounts for possible economies of scale and technological progress.

The current incentives from the French administration for the purchase of an electric vehicle are €6300 per vehicle. Incentives will decrease in the future as demand rises.

EV battery rental in 2016 is based on Renault rates. Rental rates are presumed to be directly proportional to battery size times battery cost per kilowatt-hour. Battery cost in 2021 is set according to a $8 \pm 8\%$ decline *(26)* between 2011 (release date of the Kangoo Z.E.) and 2021. The choice of the battery size of 40kWh is justified subsequently, as it is close to offering the maximal coverage.

Infrastructure's residual value considers the subtraction of the accounting depreciation (here, half of the price) from the purchase price. Prices are similar to those of level II AC public infrastructure *(27)* and in line with the testimonies in our preliminary interviews. Network reinforcement works, if needed, for instance for big fleets, could add up a significant cost *(10)*.

ICEV consumptions are based on the NEDC (New European Driving Cycle) consumption range increased by 37%, to account for real driving conditions, based on findings of *(28)*. A $\pm10\%$ variation is added in order to take into account the important impact of driving style. EV consumption rates are based on *(29)*. When computing worst range, consumptions are increased by 10% due to cold temperature, and EV consumptions are further penalized by 2.5kWh/100km for heating. ICEV and EV consumptions are considered linearly linked together i.e. a user who has a high diesel consumption would have a high electricity consumption too.

Residual values of EVs are a great unknown today. By lack of evidence and of quantitative data, residual values are likely to be, for electric and conventional vehicles, in the range from equal in Euros to equal in percentage (ICEV data are derived from used vans sold by the Renault network in France).

Energy prices are given excluding VAT. Minimum and maximum diesel price scenarios are derived from the June 2016 Renault's reference scenario on crude oil prices, and then averaged on the four years' time period. Electricity rates are based on the average annual growth rate of 5.3% between 2006 and 2015 in France (professional fares).

Results

Statistical distribution parameters are given in Table 2 for replicability. The table also gives the results of the model run on different activity clusters, for the 2016 and 2021 assumptions. The results are corrected to account for the peak-use constraint, the occasional use of the vehicle for trips exceeding the range of an EV. Given the available data, the factor is set for 2016 (resp. 2021) equal to the proportion of vehicles which declare not doing trips of more than 80km (resp. 150km) on a monthly basis, among those driving in average less than 80km a day (resp. 150km). Under the denomination "craftsmen" are business users using their vehicle for "transporting tools, samples, materials or waste".

Analysis of the Results for the 2016 Assumption

Before correction, the market share is about 17% for the whole market, and varies between 17% and 20% for the activity clusters. Differences are small, which was to be expected as the only

TABLE 2 Statistical Distribution Parameters and Model Outputs for Several Business Activities

Outputs	Freight for hire	Freight for own account	Craftsmen	Passenger transport	All
$\boldsymbol{k}$	1.959	1.375	1.344	2.2194	**1.542**
$\boldsymbol{\theta}$	12234	12748	17425	10367	**15784**
			Results for the 2016 assumptions		
St. dev. of $\boldsymbol{\varphi}$ (before correction)	0.12	0.12	0.11	0.13	**0.11**
$\boldsymbol{\overline{\varphi}}$ (before correction)	19%	20%	17%	20%	**17%**
Corrective factor $\boldsymbol{\gamma}$	0.51	0.43	0.40	0.25	**0.34**
$\boldsymbol{\overline{\varphi}}$ (after correction)	10%	9%	7%	5%	**6%**
			Results for the 2021 assumptions		
St. dev. of $\boldsymbol{\varphi}$ (before correction)	0.18	0.15	0.15	0.19	**0.16**
$\boldsymbol{\overline{\varphi}}$ (before correction)	22%	17%	19%	23%	**20%**
Corrective factor $\boldsymbol{\gamma}$	0.74	0.81	0.62	0.51	**0.64**
$\boldsymbol{\overline{\varphi}}$ (after correction)	16%	14%	11%	12%	**13%**

TABLE 3 Sensitivity of φ with Respect to Varying Parameters

2016 assumptions	
Varying parameter	**Sobol's total sensitivity index**
Residual value uncertainties	72.2%
Consumption	24.5%
Infrastructure costs	8.9%
Diesel price	0.9%
Number of Working Days	0.5%
Electricity price	0.07%
2021 assumptions	
Varying parameter	**Sobol's total sensitivity index**
Incentives	34.3%
Diesel price	29.4%
Residual values uncertainties	14.2%
Infrastructure costs	7.9%
Consumption	6.0%
EV purchase price	4.0%
ICEV purchase price	3.7%
Electricity price	2.5%
Battery rental	1.5%
Number of working days	0.7%

differencing factor so far is the distribution of average annual driven distances. Standard deviations are very high, showing the sensitivity of TCO computations with respect to input parameters.

