

## What future for electric light commercial vehicles?: a prospective economic and operational analysis of electric vans for business users, with a focus on urban freight

Pierre Camilleri

#### ▶ To cite this version:

Pierre Camilleri. What future for electric light commercial vehicles?: a prospective economic and operational analysis of electric vans for business users, with a focus on urban freight. Infrastructures de transport. Université Paris-Est, 2018. English. NNT: 2018PESC1105. tel-02131030

#### HAL Id: tel-02131030 https://theses.hal.science/tel-02131030

Submitted on 16 May 2019

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

## DOCTORAL THESIS IN TRANSPORTATION AT THE UNIVERSITY OF PARIS-EST DOCTORAL SCHOOL "VILLE, TRANSPORT ET TERRITOIRES"

## What future for electric light commercial vehicles?

A PROSPECTIVE ECONOMIC AND OPERATIONAL ANALYSIS OF ELECTRIC VANS FOR BUSINESS USERS, WITH A FOCUS ON URBAN FREIGHT

## Pierre CAMILLERI Under the direction of Laetitia DABLANC

#### COMPOSITION OF THE JURY:

Laetitia DABLANC, Research Director, IFSTTAR (Thesis Director)

Jing DONG, Associate Professor, Iowa State University (Rapporteur)

Matthieu DE LAPPARENT, Associate Professor, Haute Ecole d'Ingénierie et de Gestion du Canton de Vaud (Rapporteur)

Cathy MACHARIS, Professor, Vrije Universiteit Brussel (Examiner)

Patrick PLÖTZ, Researcher, Fraunhofer Institut (Examiner)

**INVITED MEMBER:** 

Pierre EYKERMAN, Researcher, Renault (Company supervisor)







#### **ACKNOWLEDGEMENT**

I would like to express my great gratitude to my thesis director, Laetitia Dablanc, and my company supervisors, for some time My-Linh Liburski Tran and then Pierre Eykerman, for their valuable and constructive suggestions throughout my research and their availability.

It is a great honor to have Jing Dong, Matthieu de Lapparent, Cathy Macharis and Patrick Plötz on my thesis jury.

I would also like to thank François Combes, Virginie Boutueil, Jean Grébert, Hélène Wiedeman and Gilles Abdelaziz for their quality advices which were of great help to me.

I enjoyed working with Philippe Lepaisant and Eduin Le-Nain, and I thank them for the opportunities they gave me and the trust they placed in me.

I thank Jens Klauenberg, Jardar Andersen, Sönke Behrends, Ivan Sanchez-Diaz and their teams for their warm welcome, as well as the DAAD and the MetroFreight project for the financial support that allowed my international study visits. I would also like to thank all those who responded positively to my requests and received me for an interview.

I warmly thank all my colleagues, fellow PhD students and my friends, for the rich discussions and good times we shared during these three years. Finally, a very special gratitude goes out to my family and my girlfriend, Mathilde, for their constant support throughout the thesis.

#### <u>RÉSUMÉ</u>

Le marché des véhicules électriques est animé par une dynamique très positive. Il s'agit cependant essentiellement d'un marché de niche. Il est donc légitime de s'interroger quant à son avenir.

D'une part, cette dynamique est portée par de fortes préoccupations environnementales et bénéficie d'un large soutien des autorités publiques. Les constructeurs automobiles ont ces dernières années fortement investi dans cette technologie, les progrès technologiques sont rapides et offrent des perspectives intéressantes.

D'autre part, des subventions conséquentes sont aujourd'hui nécessaires pour permettre aux véhicules électriques d'être compétitifs. Il est inévitable que ces subventions diminuent si le marché grandit. Deux mécanismes opposés sont donc en jeu et rendent incertain le développement du marché des véhicules électriques pour les années à venir.

Notre recherche propose d'analyser ces mécanismes pour les véhicules utilitaires légers, et plus particulièrement pour le transport urbain de marchandises. Les besoins des entreprises de transport de marchandises sont évalués à travers une quarantaine d'entretiens, menés dans quatre pays européens et analysés à la lumière de la théorie de la diffusion de l'innovation. Ces entretiens mettent en évidence les obstacles opérationnels et économiques à l'utilisation de véhicules électriques, qui sont liés à la technologie elle-même mais aussi à sa nouveauté.

Une approche quantitative complète cette étude. Elle s'appuie sur un modèle de prédiction de parts de marché, qui quantifie la façon dont les contraintes économiques et opérationnelles évoluent avec les développements technologiques. Ces contraintes sont mesurées par deux indicateurs: l'adéquation de l'autonomie du véhicule avec son usage et les comparaisons de coûts totaux de possession (TCO). Une originalité du modèle est qu'il traite le montant des subventions à l'achat d'un véhicule électrique comme une variable endogène, qui s'adapte dynamiquement aux évolutions du marché.

Afin de compenser le manque de données disponibles sur les usages des véhicules utilitaires, un modèle statistique a été développé. Ce modèle permet d'exploiter au mieux les données d'une enquête sur les véhicules utilitaires légers en France, menée par le service de la donnée et des études statistiques (SDES) du Ministère de la Transition Écologique et Solidaire.

Ces analyses confirment que l'évolution du marché du véhicule électrique n'est pas certaine et qu'elle est aujourd'hui extrêmement dépendante des aides publiques. Même dans des scénarios de soutien financier public continu, il est peu probable que l'on observe une croissance exponentielle du marché. Plutôt, le marché augmentera doucement pendant de nombreuses années à venir, le temps que la technologie s'affranchisse de sa dépendance à l'égard du soutien financier. Par exemple, notre scénario de référence prévoit une part de marché des fourgonnettes électriques de l'ordre de 13% en 2032.

Mots-clés: Véhicules électriques; Véhicules utilitaires légers; Transport de marchandises; Prévision de la demande; Modélisation des usages

#### **EXECUTIVE SUMMARY**

The electric vehicle market is driven by a very positive dynamic. However, it is essentially a niche market. It is therefore legitimate to wonder about its future.

On the one hand, this dynamic is driven by strong environmental concerns and enjoys broad support from public authorities. Car manufacturers have invested heavily in this technology in recent years. Technological progress is rapid and offers interesting prospects.

On the other hand, substantial subsidies are currently needed to enable electric vehicles to be competitive. It is inevitable that these subsidies will decrease if the market grows. Two opposing mechanisms are therefore at stake and make the development of the electric vehicle market uncertain for the years to come.

Our research proposes to analyze these mechanisms for light commercial vehicles, and more particularly for urban freight transport. The needs of freight transport companies are assessed through some forty interviews conducted in four European countries and analyzed in the light of innovation diffusion theory. These interviews highlight the operational and economic obstacles to the use of electric vehicles, which are linked to the technology itself but also to its novelty.

A quantitative approach completes this study. It is based on a market share prediction model, which quantifies how economic and operational constraints evolve with technological developments. These constraints are measured by two indicators: the vehicle's range adequacy given its use and total cost of ownership (TCO) comparisons. An original feature of the model is that it treats the amount of subsidies for the purchase of an electric vehicle as an endogenous variable that dynamically adapts to market developments.

In order to compensate for the lack of available data on commercial vehicle uses, a statistical model has been developed. This model makes the best use of data from a survey on light commercial vehicles in France, conducted by the statistical department of the Ministry of the Environment (SDES).

These analyses confirm that the development of the electric vehicle market is not certain and that it is currently extremely dependent on public support. Even in scenarios of continued financial support from public administrations, exponential market growth is unlikely. Rather, the market will grow slowly for many years to come, the time for technology to overcome its dependence on public financial support. For example, our reference scenario forecasts a 13% market share for electric vans in 2032.

Keywords: Electric vehicles; Light commercial vehicles; Freight transport; Demand forecasting; Usage modeling

#### TABLE OF CONTENTS

A	CKNOW	VLEDGEMENT	3	
R	ÉSUMÉ		5	
E	XECUTI	IVE SUMMARY	7	
Τ.	ABLE O	F CONTENTS	9	
L	IST OF I	FIGURES	15	
L	IST OF	TABLES	19	
IN	NTRODU	UCTION	21	
P	ART I -	- CONSTRAINTS AND OPPORTUNITIES OF ELECTRIC VEHIC	LES FO	R
		REIGHT OPERATORS		
1		ΓERY ELECTRIC VEHICLES, PROMISING PROSPECTS FOR THE		F
	27	,		
	1.1 A E	BRIEF HISTORY OF ELECTRIC VEHICLES: A CENTURY-OLD TECHNOLOGY WIT	ΓΗ RECEN'	Т
	DEVELO	PMENTS	28	
	1.1.1			8
	1.1.2	An "eternally emerging" technology		
	1.1.3			
	1.1.4			
	infra	istructure	•	_
	-	ALTERNATIVE MOTORIZATIONS IN A TECHNOLOGICAL RACE		
	1.2.1	Road transport and pollution	30	6
	1.2.2	Internal combustion engine vehicles dominate the current mark	ket3	7
	1.2.3	Biofuels	4	.1
	1.2.4	Battery electric vehicle technologies	4	2
	1.2.5	Natural Gas	4	4
	1.2.6	Hydrogen fuel cell	4	6
	1.2.7	Hybrid electric vehicles	4	7
	1.3	Environmental and social assessment of electric vehicles	47	
	1.3.1	Comparative life cycle assessment	48	8
	1.3.2	Socio-economic assessment	5	1
	1.3.3	Battery second life and recycling	5	1
	1.3.4	Smart grid and energy grid interactions	52	2
	Снарте	ER CONCLUSION	55	
2	A DI	VERSITY OF USES OF LIGHT COMMERCIAL VEHICLES	57	
	2.1	DESCRIPTION OF THE LIGHT COMMERCIAL VEHICLE FLEET	58	
	2.1.1	Scope of studied commercial vehicles	5	8

2.1.2	What are the vehicles used for?	60
2.1.3	Distances driven and age of light commercial vehicles	63
2.1.4	Link between LCV market and regulations	65
2.1.5	Variety of fleets and fleet managements	66
2.1.6	Defining freight activities	67
2.2 I	DEMAND IN URBAN FREIGHT68	}
2.2.1	Urban freight, an industry supporting businesses	68
2.2.2	Evolution of the demand	69
2.2.3	Urban freight demand varies between business activities	71
2.3 S	Supply of urban freight74	:
2.3.1	Employment and urban freight	74
2.3.1	Urban freight and road transport	75
2.3.1	Third account and own account	
2.3.2	A very competitive environment	79
2.4	QUALITY OF URBAN FREIGHT80	)
2.4.1	Pollution	
2.4.2	Congestion	81
2.4.3	Noise	82
2.4.4	Safety	82
Снарте	r conclusion83	}
3 CON	STRAINTS AND OPPORTUNITIES OF ELECTRIC VEHICLES	FOR
FREIGHT	OPERATORS85	,
3.1 F	REVIEW OF EXPERIMENTAL PROJECTS ON ELECTRIC VEHICLES AND BUSINESS	USERS
8	36	
3.1.1	1 3	
3.1.2	Implications of the technical specificities of EVs	88
3.1.3	Implications of the novelty of the market	
3.1.4	Mitigate constraints with regulation	
3.1.5	Temporal dynamics	
3.2 I	NTERVIEWS: A SLOW BUT PROMISING CONVERGENCE OF SUPPLY AND DEMAND	100
3.2.1	Methodology	
3.2.2	Perceived relative advantage of electric vehicles	
3.2.3	Perceived complexity	
3.2.4	Trialability and perceived risk	115
3.2.5	Observability	117
Снарте	r conclusion118	