After correction, the results give an overall market share $\bar{\varphi}$ of 6%, ranging from 5% to 10% according to activity. This shows that the correction based on the regularity of trips is essential. The comparison with the actual market share of eLCVs of around 1.2% deserves some comments: (i) since only small LCVs are investigated (approximately 60% of the market in France), and since the current eLCV market is mainly developed on this segment, the actual market share on this segment might be closer to 2% than to 1.2%; (ii) the order of magnitude is right; and (iii) the methodology only accounts roughly for the main constraints given by the electric vehicle, so $\bar{\varphi}$ cannot be taken as a realistic market forecast, but is to be seen as an upper bound. In particular, failing to take into account the difficulty to install charging infrastructures explains partly the differences with the actual market share.

The two (for own account and for hire) freight activities' market shares are significantly higher than the others, which confirms a true potential market for these activities. This is already slightly the case before correction, but the main reason for this is the regularity of trips of these activities. Looking further into freight for hire activities shows that mail transport and home delivery activities have a potential of 11% and 12% respectively. On the other hand, urban delivery rounds for businesses and on-demand courier activities have lower potentials of 5% and 1% respectively, due to higher variability of the trips.

Table 3 underlines that the uncertain residual value of electric vehicles is by far the most impacting factor. It illustrates that in the new emerging market of eLCVs, uncertainties are slowing down market development. This is all the more so that fleet managers might take ICEV residual values in Euro (or no residual value at all) as reference for their computations, which is the lowest assumption here. Other uncertainties, such as future diesel and electricity prices, have a very low impact on the final results' variability, as they are short term forecasts.

Consumption and infrastructure costs, depending on the use of the vehicle and the company's facilities, are second and third explaining factors of the variability of the result.

Analysis of the Results for the 2021 Forecasts

The second part of Table 2 presents the results for the 2021 projections. There is more than a doubling of the overall market share to 13%. Standard deviations are even higher than for the 2016 assumptions (due to forecasting uncertainties), and freight activities are still ahead of other activities, with a potential of 16% for freight for hire, and 14% for own account.

Table 3 shows that forecasting uncertainties have the upper hand. With close sensitivity indexes, incentives and diesel prices weigh the most on the success or failure of electric light commercial vehicles, and this even without considering the complete withdrawal of subsidies, but keeping at least a €2000 bonus. Resale value uncertainties of used eLCVs still have an important impact on the competitiveness of eLCVs, but might be cleared by then as more and more electric vehicles will land on the second hand market.

A doubling of potential for eLCVs despite the drop in subsidies is a positive signal, but the hypothesis of a market reduced to one single battery size may underestimate their potential in future forecasts. Indeed, the decrease in battery prices enables car manufacturers to aim for both small and large batteries.

Exploring the Impact of a Broader Range of Battery Sizes

A market offering eLCVs with two different battery sizes (thereafter, *two-model market*) instead of one (thereafter, *one-model market*) is investigated. The difference between the two explored battery sizes echoes on the battery rental rates and the range (having two contradictory effects on the competitiveness). The market share estimate is therefore supplemented as following:

$$\varphi = \Pr(\{\mathrm{v}_1(D) \text{ or } \mathrm{v}_2(D) \text{ is EV} - \text{qualifying}\})$$
$$= \varphi_1 + \varphi_2 - \Pr(\{\mathrm{v}_1(D) \text{ and } \mathrm{v}_2(D) \text{ are EV} - \text{qualifying}\})$$

Where:

v_i: Vehicle model i, $i \in \{1,2\}$

φ_i: Market share estimate of each vehicle model i taken separately, $i \in \{1,2\}$

The estimate remains uncorrected ($\gamma_1 = \gamma_2 = 1$) and thus does not account for peak-uses. In Figure 3 are plotted the heat maps and contour lines of the above defined market share estimate for 2016 and 2021 respectively, with respect to the battery sizes of the two models, varying between 20 and 60 kWh. This enables to spot the battery sizes that maximize the proportion of EV-qualifying vehicles. The market share for a one-model market as studied before can be read on the diagonal, which enables to capture the relevancy of offering different battery sizes for a carmaker. Figures have been plotted using 1 million simulations.

The top heat map shows the two optimal battery sizes at around [21kWh, 27kWh]. The gain of introducing two models instead of having one 22kWh model is less than 6% (before correction, even less with peak-use constraint). Furthermore, the two battery sizes are close with each other and address almost the same uses. So this suggests that the 28kWh model targets a niche market, which explains why major car manufacturers did not commercialize vehicles with such battery sizes up until now. The optimal value is on the edge, which suggests a strong pressure of the high battery prices towards smaller battery sizes.

The 2021 heat map presents a much different profile. First, higher potentials are not located in the same areas than in 2016, smaller battery sizes being the least competitive. Then, it is clear that the diagonal (i.e. the one-model market estimate) is substantially worse than the two-model market away from the diagonal. Optimal sizes are reached at around [29kWh, 51kWh], and the gain in market share of the two models is more than 10% (compared to a 40kWh model,

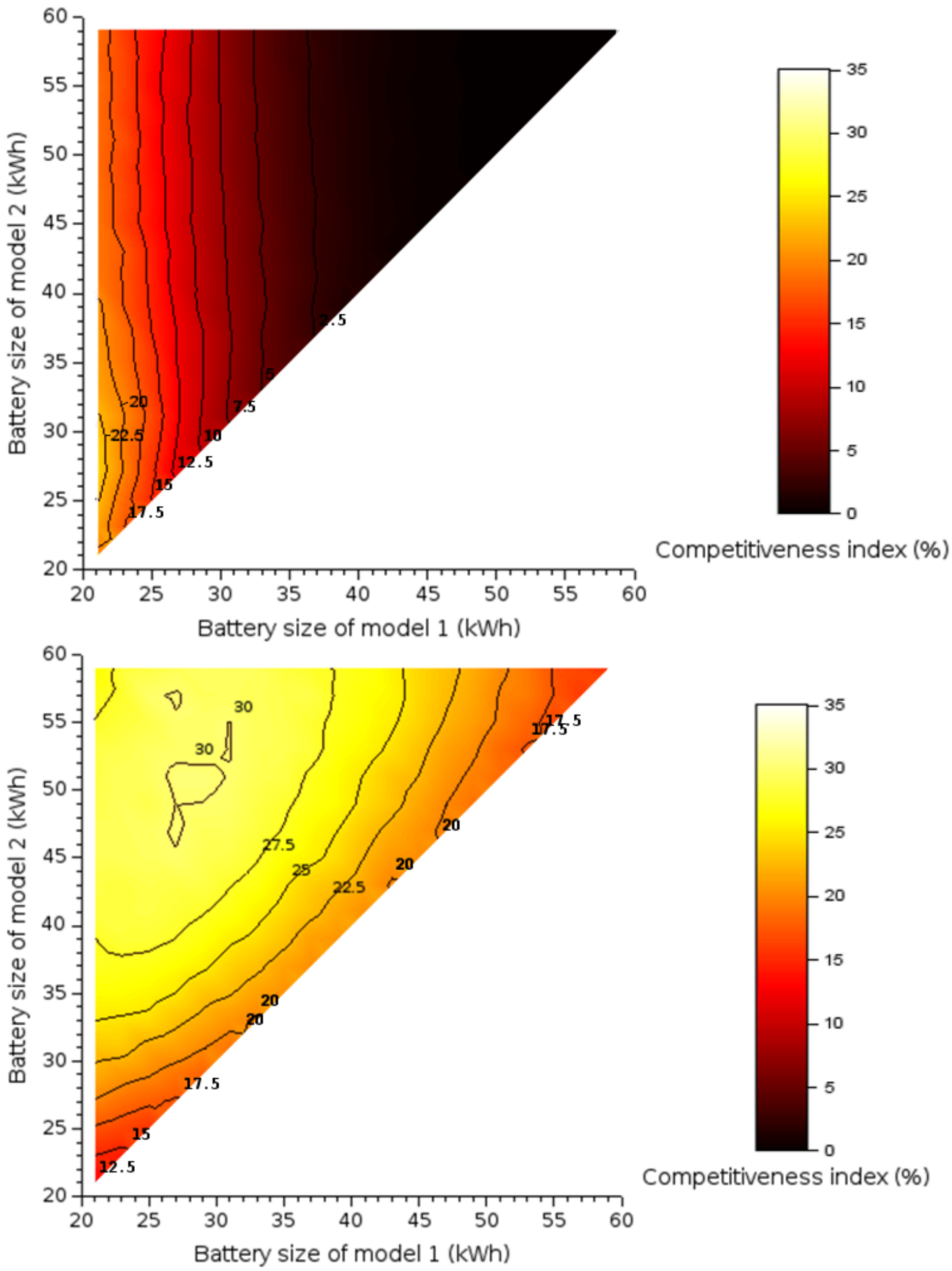

FIGURE 3 Potential for electric vans in a two-model market, with respect to the two battery sizes (top: 2016 assumptions; bottom: 2021 assumptions)