	- A MARKET SHARE MODEL BASED ON ECONOMIC A		NGE
	AINTS		
	DELING DAILY VEHICLE KILOMETERS TRAVELED		
	LITERATURE ON STATISTICAL MODELING OF DAILY VEHICLE KILOMETI	ERS TRAVI	ELED
	124		
4.1.1	Fitting agent-by-agent statistical distributions on longitudir		
4.1.2			126
	A DVKT MODEL		
4.2.1			
	Model concept		127
4.3 J	JUSTIFICATION OF THE MODEL SPECIFICATION		
4.3.1	A longitudinal database on Indian taxis	•••••	129
4.3.2	Choice of the DVKT distribution		129
4.3.3	A reparameterization $\Phi$ to bring up the average		132
4.3.4	Choice of the parameters' distribution		133
4.3.5	Wrap-up		135
4.4	Maximum likelihood fitting procedure	136	
4.4.1	General setting	•••••	137
4.4.2	SDES setting		137
4.5 l	Model estimation on the SDES database about light commerc	CIAL VEHI	CLES
in Fran	CE	140	
4.5.1	Database and pre-processing		140
4.5.2	Model fit		142
4.6	ASSESSING THE GOODNESS OF FIT OF THE MODEL	143	
4.6.1	Identification of the error sources		144
4.6.2	Statistical uncertainty on the data		144
4.6.3	Inspection of the marginal distributions	•••••	146
4.6.4	Size of the sample and fitting procedure	•••••	147
Снарте	R CONCLUSION	149	
5 ELEC	CTRIC VEHICLE MARKET SHARE MODELING	151	
5.1	CONSTRAINTS QUANTIFICATION AND MARKET FORECAST METHODS	153	
5.1.1	Quantifying the economic performance		153
5.1.2	Quantifying the operational performance		
5.1.3	Variability and optimism of market forecast methods		
5.1.4	Agent-based models		
5.1.5	Stated preferences and discrete choice models		
5.1.6	Diffusion models		
	OVERVIEW OF THE MODEL		

5.2.1	Motivation for the methodology	166
5.2.1	Model architecture	168
5.3	The decision model173	3
5.3.1	Explicit computation of the probability of requiring adaptation	174
5.3.2	Explicit computation of the range	176
5.3.3	Modelling the uses	
5.4	From Static Potentials to Market share time series	3
5.4.1	Successive vehicle generations and battery capacities	178
5.4.2		
5.4.3	Integrating diffusion	181
5.5	Sensitivity assessment	
5.5.1	Individual variability and volatile parameters	182
5.5.2	Graphical sensitivity	184
5.5.3	-	
Снарт	ER CONCLUSION	
ווו ידים אכ	- MODEL RESULTS AND DISCUSSIONS187	7
	RIFICATION SCENARIOS FOR LIGHT COMMERCIAL VEHICLES .189	
6.1.1	TOTAL COST OF OWNERSHIP COMPUTATIONS AND INPUT DATA 190  Model parameters	
6.1.2	•	
6.1.2		
6.1.3		
	· · · · · · · · · · · · · · · · · · ·	
6.1.5	3	
6.1.6		
6.1.7		
6.1.8		
	TCO EXPLORATION	
6.2.1		
6.2.2	3	
	MARKET POTENTIAL AND PAST MARKET SHARES	
	REFERENCE SCENARIO	7
6.5	INVESTIGATION BY BUSINESS ACTIVITY	)
6.6	CUSTOMER USAGE PROFILES AND ELECTRIC KILOMETERS TRAVELED	
6.6.1	Average driven distances	212
6.6.2	2 Dominant constraints	213
6.6.3	B Total kilometres travelled by electric vehicle	214
Спурт	ER CONCLUSION	3

7	SEN	SITIVITY ANALYSIS	219
	7.1 Di	SCUSSION ON MODEL'S LIMITATIONS	220
	7.1.1	Model transfer from taxis to light commercial vehicles	220
	7.1.2	Diversification of supply	
	7.1.1	Unchanged uses	220
	7.1.1	Numerical uncertainties	221
	7.1.2	Scope of the study	221
	7.1.3	From bonus to malus	222
	7.1.4	No technological breakthrough	222
	7.2	Sensitivity to model assumptions	223
	7.2.1	Probability of requiring adaptation threshold of acceptability.	223
	7.2.2	Alternative incentive assumptions	224
	7.3	Effect of the broadening of supply	226
	7.4	PUBLICLY ACCESSIBLE INFRASTRUCTURE	228
	7.5	Sensitivity on model inputs	230
	7.5.1	Most influential inputs	230
	7.5.2	Variable costs sensitivity	232
	7.5.3	Fixed costs sensitivity	234
	7.6	Chapter conclusion	236
C	ONCLU	JSION	239
	CURREN	NT LOW MARKET SHARES ARE WELL EXPLAINED	240
		HOPES SHOULD BE PLACED IN TECHNOLOGICAL CHANGE?	
		REFERENCE SCENARIO CONSERVATIVE?	
	SUPPOR	TING THE UPTAKE OF THE ELECTRIC VEHICLE MARKET	243
		DOLOGICAL CONTRIBUTIONS AND RECOMMENDATIONS FOR FURTHER	
			244
L		ACRONYMS	
A	PPEND:	IX 1: ASSUMPTIONS FOR MARKET SHARE PREDICTIONS, SM	ALL VANS'
Sl	EGMEN	T	249
		AN: FIRST GENERATION	
SI	MALL V	AN: SECOND GENERATION	252
SI	MALL V	AN: THIRD GENERATION	253
SI	MALL V	AN: FOURTH GENERATION	254
B	IGGER '	VAN (3.5T GROSS WEIGHT): FIRST GENERATION	255
		IX 2: ALTERNATIVE ESTIMATION PROCEDURE WITH LONG	
D	ATA		257
B	IBLIOG	RAPHY	259

#### LIST OF FIGURES

- **Figure 1** Number of electric car manufacturing companies in France between 1893 and 1956 ((Fréry, 2000), after (Shacket, 1980)) 29
- **Figure 2** Paris in smog 32
- **Figure 3** Market shares of electric passenger cars (a.) and number of publicly accessible charging station (b.) in the European Union (EAFO, 2017) 35
- **Figure 4** Divergence between real-world and manufacturers' type-approval **CO2** emission values for various on-road data sources ((Tietge et al., 2015), updated 2017) 40
- **Figure 5** Total emissions of modeled biofuel pathways, by or for regulators in the United States and Europe (Malins et al., 2014). ILUC: indirect land use change.
- **Figure 6** Normalized impacts of vehicle production, use and disposal, from (Hawkins et al., 2013). Results for each impact category have been normalized to the largest total impact. Global warming (GWP), terrestrial acidification (TAP), particulate matter formation (PMFP), photochemical oxidation formation (POFP), human toxicity (HTP), freshwater eco-toxicity (FETP), terrestrial eco-toxicity (TETP), freshwater eutrophication (FEP), mineral resource depletion (MDP), fossil resource depletion (FDP), internal combustion engine vehicle (ICEV), electric vehicle (EV), lithium iron phosphate (LiFePO4), lithium nickel cobalt manganese (LiNCM), coal (C), natural gas (NG), European electricity mix (Euro). 50
- **Figure 7** Distribution by gross vehicle weight and by body type of French LCVs (own production on the basis of the SDES survey on LCVs, France, 2010) 59
- **Figure 8** Distribution of professional LCVs across activity sectors and by declared primary use of the vehicle (own production on the basis of the SDES survey on LCVs, France, 2010) 60
- **Figure 9** Number of business users by declared intersection of uses (own production on the base of the SDES survey on LCVs, France, 2010) 62
- **Figure 10** Distribution of annual driven distances for different classes of declared main use (entries with no main use are dropped, own production on the base of the SDES survey on LCVs, France, 2010) 64
- **Figure 11** Distribution of ages for different classes of declared main use (entries with no main use or valid purchase year are dropped, own production on the base of the SDES survey on LCVs, France, 2010) 64

- **Figure 12** Number of deliveries / pick-ups by job and week, by sector of activity, in Île-de-France (Paris region) (LAET, 2014) 72
- **Figure 13** Typology of freight tours and corresponding visual representations (excerpt) (Beziat et al., 2015) 73
- **Figure 14** Logistics sprawl in Paris metropolitan area (2000-2012) (Heitz & Dablanc, 2015) 76
- **Figure 15** Share of deliveries performed with each size of vehicle in the Paris region (Urban Freight Survey, (LAET, 2014)) 77
- **Figure 16** Share of deliveries / pick-ups for third account (in blue), for own account performed by shippers (in red) and own-account performed by recipients (in orange) for different economic activities. Data for France from (Patier, 2004).
- **Figure 17** Example of Weibull, log-normal and gamma distributions fitted on the DVKT of one agent (a. density, b. cumulative distribution functions) 131
- **Figure 18** Boxplots of the distribution of the negative log-likelihood (normalized by the number of agents) for three distributions fitted on each agent of the Indian taxi database. In the box, shares of agents for which each distribution scores the best according to the log-likelihood. 132
- **Figure 19** Kernel density function of the joint distribution of the parameters p1, p2 after re-parameterization. 133
- **Figure 20** Parameter pairs of individually fitted Weibull distributions and its kernel density (a.), and corresponding Clayton copula based density with generated pairs in red (b.) 135
- **Figure 21** Comparison of observed and modeled average distances traveled (a.) and probabilities of requiring adaptation with range 80 km and 150 km (b.) 143
- **Figure 22** Size of confidence bands (at level 0.05, 0.2 and 0.4) of the empirical cumulative distribution function, according to the size of the sample (number of agents) 145
- **Figure 23** Performance of the model (estimated on longitudinal taxi data) on the prediction of the PRA with 100, 200, 300 and 400 kilometers of range 146
- **Figure 24** Fraction of private vehicles that can be replaced with EVs as a function of the vehicle range and the number of allowable adjustments days (data on private vehicles from the region of Atlanta) (Pearre et al., 2011) 159

- **Figure 25** Example of optimistic forecasts for electric vehicles, from (Fréry, 2000) 161
- **Figure 26** Share of actual and estimated hybrid electric vehicle penetration rate using consumer choice method studies (Al-Alawi & Bradley, 2013) 162
- **Figure 27** An agent-based constraints analysis. Not all input parameters are exogenous to the model: some are solutions of an optimization problem or an equation. See Figure 28. 170
- **Figure 28** Whole model architecture: the orange boxes correspond to the constraint analysis as shown in Figure 27. 171
- **Figure 29** Decision model for one individual (excerpt of Figure 27) 174
- **Figure 30** Schematic representation of the 3 steps to compute market share time series 178
- **Figure 31** Schematic regulatory mechanism: the points represent the equilibrium points for which demand (blue lines, modeled by exponential functions) causes expenditures that exactly respect the budget of public administrations (orange lines). 180
- **Figure 32** Difference in potential market share distributions with different assumptions: 1- constant shares of distance driven on highway and in cities ('Fixed'), 2- independently distributed use variables ('Independent') or 3- jointly distributed use variables (jointly bootstrapped average driven distance, share of distance driven on highway and in cities). 199
- **Figure 33** TCO comparison for electric and conventional small LCVs, by expenditure items (a. and b.) and total (c.), assumptions of 2017. Confidence bands are at 50 %. 202
- **Figure 34** TCO comparison for electric and conventional bigger LCVs, assumptions of 2018. 203
- **Figure 35** Observed past market shares vs. computed past *potential* market shares (lower bound only with incentives from public administrations, upper bound with €2,000 additional incentives) 206
- **Figure 36** Market share potential (assumptions of 2022) as a function of the battery capacity 208
- **Figure 37** Reference scenario for market shares and incentives. The lower (resp. upper) confidence interval limit is given for a total state budget allocated to electric LCVs of €50M (resp. €60M) 209

- **Figure 38** Comparison of market projections for three different business classes (all light commercial vehicles, unlike other figures focusing on small vans). 211
- **Figure 39** Potential EV market shares as a function of the average daily driven distances for the second (2017-2022), third (2022-2027) and fourth (2027-2032) generations of small vans.
- **Figure 40** Evolution with time of the range and TCO constraints for electric vans. 214
- **Figure 41** Scenario with a loosened range constraint, with a PRA threshold 5 times and 10 times greater than in the reference scenario respectively.
- **Figure 42** Alternative strategies from public authorities, either reducing public expenses progressively (Constant potential, keeping the market shares constant) or systematically (Rapid decrease, decreasing the subsidies by  $\leq$  500 per year) or wanting to double public support to electric LCVs ( $\leq$  100M budget of public administrations) 225
- **Figure 43** EV market potential resulting in 2027 (a.) and 2032 (b.) as a function of two battery capacities (instead of one) supplied by car manufacturers 227
- **Figure 44** Impact of the supply of two different battery capacities (35 kWh and 50 kWh from 2022 to 2027, 42 kWh and 68 kWh from 2027 to 2032) by car manufacturers 227
- **Figure 45** Simulating a wide coverage of the territory with publicly available charging stations of 50 kW or 22 kW. 229
- **Figure 46** Sobol's total sensitivity indices for the potential of the second generation of small electric vans (2022): on the resale value of electric vehicles (Resale), the purchase and installation price of charging infrastructure (Infra), the price of electricity (Electricity) and the price of Diesel at the pump (Diesel). 230
- **Figure 47** Sobol's total sensitivity indices for the potential of third generation of small electric vans (2027): on the purchase price of EVs (EV MSRP), their resale value (EV Resale), and the purchase and installation costs of charging infrastructure (EV *Infra*), the price of electricity (Electricity), the price per kWh of battery (Battery), the purchase price of ICEVs (ICEV MSRP) and the price of Diesel (Diesel). 231
- **Figure 48** Different scenarios with variable Diesel prices (from -20% to +20% compared with the reference scenario). 232
- **Figure 49** Different scenarios with variable fixed costs (cost reductions from €1,000 to €3,000 in 2022 for EV fixed costs) 235