which almost maximizes the one-model market). As battery sizes target different types of buyers, and as potential gain is greater in the future than today, it seems more likely that a broader range of battery sizes will be provided when battery prices are reduced.

Thus, it is important to take this result into account when evaluating electric vehicles, as e.g. TCO comparisons between only one EV and one ICEV may underestimate the EVs' competitiveness.

LIMITATIONS AND CONCLUSION

Limitations

Although we called φ a market share estimate, the results are not to be taken as accurate market forecasts. First, this would assume that business stakeholders have perfectly rational behaviors, and a detailed knowledge of the technology. Then, several constraints have not been investigated, among which one at the forefront: the possible infrastructure and charging difficulties. Also, sensitivity results highly depend on the ranges of the inputs. So, the output has to be interpreted cautiously and with a good understanding of the inputs and underlying assumptions.

The methodology is based on TCO computations. As the market share estimate only depends on TCO differences, the expenditure items that have been left apart are considered equal for EVs and ICEVs. In particular, it is implied that eLCVs can be operated in a similar manner to ICEVs. When this is not the case, the necessary operational adjustment is often a huge barrier: for example detours by the driver to go to the premises (and thus additional wage costs) or significant network reinforcement works severely impact eLCV TCO.

If the variables are not explicitly linked, they are assumed to be independent. This approximation affects for instance the consumption, as vehicles driving long distances are more inclined to drive a lot on highways, and thus having high consumptions. However, this assumption is validated by the sensitivity analysis, which gives the consumption variations as being of second order.

Several carmakers prefer to sell the battery along with the car instead of leasing it. Under the assumptions of a perfectly rational customer, perfect information on the technology, and a perfect substitution of the services provided by the business models, the discounted costs should be identical. In practice, none of these assumptions are strictly true: e.g. preferences are affected by culture (no perfect rationality), the formation of the residual value of the battery is complex and unknown (no perfect information), and battery leasing often comes along with warranties and can affect the resale of the vehicle (no perfect substitution). Comparison of battery rental and sale is thus a complex problem.

A big limitation of the exploration of two battery sizes is that the results have not been corrected to account for peak-use constraints. This should favor smaller battery sizes (which would be more penalized by the peak-use). Taking the price per kilowatt-hour constant is also a strong hypothesis, as different battery sizes require different chemistries.

All this underlines that the methodology aims more at a rough evaluation than at a precise estimation, but the sensitivity shows that a better knowledge of the use (e.g. consumption) of the vehicles would not provide a much better level of precision of the joint TCO and range constraints results, given the high uncertainties and volatility of other first order exogenous parameters.

Conclusion

A methodology was presented, which lies between the total cost of ownership computations and the disaggregated constraints analysis, to evaluate the potential market development of electric vans compared with conventional ones. A proportion of *EV-qualifying* vehicles is estimated, based on current uses, range and economic criteria.

The methodology has been applied to the evaluation of electric vans in France, which is an example of a segment where data is less available than for private car uses. In particular, limited information is provided on daily driven distance distributions. Results show that even if future projections are uncertain, all indicators tend towards a growth of the electric van market. Decrease in battery prices should increase the range of supplied battery sizes, better fitting the different uses. This suggests that for electric vehicle forecasts to be accurate, several models with different battery sizes should be considered.

Social and regulatory factors, not included in the model, should further promote the development of the electric van market. Regulatory factors are evolving fast: as a result of growing global and local environmental concerns, the use of alternative fuels is gaining comparative advantages. See for example the increase in traffic restrictions for polluting vehicles (ban of old diesel vehicles in Paris since 2015, Ultra-Low Emission Zone being planned for 2020 in London). Social and behavioral constraints should be reduced as the range grows. These issues represent important areas of research for the future, especially in the urban freight transportation sector, which represents a potentially interesting market for electric vehicles, as explained in the paper.

Nevertheless, the fact that today, electric vehicles are heavily subsidized makes the forecasted evolution not as impressive as some technological innovation-based market developments that have been experienced in the past.

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