#### **LIST OF TABLES**

**Table 1** Share of pollutants in the Paris region related to freight activities (Koning et al., 2017) 81

**Table 2** Summary of main constraints and opportunities, with their related temporal dynamics 99

Table 3 Interviewed companies and organizations 101

**Table 4** Summary of main findings. Crucial elements are in bold. 120

**Table 5** Information about the three compared distributions. *erf* stands for the error function,  $\gamma$  stands for the lower incomplete gamma function,  $\Gamma$  for the gamma function. (1) Parameters of the log-normal distribution are the expectation and standard deviation of the logarithm of the variable, which follows by definition a normal distribution. 130

**Table 6** Negative log-likelihoods of different parameters' distributions  $D\mathcal{P}$  (divided by number of agents), with the Weibull distribution as DVKT distributions  $D\mathcal{A}$ . In bold are the best fits. 134

**Table 7** Akaike Information Criteria (AIC) for the Gumbel, Clayton, Frank and independent copulas applied on parameter pairs (p1,p2), with log-normal and Weibull marginal distributions respectively. 135

**Table 8** Bivariate Kolmogorov-Smirnov statistics of the estimated model compared to the original model from which the data are generated, for different estimation procedures, and different sample sizes. Long = longitudinal estimate. ABA = agent-by-agent estimate. SDES = SDES estimate 148

**Table 9** Distances traveled by small electric vans, and shares in the total vehicle fleet (on the basis of the lower subsidy assumptions in the reference scenario) 215

**Table 10** Table of correspondence for variable cost scenarios (with 2032 assumptions) 233

**Table 11** Use and model parameters fitted on the LCV SDES database 249

**Table 12** Reference energy prices scenario 250

**Table 13** Public incentives 250

## INTRODUCTION

Environmental awareness has been growing in recent years. Both local pollution and global pollution are of concern. The World Health Organization estimates that in the European region, the average loss of life expectancy due to air pollution is almost one year. In 2009, 83% of the population in European cities was exposed to  $PM_{10}$  particulate matters levels exceeding the World Health Organization guidelines (World Health Organization Regional Office for Europe, 2015). Climate change is also a major concern, with forecasts of rising water levels, global warming, and the fear of more and more natural disasters (IPCC, 2014). The European Union and the States set ambitious targets for reducing this pollution. In the European Commission roadmap 2050 low carbon economy (European Commission, 2011a), the EU should cut greenhouse gas emissions to 80% below 1990 levels by 2050, with intermediary targets of 40 % by 2030 and 60 % by 2040.

Transport is a major contributor to this pollution. However, it is a sector for which environmental improvement has been small in the past decades. The evolution of greenhouse gas emissions from transport has changed little in France in 10 years, unlike other sectors (such as waste treatment or manufacturing industry) which have been able to set a lasting downward trend. This is due in particular to the increase in traffic (both for passengers and goods), also affecting local pollution.

Transport is the source of 29% of greenhouse gases emissions in France, 95% of which are due to road transport. For road transport, passenger cars account for 56%, heavy vehicles for 22% and light commercial vehicles for 20%.

Freight transport accounts for almost 30% of  $PM_{10}$  and  $NO_x$  in the Île-de-France region (the Paris region) (Koning et al., 2017).

Electric vehicles seem to be part of the solution to reduce the environmental impacts of transport. The European strategy for low-emission mobility (European Commission, 2016) explicitly mentions the transition to low-and zero-emission vehicles in order to reach the ambitious environmental mitigation targets. Battery electric vehicles have the advantage that they do not emit exhaust gases and therefore do not produce local pollution during operation. The carbon footprint can also be advantageous, depending on the source of electricity production.

The electrification of light commercial vehicles is therefore a substantial challenge for the reduction of pollutant emissions from transport, especially since some activities using light commercial vehicles, such as urban freight, seem well suited (technically and economically) to this transformation. Therefore, this work is focused on the study of electric light commercial vehicles, with a particular focus on urban freight transport activities.

At the beginning of the 2010 decade, interest in electric vehicles increased. Driven by the technological improvement of batteries (in particular thanks to the market for portable electronic devices), environmental awareness and the increase in the price of oil, car manufacturers have supplied production battery electric vehicles, sometimes with ad hoc designs such as the Renault Zoé and BMW i3. Small vans also entered the market at the same time. Since then, supply has not stopped evolving and today, announcements of future models abound. Technology upgrades have almost doubled battery capacity at a constant cost in less than 10 years.

For light commercial vehicles, legacy manufacturers are entering the electric commercial vehicle segment (with the upcoming marketing of the Mercedes e-Vito for example). Larger vans just have been or are about to be released, while they were absent of most car manufacturers' supply until now. In 2018, Renault just launched the Renault Master Z.E. Ford and Streetscooter (a subsidiary of Deutsche Post/DHL) have announced the marketing of the Work XL van of equivalent size. Daimler and Tesla made announcements in the heavy vehicle segment with the e-Fuso and Semi respectively.

The current scarcity of production models in the mid-size and heavy truck segments does not prevent many experiments. This is the case, for example, of UPS, which is testing electric vehicles extensively, for example new prototypes of the Arrival brand.

Despite this proliferation, these vehicles only represent niche markets. In the European Union, electric light commercial vehicles accounted for only 0.8% of the market in 2017. And the same is true for passenger cars, for which the average European market share does not exceed 1% in 2017. It should be noted, however, that these markets are growing.

It is therefore crucial, in this pivotal moment when everything still seems possible, to be able to evaluate what promises this technology can hold for the future. The trend is there, and the importance that this technology holds in the public discourse (public authorities, media) suggests that it is a technology with very high potential. On the other hand, the limited range imposed by the technology, and the current lack of economic competitiveness compared with firmly established conventional vehicles, raise serious questions. In the past, many studies have tended to make overly optimistic forecasts.

The obstacle of limited range and that of additional cost are two major constraints of electric vehicles, which have been studied extensively. However, studies that cross these two factors are rarer, despite the fact that they invite contradictory behavior: the less you drive, the less limited range is an obstacle, but the more you drive, the more you benefit from the low operating costs of electric vehicles. These studies are often based on longitudinal studies, i.e. based on long observation periods, expensive and not very available for segments other than passenger vehicles.

Our work focuses exclusively on light commercial vehicles. Particular attention has been paid to integrating possible future developments into our analysis. We have conducted a holistic study on the subject, with two complementary approaches. A qualitative approach led us to conduct 40 interviews with carriers in four European countries. These interviews were guided by the innovation diffusion theory. These interviews provided the basis for a market share model to assess the present and future competitiveness of light commercial vehicles. A quantitative approach has enabled us to evaluate today and in the 15 years to come, thanks to modeling, the market shares that electric vans are likely to gain.

An originality of our approach lies in the fact that the absence of longitudinal data has forced us to develop a usage statistics model, in order to be able to exploit cross-sectional data (collected in a single survey) on French light commercial vehicles. In addition, the subsidies granted for the purchase of electric vehicles, as well as the battery capacities supplied on the market, were treated endogenously to the model for market shares. Indeed, the amount of

subsidies for electric vehicles are calculated on the basis of a total budget that public authorities are willing to invest to support the demand for electric vehicles. This amount therefore varies according to the potential market for electric vehicles. As for battery capacities, we obtain them by maximizing potential market shares. As a result, market share forecasts have a lower sensitivity to input parameters, allowing more robust result interpretations.

The first part is devoted to quantitative analysis. In the first two chapters, we thoroughly inspect our two subjects of study, namely battery electric technology (Chapter 1) and uses of light commercial vehicles, with a focus on urban freight transport (Chapter 2). Then we analyze how the use of electric vehicles for business light commercial vehicle users creates both constraints and opportunities, and we present the results of our interviews in Chapter 3.

The second part introduces and evaluates the models that have been used for the quantitative analysis of the battery electric technology. Chapter 4 is reserved for statistical usage modeling, while Chapter 5 introduces the prospective market share model.

Finally, the third part implements these models. Chapter 6 develops a reference scenario and the lessons that can be drawn from it. Chapter 7 finally analyses the sensitivity of this model to input parameters and explores the integration of new market mechanisms, such as supply diversification or the use of publicly available recharge infrastructure.

This thesis was conducted in the frame of a collaboration between the car manufacturer Renault and the French Institute of Science and Technology for Transport (IFSTTAR). Part of the research took place in Renault's research department, in contact with teams working in particular on alternative technologies and new mobility.

PART I - CONSTRAINTS AND OPPORTUNITIES OF ELECTRIC VEHICLES FOR URBAN FREIGHT OPERATORS

# 1 BATTERY ELECTRIC VEHICLES, PROMISING PROSPECTS FOR THE FUTURE

Throughout the dissertation, electric vehicles will be considered as a positive and desirable innovation (what Rogers (2010) calls the "pro-innovation bias"), so it is important to put it in context.

In this chapter, we will explain how this technology compares with current dominant technologies, starting with a presentation of the emergence of this century-old technology. The search for solutions to alleviate the negative externalities of road transport in recent years has led to a proliferation of alternative technologies, among which the battery electric technology is one solution among others. We therefore wish to give an overview of these solutions, and highlight the singularities of battery electric vehicles, and the relevance of this solution. It is obviously not perfect, however, and so we wish to explore the virtues, weaknesses, risks and opportunities presented by this technology.

Battery electric vehicles, losing competition with internal combustion engine vehicles over a century ago, seem to be back in the spotlight. Thanks to high-energy on-board accumulators that power an electric engine, the technology has the advantage of producing no exhaust emissions. However, this advantage is offset by other negative externalities during battery or electricity production. It presents nonetheless interesting future developments

opportunities, capitalizing on its qualities and smoothing out its drawbacks. We will abbreviate battery electric vehicles by *electric vehicles* or EVs. (Others sometimes use the abbreviation BEV to differentiate battery electric vehicles from other electric systems, such as plug-in hybrid electric vehicles or fuel cell vehicles. In such cases, we will explicitly mention it.)

After giving a brief recall on the history of electric vehicles and their current market and dynamics in section 1.1, different envisaged alternative fuels are reviewed in section 1.2, and a focus on electric vehicles' short and long-term opportunities are presented in section 1.3.

## 1.1 A brief history of electric vehicles: a century-old technology with recent developments

#### 1.1.1 A century-old technology

Electric vehicles are often perceived as a recent innovation, as a novelty. This is far from being the case. More than a century ago, electric vehicles (EVs) would be on the streets, and had a much larger market share than today. The first electric car is even 50 years older (1834) than the first internal combustion engine vehicle (ICEV). On the commercial front, the two technologies are, however, contemporary from the end of the 19<sup>th</sup> century, and prognostics on the future winner of this duel were divided (Fréry, 2000). "Oil, electricity and steam have been competing over the past few years for the lucrative honor of providing engines for automobiles, the favorite mean of transport", reads in 1899 in La Nature (a magazine dedicated to popular Science) (Garçon, 2003).

According to Garçon's analysis, EVs replaced horses easily and advantageously at the time. The organizations were similar: while horses must be cared for in the stables, electric vehicles must be connected to charging stations. In the first decade of the 20th century, the coexistence of two types of automobiles for two different types of uses is considered. Electric vehicles are suitable for urban travel, where gasoline-powered vehicles allow long journeys on the roads. History shows that ICEVs are the only winners in this duel, as shown by the rapid decline of electric car manufacturers from 1910 onwards (Figure 1).

<sup>&</sup>lt;sup>1</sup> Author's translation

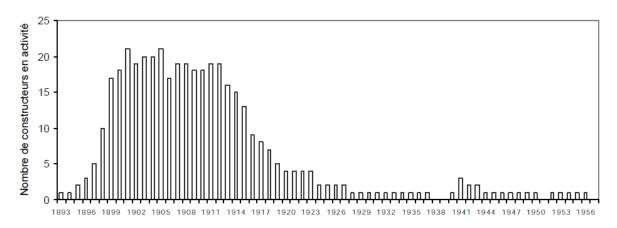


Figure 1 Number of electric car manufacturing companies in France between 1893 and 1956 ((Fréry, 2000), after (Shacket, 1980))

According to Garçon (2003), EVs have faced several obstacles. There was of course the question of the technical difficulty to improve the battery capacity and thus the range, resulting in a limitation of its uses. We are still facing this difficulty today.

Yet, the question of the representations is interesting. The social and economic contexts were very different with today. Electric vehicles were at first appealing, as they combined two major innovations at that time: electricity and automobile. Automobile races have played a central role in degrading their representation. First, car competitions would be organized, challenging the range, the speed, but also a full range of specifications including maneuverability, comfort, etc. "In this context, each engine technology suffered its defeat"<sup>2</sup>, comments Garçon (2003). The races served a collective imaginary about speed and about travelling, around the possibility of long distances, dominating the other vehicle characteristics and putting aside limited EVs (Garçon, 2003). In line with this, Fréry (2000) observes that today, customers are still ready to pay significantly more for modularity, even though it is almost never used. He gives the example of modular minivans.

EVs, easier to start, easier to drive and cleaner to use, seemed also to be reserved for female customers ("À quand la voiture électrique ?," 1968; Fréry, 2000). According to Fréry (2000), the marketing position around this clientele has penalized the electric vehicle market, especially after the invention of the electric starter (1911), which corrects a major disadvantage of the gasoline vehicle.

<sup>&</sup>lt;sup>2</sup> Author's translation

At last, the same author claims that the process innovation operated with the production of the Ford Model T is another blow to EVs. Indeed, in 1908, Ford initiates mass production with this model. All versions of the model T had a common platform and a unique engine (Alizon et al., 2009). This approach did not let much room for an electric motorization.

#### 1.1.2 An "eternally emerging" technology

Since then, electric vehicles only occupied a marginal role in the automobile landscape. A few jolts have been observed at different times in history, usually in connection with oil crises or shortages: during World War II (observable on Figure 1) and the oil crises of the 1970s. The last years of the 20<sup>th</sup> century witnessed also a gain of interest in electric vehicles, with especially (but not only) the mass produced and emblematic General Motors EV1. Claiming that the vehicle was not profitable, General Motors took the EV1 off the market and destroyed almost all vehicles. The documentary "Who killed the electric car?" questions the role of lobbies, especially from the car and oil industries, in leading this program to failure by purpose, mainly because of the fear of long-term revenue losses (Paine & Kirsch, 2006).

None of these jolts has had any durable effect on the electric vehicle market.

The technology seemed to have not been up to the task, even if great expectations of technological progress have often accompanied the analysis of alternative fuels. Fuel cells are already mentioned as a future technology in 1968 ("À quand la voiture électrique?," 1968), yet we are apparently today at the same point as 50 years ago when we realize that the voiceover of this documentary could have been written today.

This is what Fréry (2000) qualifies as "indisputable failure" of a technology that has generated an excess of optimism on very long periods. He qualifies such technologies as "eternally emerging".

#### 1.1.3 Recent developments: maybe an actual new start

Since the years 2000, many things seem to have changed, both in the industry and in people's awareness of environmental issues. Are electric vehicles on the edge of a breakthrough, or are we – again – lured by our excess of optimism?

-

<sup>&</sup>lt;sup>3</sup> Author's translation

We have observed an unprecedented deployment of charging infrastructure and a significant expansion of electric models supplied by car manufacturers (see subsequent sub-section 1.1.4). Interest in EVs is rapidly growing (Hanke et al., 2014). Despite of this, EVs remain still globally a niche market. Some localized countries and cities have notably high market penetrations of EVs, which are then most often heavily subsidized.

### 1.1.3.1 Technological progress, regulations, environmental awareness and rising oil prices are drivers for the new electric vehicle market

One similarity with the previous jolts is that the price of oil did go up at high speed in 2008, and although it was followed by a recession, the upward trend was seen as an element favoring research and investment in electric vehicle technology<sup>4</sup>. Among the other reasons put forward by the CEO of Renault-Nissan for justifying his interest into electric technologies are technological progress and more and more stringent regulations. Lithium-ion technology, which development has been largely due to the proliferation of portable electronic devices, has indeed dominated the recent production of car batteries.

Environmental problems are becoming more and more important, and environmental awareness truly increased in recent years. This is particularly visible in the involvement of public authorities in the development of environmental impact mitigation strategies. Impacts exceed the mere air pollution, but encompass elements as diverse as global warming, noise pollution, land consumption by vehicles (which was one century ago a major argument to the replacement of horse carriages by cars, and which is today a central question of sharing of public space between different modes of transport, pedestrians, bicycles etc.), or impact of infrastructure on biodiversity.

However, current attention is focused largely on climate change and local pollution. A widespread effort by many countries aims to reduce greenhouse gas emissions, mainly CO<sub>2</sub>. Fine particles and nitrogen oxides pollution is a hot topic; dense cities are the most concerned. Pollution peaks put them into smog ( Figure 2). For this reason, more and more stringent regulations are expected in the future, and road transport is in the spotlight (Airparif, 2017).

\_

<sup>&</sup>lt;sup>4</sup> "Renault-Nissan CEO Carlos Ghosn: 'Now Is the Time for the Electric Car'." *Knowledge@Wharton*, 28 Oct. 2009, knowledge.wharton.upenn.edu/article/renault-nissan-ceo-carlos-ghosn-now-is-the-time-for-the-electric-car/.

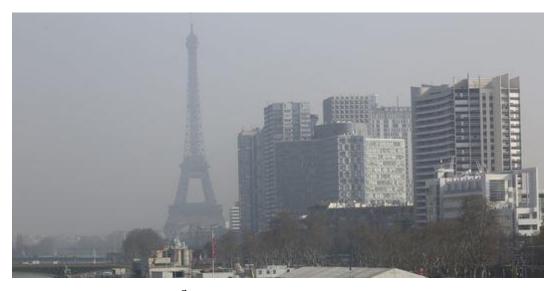


Figure 2 Paris in smog<sup>5</sup>

#### 1.1.3.2 A diversification of the supply in electric vehicles

A clear evolution of the vehicle supply has been observed in the past decade. For years, most electric vehicles were experimentally modified conventional vehicles, or small scale either artisanal or custom-made vehicles. Since 2010, there is a growing number of mass-produced electric vehicles, covering more and more segments. Legacy car manufacturers, like Renault and BMW, also supply a range of electric vehicles, some of which are designed for being electric (and not just mere transformed conventional vehicles) like the Renault Zoé, or the BMW i3.

Among the major changes is the fact that new car manufacturing companies produce exclusively electric vehicles. One of them, Tesla Motors, was the subject of a documentary by the same director than "Who killed the electric car?", entitled: "Revenge of the electric car" (Paine & Morgan, 2011). Another one is a company purchased by the Deutsche Post DHL Group, StreetScooter, which is an electric LCV manufacturer.

The LCV market is nevertheless still very sparse and focused on small vans<sup>6</sup>. In 2017, 87% of the electric utility vehicle market is divided between only

32

<sup>&</sup>lt;sup>5</sup> Le Monde. "Nouveau Pic De Pollution Attendu Ce Mercredi à Paris." Le Monde.fr, 8 Apr. 2015, www.lemonde.fr/planete/article/2015/04/08/un-nouveau-pic-de-pollution-attendu-ce-mercredi-a-paris\_4611227\_3244.html.

<sup>&</sup>lt;sup>6</sup> As may show a filtering of utility vehicles on: <a href="http://www.automobile-propre.com/voitures">http://www.automobile-propre.com/voitures</a> (at time of writing, retrieved March, 1, 2018).

five different models, all small vans: the Renault Kangoo ZE, StreetScooter Work, Nissan e-NV200, Peugeot Partner EV and Citroen Berlingo EV (EAFO, 2017).

Indeed, the supply of larger vans on the market is very scarce; it basically boils down to converted conventional vehicles<sup>7</sup> (such as the Gruau Electron II on the basis of a Fiat Ducato). However, several bigger electric vans are about to be (or just has been) commercialized by historic car manufacturers, with among others the very recent marketing of the Renault Master Z.E., or announcements around the Ford Work XL<sup>8</sup> or the Mercedes eSprinter (planned for 2019).

The relative delay of the LCV market compared with the passenger car market can be explained by the difference in volume the markets exhibit. In Europe (meant as EU, EFTA, and Turkey in the figures) in 2016, the passenger cars registrations outnumber the electric LCVs by more than a factor seven (around 15 million passenger vehicles and 2 million LCVs (ACEA, 2017)).

The truck market, in units, is even much smaller than the van market: in France in 2017, 19,000 heavy trucks were registered against 316,000 light commercial vehicles. Electric trucks are already used in several experiments and demonstrations, but the vehicle is often still in the prototype state. Moultak et al. (2017) listed a range of demonstrations with medium and heavy electric trucks, mainly used for last-mile logistics. As a logical follow-up to these experiments, several manufacturers have announced the marketing of electric trucks, such as BYD<sup>9</sup>, Renault Trucks<sup>10</sup> or Daimler<sup>11</sup>. Tesla has also announced the marketing of a truck by 2020, the Tesla Semi.

-

 $<sup>^{7}</sup>$  Converted vehicles are not taken into account in the counts of the European Alternative Fuels Observatory

<sup>&</sup>lt;sup>8</sup> Torregrossa, Michaël. "Ford Work XL: Un Utilitaire Électrique Gros Volume Pour La Poste Allemande." Automobile Propre, 17 Aug. 2017, www.automobile-propre.com/ford-work-xl-utilitaire-electrique-gros-volume-poste-allemande/.

<sup>&</sup>lt;sup>9</sup> Field, Kyle. "BYD Opens Up About Its Electric Truck Plans (CleanTechnica Exclusive)." *CleanTechnica*, 6 June 2018, cleantechnica.com/2018/06/01/byd-opens-up-about-its-electric-truck-plans-cleantechnica-exclusive/.

<sup>&</sup>lt;sup>10</sup> Renault Trucks Corporate. "Renault Trucks Will Start Selling Electric Trucks in 2019." Renault Trucks Corporate - Press Releases: Renault Trucks Will Start Selling Electric Trucks in 2019, 8 Feb. 2018, corporate.renault-trucks.com/en/press-releases/renault-trucks-will-start-selling-electric-trucks-in-2019.html.

## 1.1.4 Electric vehicle market share and publicly accessible charging infrastructure

In France and Europe, the share of EVs is approximately the same for passenger and LCV markets, small but growing, with 0.81% for passenger vehicles and 0.47% for LCVs in average in Europe in 2017 (EAFO, 2017). Less than a decade ago, the market was virtually non-existent (see Figure 3 a.).

Norway is the leading country in electromobility, with more than 20% market share for private cars in 2016 (close to 40% if counting plug-in hybrid electric vehicles). The difference with the electric LCV market is striking: the same year, the latter hardly reached 2%. This difference can be explained by different taxations for private and business conventional vehicles, affecting the relative competitiveness of electric competitors.

In a study by the ACEA (2018), the positive correlation between GDP per capita and market share of electric vehicles underlines the lack of affordability of electric vehicles. With more than twice the GDP per capita as the EU average, the report questions the possibility of seeing the Norwegian case as a benchmark rather than an exception.

Other countries (where interviews have been conducted for this research) exhibit electric LCV market shares at 1.4% for France, 1.1% for Germany and 0.5% for Sweden. Today, electric LCVs for urban freight remain a niche market.

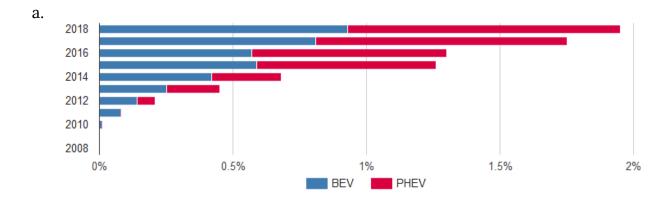
Postal companies are among the biggest customers of electric LCVs, the French company La Poste bought 5,000 electric vans between 2011 and 2015. The Deutsche Post DHL Group, in Germany, uses a growing fleet of more than 2,500 electric vans, bought since 2014 and the launch of its own production through a purchased subsidiary company StreetScooter.

The figures also highlight that the market is overwhelmingly composed of small vans, in agreement with the very limited diversity of supplied vehicles in the upper size segments.

Surveys about the use of EVs point toward an extensive use of private infrastructure for private users and company infrastructure for business users (Frenzel et al., 2015). It is confirmed by the fact that in Europe, the number of EVs

34

<sup>&</sup>lt;sup>11</sup> TORREGROSSA, Michael. "E-Fuso Vision One: Daimler Révèle Son Poids-Lourd Électrique à Tokyo." *Automobile Propre*, Automobile Propre, 26 Oct. 2017, www.automobile-propre.com/e-fuso-vision-one-daimler-revele-poids-lourd-electrique-a-tokyo/.



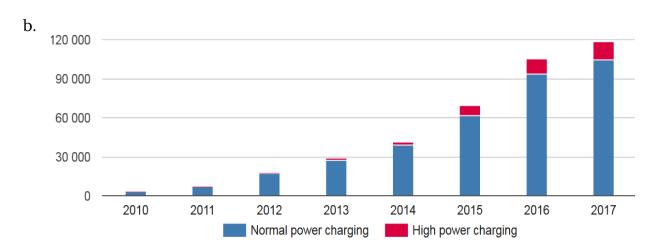


Figure 3 Market shares of electric passenger cars (a.) and number of publicly accessible charging station (b.) in the European Union (EAFO, 2017)

is almost four times as important as the number of publicly accessible infrastructure (Global E.V., 2017). Privately owned infrastructure has typically a power between 3 kilowatts and 7 kilowatts. However, publicly accessible charging infrastructure is often considered as a prerequisite for reaching a mass market (Sierzchula et al., 2014; Lutsey, 2015) and existing offers are already used by some of current EV-owners (Frenzel et al., 2015).

In Europe, around 120,000 publicly accessible charging positions are listed on (EAFO, 2017), among which about 13,500 provide fast charging (meant as powers strictly superior to 22 kW and up to 120 kW). The number of publicly accessible charging stations, normal and fast, has continuously risen since 2010 in Europe (see Figure 3 b).

These positive dynamics must not obscure the fact that nothing is yet certain for the future of EVs.

#### 1.2 Alternative motorizations in a technological race

Battery EVs are only one element in the potential trajectory towards cleaner road transportation, alongside fuel cell technologies (mainly hydrogen), or many

possible hybridizations (electric or with internal combustion engine). For heavier vehicles or vehicles traveling long distances, the preference is today for natural gas and bio-fuels. Among car-manufacturers and energy producers, future technologies are plural and not yet definitely defined. Everyone wonders what strategy to adopt.

In order to break through and be a credible alternative to conventional vehicles, these technologies must become economically competitive, and the new constraints they impose must be removed. A challenge is that they provide sufficient power to move the car at high speed, with sufficient energy for a full day's activity. With a system embedded in the vehicle, it must satisfy constraints in terms of weight and volume, safety and time for refueling. Durability is also central, as the proper functioning of the vehicle should be ensured over its lifetime. At last, compared with a reference technology, costs play a vital role as well (Syrota, 2008).

EUCAR (European Council for Automotive R&D), CONCAWE (Environmental Science for European Refining) and the JRC (European Joint Research Center) have been monitoring energy uses and GHG emissions of alternative fuels for more than a decade, allowing a comparison with identical methodologies (Edwards et al., 2014).

#### 1.2.1 Road transport and pollution

The road transportation sector is a significant contributor to both global warming emissions and air pollution. Emissions are mostly linked to fuel combustion, but also to abrasion (brakes, tires, road, etc).

Transportation accounted for about 21% of greenhouse gas (GHG) emissions in 2014 in the European Union, and as much as 29% in France in the same year. In addition, and contrary to other sectors (as the energy industry), road transport GHG emissions have continuously increased until 2005 and are even increasing again in France since 2015, due to increasing traffic (CGDD, 2017c). As a result, the level of annual GHG emissions attributable to road transport in Europe exceeds 750 million tons of carbon dioxide equivalent (SDES, 2016).

Air pollution is an acute public health problem, especially in dense cities, with a majority of cities over the world exceeding the World Health Organization quality guidelines (WHO, 2016), and the megatrend of urbanization will exacerbate this problem. It is responsible, according to WHO estimates, of

600,000 premature deaths in the European region in 2010 (World Health Organization Regional Office for Europe, 2015).

A significant share of local pollutants is attributable to road transport. Most preoccupying pollutants in Paris are the following (Airparif, 2017):

- Particulate matters  $PM_{10}$  and  $PM_{2.5}$  (diameters smaller than 10 and 2.5 µm respectively) increase the risk of cardiovascular and respiratory diseases, as well as lung cancer. The shares of transport in PMs for France, in 2012, are 14% for  $PM_{10}$ , 18% for  $PM_{2.5}$ , and 17% for  $PM_{1.0}$ ) (Nicco et al., 2014). Close to traffic, concentrations of particulate matters are doubled (Airparif, 2017).
- Nitrogen dioxide ( $NO_2$ ) can cause inflammation of the respiratory tracts and affect the lungs after a long-term exposure. Road traffic is the main contributor to nitrogen oxide ( $NO_x$ ) emissions with more than half of regional emissions (France, 2012, Nicco et al. (2014)).
- Despite a sharp drop at the end of the 1990s, benzene emissions still exceed annual quality objectives near urban roads. This cancerigene substance is mainly attributable to gasoline vehicles (Airparif, 2017).

To that, the continuous growth of global vehicle ownership must be added. Regions such as Asia, Oceania, and the Middle East have seen their motorization rate per 1,000 inhabitants increase by 150% between 2005 and 2015, while it increased globally by 25% over the same period (ACEA, 2017). The global stock could reach over 2 billion units in 2030 (Dargay et al., 2007), from about 1.3 billion units in 2015<sup>12</sup>.

Light commercial vehicles and urban freight are not spared by these negative local pollution externalities (see section 2.4). All this illustrates the need to find solutions to reduce the environmental impact of road transportation.

# 1.2.2 Internal combustion engine vehicles dominate the current market

We will call conventional vehicles, internal combustion engine vehicles running from the combustion of either gasoline or diesel. These vehicle categories represent the vast majority of vehicles currently on the roads. Fossil fuels in that case are petroleum products, and the technologies are solidly anchored, as they

-

<sup>12</sup> http://www.oica.net/category/production-statistics/2015-statistics/

have been dominating for a century, and thus benefit from one century of technological improvements.

However, their dominant position seems to be called into question because of their environmental impact.

#### 1.2.2.1 Increasingly stringent regulations target conventional vehicles

New cars and vans are tested in the EU following a test procedure that came into force in the early 1990s, the New European Drive Cycle (NEDC), compulsory for all vehicles before market introduction. This procedure is called *emissions type approval* or *emissions certification process* (Mock, 2017).

European emissions standards (Euro standards) impose maximum levels of local pollutant emissions for new cars (e.g.  $\rm CO_2$  is not taken into account by these standards). These standards have led to important improvements on ICEVs, with maximum emission limits that have dropped by 82% to 96% depending on the pollutant between 1992 (Euro 1 standard) and 2014 (Euro 6 standard).

The Euro standards, while remaining theoretically neutral and not imposing the technological solutions used, have contributed to the generalization of certain technological devices on conventional vehicles. Thus, the Euro 1 standard has caused widespread use of the catalytic converter for gasoline vehicles. As for the Euro 5 standard, it almost imposes the equipment of diesel cars with particulate filters. The latest equipment that is spreading as requirements become more stringent is the  $NO_x$  trap.

Concerning  $CO_2$  emissions, after a voluntary commitment for 2009 that the car manufacturers failed to meet, the European Commission adopted in 2009 a  $CO_2$  target for 2015, and in 2013 a new target at 95 g/km for 2021. In addition, improved consumer information and vehicle taxes penalizing vehicles with the most emissions should have strengthened this initiative. However, by weakening the first and blocking an EU-wide measure for the second, member states have weakened the action of the European Commission. In addition, the lack of enforcement of the regulations has strongly penalized the effectiveness of EU action against GHG emissions (Mock, 2018).

#### 1.2.2.2 Discrepancies between emissions type approval and real-use emissions

In addition, the NEDC procedure does not represent real-life conditions and discrepancies have been observed for diesel vehicles between test results and on road emissions, both on local pollutants and on  $CO_2$  emissions (the NEDC test

procedure was actually not designed for CO<sub>2</sub> measurements). The gap between real-life conditions CO<sub>2</sub> emissions and the normalized test procedure has even been increasing with time (largely due to "optimization" of the tests results by car manufacturers, not leading to real-world improvements) as shown in Figure 4 (Tietge et al., 2015).

The NEDC test procedure will be gradually replaced by the new Worldwide Harmonized Light Vehicles Test Procedure (WLTP) (Tietge et al., 2015). Another procedure will come in addition, which aim is to avoid specific optimization from car manufacturers to the standard test: the real driving emission (RDE) test. This test will be based on on-road measures of  $NO_x$  and particle matters emissions with a portable emissions measurement system. It has already been in use since 2014 for determining heavy vehicles' compliance with the Euro VI emissions regulations, and since 2017 for light-duty vehicles. The upper authorized emission limits in this test will then progressively decrease until the final phase, Euro 6-d, allowing emissions up to 1.5 times the Euro 6 emissions standards (Mock, 2017).

#### 1.2.2.3 Have low-consumption conventional vehicles a future?

Improvements on ICEVs could be one pathway towards a more efficient transportation sector. However, given the history recalled above, it is quite unlikely that it is enough to reach EUs' climate goals for 2030. Mock (2018) notes that these goals would be more effectively met with the development of the EV market. Vogt-Schilb and colleagues (2009) also argue that low-consumption conventional vehicles cannot be a long-term solution as they are subject to a "long-term unsustainability of a transportation system based on high mobility levels and widespread use of refined oil, thus contributing to a lock in carbon intensive trajectories".

In the short term, developments in gasoline and diesel technologies will probably nevertheless continue to contribute to the reduction of energy use and GHG emissions (Edwards et al., 2014). A GM executive said very recently that "internal combustion engines, including the diesel, can still play a role in the years to come"<sup>13</sup>.

Finally, upcoming stringent and better enforced regulations will require more expensive additional pollution control systems. Thus, the higher purchase

 $<sup>^{13}</sup>$  Hetzner, Christiaan. "GM Still Confident of Diesel's Future." Autoweek, 18 June 2018, autoweek.com/article/diesel/gm-doubles-down-diesel.

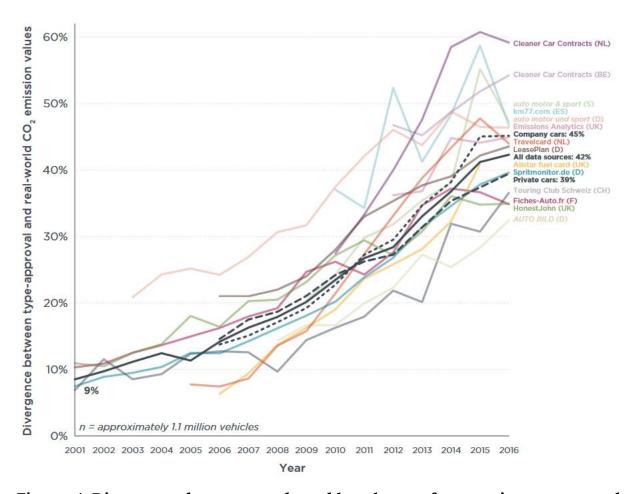


Figure 4 Divergence between real-world and manufacturers' type-approval  ${\rm CO}_2$  emission values for various on-road data sources ((Tietge et al., 2015), updated 2017)

prices of ICEVs give the opportunity to alternative technologies to become more competitive in comparison.

#### 1.2.2.4 A geopolitical dependence

Another major issue concerning conventional vehicles is the geopolitical dependence they generate. Oil production is concentrated in a small number of countries and the market is thus subject to this oligarchy.

According to Luciani (2015), the recent rise in oil prices (particularly acute in 2008) was pushed mostly by speculation: there was never a risk for a lack of supply, but the shortage was created from scratch. "Sooner or later, reality takes over", and the prices drop again.

The increase in the price of a barrel has led to investments in new oil resources, and pushed American production. However, the drop in prices was enough to make investments much less profitable that when prices were high.

The dependence on petroleum products for automobile fuels accentuates the geopolitical stakes.

#### 1.2.3 Biofuels

Biofuels, as opposed to fossil fuels, is produced through biological processes, derived directly from plants, or indirectly from agricultural or other waste. With an important growth in the last decade, biofuels contribute to a share of 3% of global transportation energy use, supported by policies in many countries (USA, EU, etc.). There have been extensive debates on the actual environmental benefits of biofuels when assessing the complete life cycle. The idea behind the environmental gains in GHG emissions of biofuels is in the fuel production (and not at the tailpipe): the carbon released in combustion has been sequestered recently from the atmosphere rather than released from fossil carbon stores (Malins et al., 2014).

The amount of release of stored carbon during the biofuel production is however unclear and could cripple the relevance of this solution. It is directly linked to land use changes, as land use is not normally carbon neutral: soils store a large amount of carbon (possibly increasing over time). The life cycle assessment is all the more difficult as different pathways for biofuel production with different carbon intensities are still open, as shown in Figure 5. Edwards et al. (2014) qualify biofuels as "fundamentally inefficient in the way they use biomass, a limited resource". Competition between food and fuel industry and implications of policy changes on agriculture have to be anticipated and monitored as well.

However, Tilman et al. (2009) defend the relevance of biofuels when "done right", for instance by exploiting lands, residues or waste that are not otherwise valorized.

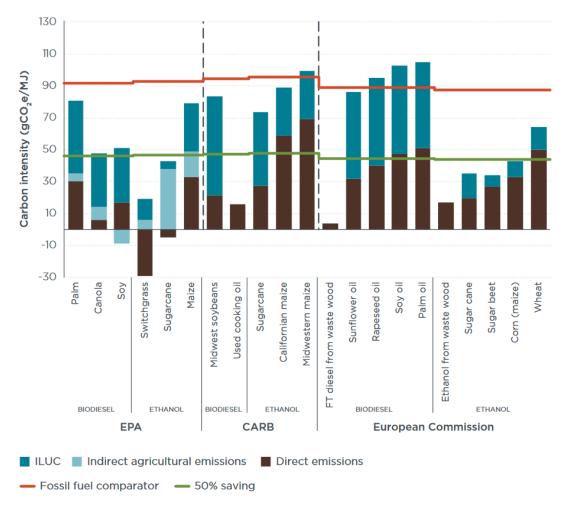


Figure 5 Total emissions of modeled biofuel pathways, by or for regulators in the United States and Europe (Malins et al., 2014). ILUC: indirect land use change.

## 1.2.4 Battery electric vehicle technologies

Battery electric vehicles are equipped with on-board high-energy accumulators, powering an electric engine. The difficulty of direct electric propulsion is the storage of electricity, today mostly done with lithium-ion chemistry. Current batteries impose a limited range, and/or a significant additional cost. Most models benefit from regenerative braking, where braking energy is converted back into electricity where it would otherwise be lost on thermal energy.

The car battery responds to constraints that are very specific to automobile uses, between which a compromise must sometimes be found. These constraints are:

• **Vehicle Performance**: the operational performance of the vehicle depends on battery power and energy. The power enables accelerations and high

speeds, whereas energy provides the range of EVs. The energy density of the battery is also a vital criteria, as it directly impacts weight and volume of the battery, and thus vehicle architecture, range, payload etc. The battery charging performance is also crucial, as the vehicle is immobilized during its charge.

- **Cost**: as any other alternative fuel, BEVs cannot afford excessive price differences with conventional vehicles. The cost difference is over all due to the cost of the battery.
- **Safety**: safety is inevitably a central point for automotive use. It includes both safety in normal operation conditions, but also in case of an accident. It is indeed necessary to know how to predict and control the behavior of the battery in such circumstances.
- **Lifetime**: Finally, the ageing of the battery is also a key point of the car use: its performance and safety must be ensured at least over the period of use of the vehicle or the battery amust be easy to replace.

In Europe, the electricity network has excellent territorial coverage. However, for an optimal use (reasonable charging times), the network needs to be equipped with interface charging infrastructures.

The upward trend for electric vehicles has been observable for a decade now, and continuous improvements on the batteries can be noticed for lithiumion batteries. Second generation vehicles (around 2017) have a 50% improved battery capacity in comparison to the first generation (around 2010), at a similar cost, a similar size, and a similar weight.

The fact that the technology is relatively new and newly explored opens up to opportunities that remain to be discovered. Beyond the batteries, improvements on the motor, the power electronics and auxiliary equipment allow reducing consumption, and thus increase the range with constant battery capacity<sup>14</sup>. While many EVs are still built on an adaptation of ICEVs architectures, specific vehicle architecture for EVs (by design) may further improve its performance.

\_

<sup>&</sup>lt;sup>14</sup> As for instance on the Renault Zoé, in 2015: TORREGROSSA, Michael. "Renault R240 - A La Découverte Du Moteur Électrique 'Made in Cléon." *Automobile Propre*, Automobile Propre, 29 June 2015, www.automobile-propre.com/renault-r240-decouverte-moteur-electrique-made-in-cleon/.

Design opportunities, like the simplification and reduction in the number of different platforms, is identified in Sperling (2018) as a way for car manufacturers to benefit from economies of scale, accelerating purely technological progress. While electric vehicles are making their way from a niche market to mass market, substantial gains are still to be made. This is in any case the bet of Elon Musk, CEO of Tesla Motors, who has invested \$ 5 billion in a mega-battery plant project, hoping for economies of scale 15.

Battery research is very active. Lithium-ion batteries do probably have some more room for improvements (improvements of around 30% seem realistic (Van Noorden, 2014)), but researchers believe that the technology is nearly at its full potential.

Pathways to long-range EVs would most probably require breakthrough battery technologies, which promise to double or triple the energy density and the range of electric vehicles, provided they pass all of the requirements exposed above. Van Noorden (2014) identifies battery technologies with great potential, with different electrode materials and electrolytes, such as magnesium-ion, lithium-sulfur, or sodium-oxygen chemistries.

The environmental impact of electric vehicles is discussed in a separate section (1.3).

A future with long-range or very-fast charging EVs is not excluded and many technologies developed may lead to a revolution of the batteries. However, they have to be taken cautiously as the path from the laboratory to the car is long, uncertain and tedious.

#### 1.2.5 Natural Gas

Natural gas is an alternative fossil fuel to diesel and gasoline. Compressed Natural Gas (CNG) has a composition identical to that of gas distributed in French domestic networks (used for heating or cooking for example), it consists essentially of methane (CH<sub>4</sub>). Its storage is mostly done in gaseous form and under pressure (200 bars). An alternative is the liquid phase storage of Liquefied Natural Gas (LNG).

\_

<sup>&</sup>lt;sup>15</sup> NUSSBAUMER, Yoann. "Tesla GigaFactory: L'incroyable Usine De Batteries à 5 Milliards De Dollars." Automobile Propre, Automobile Propre, 27 Feb. 2014, www.automobile-propre.com/tesla-gigafactory-lusine-de-batteries-5-milliards-de-dollars/.

The technology allowing vehicles to run on CNG has existed for nearly a century, as evidenced by an article in the newspaper Le Génie Civil of 1919, (Grebel, 1919): "Before 1914, we were already preoccupied, especially in France, Italy and Germany, with the scarcity and high costs of volatile liquid fuels used in automobile engines. This shortage and this rise in prices have only increased sharply because of the war. [...] One of the ways to react to them is to use, in the engines, the domestic gas which has been used for more than 30 years in stationary engines." <sup>16</sup>

As with electric vehicles, it is the increase in the price of oil which triggered the use of this alternative fuel.

The technology is now mature (Bielaczyc et al., 2014), with today more than 18 million vehicles running on CNG around the world. CNG vehicles are now available on the market, although market penetration rates are uneven worldwide. Several countries have developed ambitious programs for its development, mainly Mercosur countries (Argentina was the first to have a proactive policy), but also Pakistan, Iran, China. In Europe, Italy, Germany and Switzerland are also examples of countries that have strong initiatives in favor of CNG (Nicolle, 2009). Note the concomitance of CNG development decisions with the opportunities presented by the national energy system, as is the case in Argentina, Brazil or Iran, for example.

The need to deploy a refueling infrastructure, however, is a point that heavily penalizes the technology in France. Today, there are 41 CNG stations and 2 LNG stations in France (to be compared with 11,356 service stations in 2014, 974 CNG stations in Italy or 921 in Germany (DENA, 2015)). The scarcity of this infrastructure restricts the use of CNG to niche activities, restrained geographic scopes or specific routes. A widespread use of the technology is not possible without the simultaneous increase in the number of stations. However, the example of Germany, which has deployed a large number of infrastructures but struggles to see growth in the share of CNG vehicles, shows that increased stations will not solve all the problems (DENA, 2015).

Edward and colleagues (2014) observe that GHG emissions of CNG vehicles lie in between those of diesel and gasoline. Messagie et al. (2014) find comparable GHG emissions for CNG Euro 4 and diesel Euro 5.

Compared with petroleum fuels, the advantages of using CNG are that it is less noisy, odorless, and ensures operational use in all point identical to that of

-

<sup>&</sup>lt;sup>16</sup> Author's translation

conventional vehicles (AFGNV, 2015). It also brings interesting possible benefits. In one study among others, Bielaczyc et al. (2014) note, after measurements on a bi-fuel gasoline/CNG vehicle, that under the European NECD regulatory test conditions, the use of CNG implied a significant reduction in non-methane volatile organic compounds (NMVOCs) and in  $NO_x$ . In terms of respiratory effects, this technology surpasses all others, including battery electric vehicles, according to Messagie et al. (2014), as both production and tailpipe emissions are low.

#### 1.2.6 Hydrogen fuel cell

Vehicles running on hydrogen also represent a zero-tailpipe-emission solution. They are powered by a fuel cell, and often assisted by a small electric battery (the same that can be found in hybrid vehicles). Hydrogen is stored onboard, as a compressed gas.

As for biofuels, hydrogen production can be done in many different ways, and the energy and GHG emissions are critically dependent on the actual choices made. It can be produced via a chemical transformation process or through electricity via electrolysis. Thermal processes from natural gas has the potential to halve GHG emissions of gasoline vehicles (Edwards et al., 2014). Yet, if hydrogen is produced using electricity, then it offers a poor energy efficiency compared with BEVs (around 55%), which casts some shadow on the environmental benefits of the technology (Edwards et al., 2014; Syrota, 2008; Wolfram & Lutsey, 2016). Life cycle assessments are therefore usually less promising than for BEVs. The vehicles could indeed have benefited from a better efficiency by directly using electricity for the propulsion. In return, hydrogen vehicles benefit from refueling times similar to ICEVs. This requires, however, an extensive network of very expensive refueling stations (several hundreds of thousands of euros, possibly as high as  $\mathfrak E$  2 million when using on-site electrolysis (Wolfram & Lutsey, 2016)).

Hydrogen cars are starting to become a reality, for instance the Toyota Miraï or the Hyundai Tucson in the USA are today on the market. The company Symbio also equipped a light commercial vehicle, the Renault Kangoo Z.E. H2, with a hydrogen fuel cell. These vehicles have very low volume sold (150 at the end of 2016 for the Renault Kangoo Z.E.), but they have the merit to defeat the arguments of "insurmountable security problems". The lack of infrastructure and the very high cost of this technology are obstacles that are unlikely to be removed in the near or medium term.

#### 1.2.7 Hybrid electric vehicles

Many hybrid configurations are conceivable. The most common today is based on an electric battery and an additional system for using petroleum products (gasoline, diesel).

Two categories of hybrid electric vehicles can be distinguished, plug-in hybrid electric vehicles (PHEV); and non-rechargeable hybrids (HEV).

If HEVs are similar to pure electric vehicle in terms of silent operations at a standstill and at low speeds, or regenerative braking, their low operating range on purely electric energy is not significant enough to have a true environmental benefit, especially since the environmental impact of the battery production needs to be integrated in the life cycle analysis. The battery weight also slightly increases the consumption of the vehicle. They may be relevant however in an intensive urban use, as the many stops and starts increase the efficiency of regenerative braking. HEVs can actually be categorized as conventional vehicles aiming for low consumption, rather than electric vehicles (Syrota, 2008).

As to PHEVs, their main benefit compared with BEVs is that the range constraint is alleviated. Nevertheless, hybridization has a cost (the architecture of the vehicle is more complicated, and the battery, even if smaller than for a pure electric vehicle, is also expensive). The main advantages of BEVs, namely the absence of tailpipe emissions, are also degraded if the use profile implies numerous trips on diesel or gasoline.

Environmental assessment of these vehicles highly depends on the uses, regular low distance uses being the most favorable. The estimation of fuel and emission savings by the NEDC test procedure will usually be rather optimistic compared with real life emissions (Riemersma & Mock, 2017).

# 1.3 Environmental and social assessment of electric vehicles

Electric vehicles have the very interesting property of having zero tailpipe emissions, and have been identified by many analysts as relevant to reduce the environmental impact of road transport.

However, environmental impacts should not be reduced to the only use phase of the vehicle, in a so-called tank-to-wheel analysis. Indeed, confusion is sometimes brought by the fact that a substantial part of the pollution of conventional vehicles occurs at this stage, due to the combustion of the fuel. But there is upstream energy production. Vehicle and battery production has to be taken into account as well. A thorough analysis through a life cycle assessment (LCA) is therefore necessary.

#### 1.3.1 Comparative life cycle assessment

The next paragraphs extensively rely on the work of Hawkins et al. (2013), especially the clear overview of Figure 6.

An LCA can be defined as "compiling an inventory of the environmentally relevant flows associated with all processes involved in the production, use, and end of life of a product and translating this inventory into impacts of interest" (Hawkins et al., 2012).

The proper identification of the processes, their associated flows, and the choice of the impacts of interest are all sources of uncertainty of the results, making the execution and interpretation of LCA complex. In a review based on 79 articles, Nordelöf et al. (2014) find a wide variability in the results (with sometimes contradictory results) and investigate some possible reasons for it. Uncertainties on the data or on the methodology (investigated technology, system boundary, etc.) are elements of explanation. Data may be inherently variable and very difficult to obtain with good precision.

The authors also notice a lack of clear definition of the goal and the scope of most LCA studies, leading to a discussion that is "easily caught up in the details of numerical results and, as a consequence, important lessons from the research field are overshadowed by an appearance of complexity and diverging outcome."

We present here only a few salient points that emerge from the studies. In the base case and with average European energy mix, electric vehicles reduce GHG emissions by 20% to 24% compared with gasoline vehicles, and by 10% to 14% compared with diesel vehicles (Hawkins et al., 2013). However, an electricity production solely by coal would result in a significant *increase* in GHG emissions (from 17% to 27% compared with diesel vehicles). The longer the lifetime of the vehicle (and battery!), the better the performance of the electric technology, as the production phase has a significant share in the total life cycle.

In countries where electricity is produced with low GHG emissions, electric vehicles are identified as the technology giving the lowest emissions (Edwards et al., 2014). For instance, with a high share of nuclear energy,

electricity in France has lower carbon intensity than the average European mix, and EVs appear much more advantageous in these conditions.

Both terrestrial acidification potential (increase in soil acidity harmful to biodiversity) and particulate matter formation are slightly worse with the European energy mix for EVs than for ICEVs. It is to be noticed that the particulate matter formation for EVs is spatially distanced from the use phase. This can create a strong geographic heterogeneity of the local environmental impacts of electric vehicles (Holland et al., 2016). The photochemical oxidation formation (POFP) or smog formation potential favors EVs by 22% to 32% compared with ICEVs.

The fact that local pollution is geographically uncorrelated from where the vehicles are used makes electrical technology particularly relevant for densely populated urban areas, where populations are most exposed.

Several environmental criteria are degraded, whatever the scenario, by the use of EVs instead of ICEVs. This is for example the case of the human toxicity (potential for health impact from exposure to harmful agents, HTP) or the freshwater ecotoxicity potentials (toxicity for living organisms in aquatic ecosystems, FETP). Metal depletion potential (MDP) is also a potential source of concern for EVs, with as much as three times the impact of ICEVs, whereas an improvement of fossil depletion potential is to be expected with the use of EVs with the European energy mix.

So finally, to sum up, electric vehicles are not to be seen as a quick fix. The effective environmental comparative impacts between EVs and ICEVs are very dependent on the energy mix and on the lifetime of vehicle and battery, and on the real fuel consumptions of internal combustion engine vehicles.

All these results show a strong relationship between electricity production and possible environmental benefits of EVs (local and global pollution).

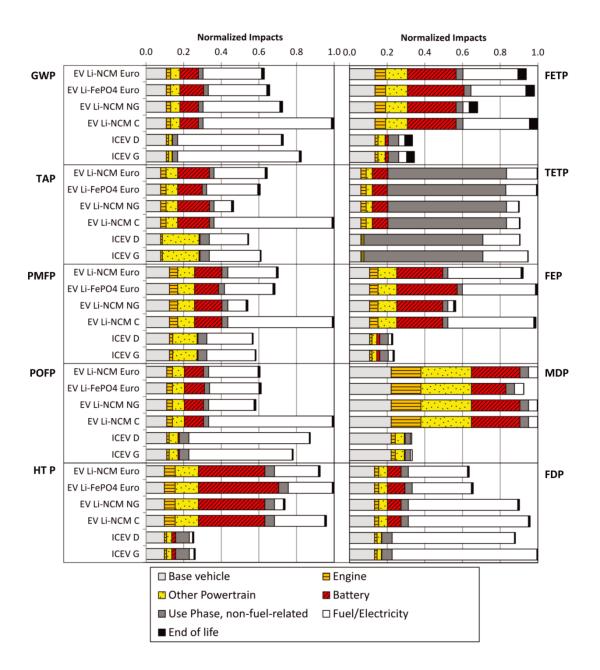


Figure 6 Normalized impacts of vehicle production, use and disposal, from (Hawkins et al., 2013). Results for each impact category have been normalized to the largest total impact. Global warming (GWP), terrestrial acidification (TAP), particulate matter formation (PMFP), photochemical oxidation formation (POFP), human toxicity (HTP), freshwater eco-toxicity (FETP), terrestrial eco-toxicity (TETP), freshwater eutrophication (FEP), mineral resource depletion (MDP), fossil resource depletion (FDP), internal combustion engine vehicle (ICEV), electric vehicle (EV), lithium iron phosphate (LiFePO<sub>4</sub>), lithium nickel cobalt manganese (LiNCM), coal (C), natural gas (NG), European electricity mix (Euro).

#### 1.3.2 Socio-economic assessment

Externalities can be monetarized in order to arbitrate between several technologies. The monetarization of the pollution is also modulated by the exposure of populations to the pollutants, for instance local pollutants will have higher costs in very dense urban areas than in rural areas.

A socio-economic assessment of EVs looks at the real costs borne by the community, including purchase and operation costs, monetarized externalities, environmental or not (noise, congestion etc.). A study conducted in France by the CGDD (2017a) finds a socio-economic benefit to EVs only in very dense urban areas in 2020, with gradual improvements until 2030 where it becomes advantageous for all urban uses (but still not for mixed uses). Externalities taken into account in this study are noise,  $CO_2$  emissions, and air pollution ( $NO_x$  and particulate matter). An opportunity cost of public funds also penalizes electric vehicles, due to the loss of conventional fuel taxes to the state.

This confirms the benefits of electric vehicles in the densest areas.

#### 1.3.3 Battery second life and recycling

After being used for automotive purposes, batteries may have a second life for stationary energy storage, and ultimately end as waste.

Against the metal depletion potential, recycling has very clear benefits, and is an indispensable way to limit EVs' impacts (Hawkins et al., 2013). In Europe, the disposal of automotive batteries in landfill sites or by incineration is prohibited, and it is up to the company "placing batteries [...] on the market for the first time", i.e. car manufacturers, to set up schemes for the treatment and recycling of waste batteries (EU, 2006). Recycling also reduces the impact of mining and processing ores and avoids processing cost and environmental impacts for waste treatment, especially when Lithium-ion is classified as hazardous waste (Gaines, 2014).

Today, the recycling sector of automotive batteries does not exist at large scale, and for a good reason: the number of batteries to recycle is very small. The increasing number of EVs on the roads will probably lead to the scrapping of an important amount of end-of-life batteries in a decade.

Observation of the lead-acid battery recycling sector, and comparison with lithium-ion batteries, provide some interesting insights about the challenges of the emergence of a recycling sector (Gaines, 2014). First, it is to be noticed that the diversity of the materials composing a lithium-ion battery

increases the difficulty of the recycling compared with lead-acid battery. Then, the high quality of the recycled lead allows re-using it directly for the production of new batteries, and is therefore profitable. Also, all manufacturers use a similar design simplifying the recycling process, contrary to lithium-ion cells' composition, which varies depending on the manufacturer. The shape of the battery may also be completely different from one vehicle to the other. All this increases the difficulty of recycling lithium-ion batteries. The latter may however benefit from experience of recycling mobile devices' batteries (Gaines, 2014).

At last, because of low profitability, there is a risk that waste batteries be exported into countries with less stringent environmental, health and safety regulations (Gaines, 2014).

Rising demand and speculation on raw metals used for battery production (copper, cobalt) may increase their prices. This would on one hand increase the purchase price of the battery, but on the other hand allow for a more profitable recycling sector<sup>17</sup>.

Contrary to what has been or is sometimes said, lithium resources are not lacking. Global stock estimates are increasing as new resources are discovered continuously. However, the concentration of lithium in specific countries (e.g. Bolivia, Argentina, Chile, or China) may lead to an important dependency on these countries. The quality of the mining (environmental and social impact) in politically unstable countries such as Bolivia is also a concern (Hacker et al., 2009).

## 1.3.4 Smart grid and energy grid interactions

The environmental performance of EVs is directly linked to the quality of the electricity production. If dirty coal-based electricity fuels the zero-tailpipe-emission vehicles, then the problem is only shifted from the tailpipes to the electricity plants, as it is evidenced for the United States (Holland et al., 2016).

However, in many of these countries, like in China, the USA, or Germany, parallel efforts towards e-mobility are paralleled with attempts at decarbonization of the electricity grid.

-

<sup>&</sup>lt;sup>17</sup> DEBOYSER, Bernard. "Le Boom De La Voiture Électrique Va Impacter Le Marché Mondial Du Cuivre." *Automobile Propre*, Automobile Propre, 6 Jan. 2018, www.automobile-propre.com/boom-voiture-electrique-impact-marche-cuivre/.

#### 1.3.4.1 Short-term interactions with the electricity industry

Beyond the direct possible environmental impacts of electric vehicles, their interactions with the energy grid promise interesting opportunities to improve overall environmental impact. These interactions are two-way: adapting the charge to the electricity production may improve the vehicles' environmental impact ("smart charging"), while taking advantage of the electricity storage capacity of vehicles connected to the grid raises opportunities for the energy sector ("smart grid"). The following paragraphs are mostly based on a study from the CGDD (2017a).

Smart charging opportunities take advantage of the temporal variability in environmental quality and prices of electricity, depending on fluctuations in demand (peaks and troughs) and supply (intermittent energies). While nuclear power plants are used continuously, variable electricity production is mainly supplied by coal, gas and oil-fired power plants. These power sources have the largest environmental footprint, so there is a true environmental interest in smoothing the production and consumption curves over time. Coordinating the charging of the vehicle with the electricity consumption troughs thus makes it possible to optimize the environmental quality of the electricity consumed.

On the contrary, the lack of smart charging capabilities could lead to the exact opposite effect, namely to increase the peak of electricity demand in the evening, when most people are coming home and plugging-in their vehicle. This would make balancing supply and demand even more complicated. It would also lead to the use of marginal electricity where costs and environmental quality would already be the worst.

Power grid operators must balance the power consumed and the power produced at all times. Back-up electric capacities are necessary to ensure the security of that balance. The economic value created by an energy service can thus be directly remunerated through a market price or a regulated contract.

Electric vehicles, when connected to the electricity grid, have the possibility to provide such an energy service thanks to their storage capacity. They can play a role at three different time scales, representing three quasi-independent markets, detailed below.

First, every day, hour by hour electricity prices are fixed for the next day given supply and demand previsions. Prices reflect the marginal costs of electricity, and thus depend on the last means of production mobilized. This wholesale electricity market allows to electricity suppliers to plan how they will

satisfy the needs of their customers one day in advance (electricity purchase and importation, own production, etc.).

Then, at a more macroscopic time scale, electric systems must ensure their ability to keep electricity production up to the maximum annual demand during winter peaks (due to electric heating at very low temperatures). This ability to ensure balance during most peaks in demand has a monetary value on a regulated market even when it is not used.

Finally, during the day, at a finer time scale of a handful of minutes, last minute rebalancing of supply and demand is performed. Production capabilities that come into play must be highly responsive to quickly adjust to these fluctuations.

The electricity industry could take advantage of the battery on these three markets, as if the sum of all plugged-in vehicles was an additional energy storage capacity. It would allow smoothing demand peaks at all three presented time scales. These interactions should however not interfere with the use of the vehicle. The question of the wear of the battery due to its interactions with the power grid is central as well: the possible gain should not be tarnished by a premature battery disposal.

The study (CGDD, 2017a) estimates the monetarized gain to be maximal on the short-term intra-day balance, with possible benefits of €250 per year with a 24 kWh BEV plugged in on a 7 kW charging infrastructure. Authors also observe that in some countries, stationary batteries are already in use for this purpose.

Ultimately, once the battery capacity is no longer suitable for automotive use (today, car manufacturers fix this limit to a state of health of the battery of 75%), it may still be used for the same purposes in stationary installations. This ensures a remaining residual value even after a first life in the car. Second-life batteries can also serve to limit the power implications of fast charging stations.

It is relevant to note that financial and environmental benefits are aligned and that the actors to be coordinated to operate smart grid and smart charging solutions (power system actors and electric vehicle users) can all benefit from this coordination. It is therefore potentially a very favorable environment for the emergence of these solutions.

#### 1.3.4.2 Long-term implications of a significant share of electric vehicles

In the long term, EV batteries interacting with the grid offers valuable flexibility for developing intermittent energies. In a scenario with 100% renewable energies by 2050, Chiche et al. (2017) explore the differences between a stand-alone electricity industry and interactions with EV batteries. Results show that EV-batteries could free from the installation of stationary batteries for the daily rebalancing. It is especially relevant for solar energy, as energy production in the middle of the day does not coincide with energy consumption peaks.

In the EV scenario, by only using less than 15% of the whole battery capacity, €1 billion can be saved every year, equivalent to 2% of the total annual costs of electricity supply.

# Chapter conclusion

Many technologies are competing to dethrone the long-time installed diesel and gasoline vehicles, each technology with its advantages and drawbacks in terms of performance, costs, environmental and social impacts, geopolitical dependencies, and with different level of maturity and mass-market supply.

Environmental assessments do not give a definitive ranking of different alternative technologies. Whatever technology develops, side effects need to be monitored, and special attention must be given to the deployment conditions, as different pathways for the same technology can lead to substantial gains as well as to a degradation of certain environmental factors.

However, if some technologies do not offer long-term perspectives, BEVs open the way to many opportunities. Electric technology seems already relevant today for urban uses, which imply low speeds and usually low distances, alleviating the performance requirements. In addition, urban trips impose jerked driving, where conventional vehicles are at their disfavor while EVs benefit from regenerative braking.

Replacing all ICEVs by EVs may not be sufficient by itself to reach an environmentally friendly road transportation sector, but as Hawkins et al. (2013) conclude, "EVs are poised to link the personal transportation sector together with the electricity, the electronic, and the metal industry sectors in an unprecedented way. Therefore the developments of these sectors must be jointly and consistently addressed in order for EVs to contribute positively to pollution mitigation efforts". Many opportunities arise from these interactions, from which only the tip of the iceberg is visible today: technological

opportunities, design opportunities, interactions with the electric grid, enabler for renewable energies, energy independence, etc.

This remark, and many others that will follow, go in the direction of a slow transition ahead towards a largely electrified fleet. Our analysis joins that of Sperling (2018) on this subject.

The rest of this work will focus on light commercial vehicles, more precisely on a specific activity, for which most of the uses are by definition in cities: urban freight transportation. It looks like a sector particularly adapted to the use of EVs. As has been presented by Thierry Koskas, head of Renault electric vehicles, this activity has been the first commercial target of the Kangoo ZE model, stressing the relevance for postal activities: "the advantage of a worker is that they make the same journey every day, so with an electric vehicle, if they are able to do it once they do it every day" (The Electric Revolution, 2011).

A number of arguments regarding the suitability of EVs for the urban transportation of goods are frequently listed: typical short distances, low average speeds, numerous slowdowns and stops, regenerative breaking, same route every day, return to company garage at the end of every operation, benefits from environmentally friendly image, frequent use, etc. (CGDD, 2014; Crist, 2012; Lee et al., 2013; Macharis et al., 2013; Taefi et al., 2015; The Electric Revolution, 2011).

It is interesting to note that this was already discussed in 1992, Brunel & Perillo (1992) mention that the commercial/professional activities represent the best development prospects in electromobility. The low level of actual electric LCV uses, even in cities, calls for a deeper exploration of the sector.

# 2A DIVERSITY OF USES OF LIGHT COMMERCIAL VEHICLES

Light commercial vehicles (LCVs) are extensively used in cities, for a wide range of applications. Most of them are an absolute necessity for the proper functioning of urban activities. This chapter proposes to highlight this diversity and to describe it with a specific focus on urban freight activities.

This section also presents the specificities of one specific activity: freight transportation in cities, or urban freight (UF). According to the SDES survey on LCVs in France (see sub-section 4.5.1.1 for a thorough presentation), nearly 30% of all vehicles for professional use have freight transport as their main activity, and 74.8% of the respondents declare that freight transport is a component of their activity. UF meets the demands of urban activities, and does not relocate unless the activity it serves relocates itself. It is a sector that generates a large number of jobs, particularly low-skilled jobs. UF is remarkably adaptable to changes in production, distribution and consumption patterns; but not without raising social and environmental problems. So it is a sector that needs to be organized.

Indeed, it generates strong externalities; the need for UF is growing, while solutions to improve its environmental performance are scarce. At first glance, however, the activity appears to represent good opportunities for electric vehicle use.

French cities often see truck traffic as an activity to be strictly regulated rather than an accompanying activity (with exceptions). As a result, urban policies are too often inconsistent and uncoordinated (Dablanc et al., 2017b).

The first section (2.1) highlights the diversity of users and usage profiles of LCVs. The second (2.2) focuses on the aims of urban freight transport, while the third shows how the current companies' organizations respond effectively to demand (2.3), but not without generating significant externalities in urban areas (2.4).

# 2.1 Description of the light commercial vehicle fleet

A common misconception on LCVs is to assume that they are mostly used for parcels deliveries or plumber interventions. Commercial vehicles are in fact used by a much wider variety of users, for a great diversity of uses that go far beyond parcel deliveries or building maintenance or works (Boutueil, 2015).

#### 2.1.1 Scope of studied commercial vehicles

Let us first introduce the objects of our interest: light commercial vehicles. They are massively used in cities, for operational, economic, and regulatory reasons.

In article 84 of the European council directive 2009/132/EC (2009), commercial motor vehicles are defined as "any motorized road vehicle (including tractors with trailers) which, by its type of construction and equipment, is designed for, and capable of, transporting, whether for payment or not, more than nine persons including the driver, or goods, and any road vehicle for a special purpose other than transport as such."

We do not have interest in all commercial vehicles. The Annex II of the Directive 2007/46/EC of the European Parliament (2007) defines different vehicle categories, from which the category of interest is the category N, which corresponds to "motor vehicles with at least four wheels designed and constructed for the carriage of goods." We therefore deliberately exclude from our scope passenger cars, minibuses and coaches (category M), defined as "motor vehicles with at least four wheels designed and constructed for the carriage of passengers", trailers and semi-trailers (category O), agricultural and forestry tractors (Category T) or non-motorized vehicles, two- or three-wheelers or quadricycles.

Within category N, unless explicitly stated otherwise, the study will mostly focus on the lightest vehicles. They correspond to category  $N_1$ , refining categorization by a mass imperative: "a maximum mass not exceeding 3.5 tons".

We will qualify these vehicles as light commercial vehicles (LCVs). This commercial vehicle class can be driven with the usual private car driving-license, unlike commercial vehicles with higher gross vehicle weights (GVW) that require a special permit. In 2013, more than 96% of registered commercial vehicles fall into category  $N_1$ .

Despite these restrictions, the vehicles of interest still show a great diversity, which the following paragraphs aim to highlight. First, the vehicles themselves are physically different, as shown for instance for France in Figure 7. We observe that there are roughly three categories of LCVs, the smallest one with a gross weight of about 1.7 tons, the second category with a gross weight around 2.7 tons, and a clear peak at 3.5 tons. The latter is directly explained by regulations: it corresponds to the biggest LCV that can be driven with the regular car driving license. It could be argued that there is a fourth, more confidential category around 2.2 tons of GVW.

These vehicles can have many different body types. The most common is a van body, which is defined by rigid walls and roof, and which could be further subdivided on a finer scale by distinguishing, for example, temperature-controlled vehicles, vehicles with liftgates, or vehicles with sliding flexible side

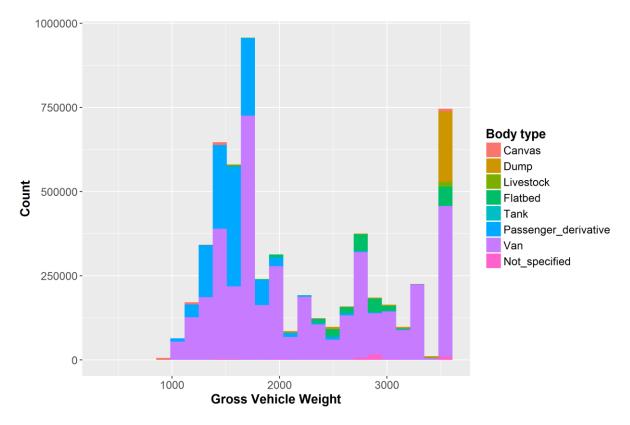


Figure 7 Distribution by gross vehicle weight and by body type of French LCVs (own production on the basis of the SDES survey on LCVs, France, 2010)

walls. Note, however, that some vehicles may have a van body type and not fall into this category (they typically have a GVW between 3.5 tons and 7.5 tons). A significant share of passenger car derivatives ("Passenger\_derivative" in the figure) is also noteworthy in the lightest LCV category (passenger car derivatives are basically passenger cars, where rear seats have been removed), while some specific equipment is reserved for larger LCVs. It is equipment often encountered for bigger trucks, for instance movable dump trucks ("Dump"), or flatbed vehicles, car carriers or chassis cabs ("Flatbed").

Our study focuses on only one category of users, namely professional users (i.e. the vehicle is owned by a legal entity: a company, an administration, an association, etc.), who account for 63% of light commercial vehicle users in France.

#### 2.1.2 What are the vehicles used for?

Among these professional users, users of light commercial vehicles are numerous and varied, and come from all sectors of activity, as shown in Figure 8. The analysis by nature of the company's activity shows that the construction industry is a major consumer of LCVs. The second sector with the most operating LCVs is the wholesale trade, accommodation and food services sector. In third place, the technical and scientific professions, and the manufacturing

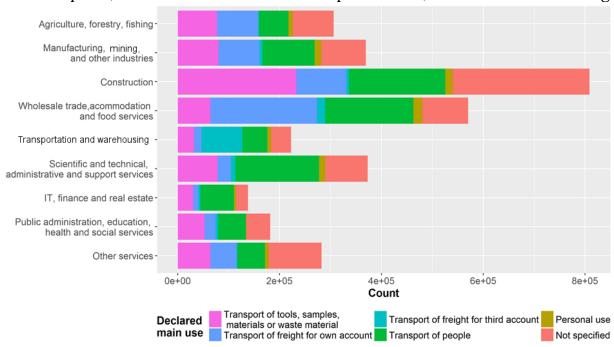


Figure 8 Distribution of professional LCVs across activity sectors and by declared primary use of the vehicle (own production on the basis of the SDES survey on LCVs, France, 2010)

and industrial goods sector are side by side. It is interesting to note that firms in which freight transport is the main activity are finally in the minority with a share of only 7% of all LCV vehicles.

Freight transportation will be identified as *for own account* when it is in the service of another activity of the same company, while it is identified as *for third account* when it is the main activity of the company, serving other companies or private individuals. The distinction will be further discussed in sub-section 2.3.1.

An analysis from the point of view of the main use of the vehicle shows that the construction sector uses mainly vehicles for the transport of tools, samples, materials or waste, and for the transport of people (defined as "transportation of personnel or customers, or other travel" in the survey). We can imagine that the boundary between transporting personnel and tools is not always obvious to the respondent.

Wholesale trade, accommodation and food services cover a large number of different activities, mainly own-account freight transport and passenger transport. Without surprise, most third-account freight vehicles operate in the transport sector.

Almost 75% of passenger vehicle derivatives are used for passenger transport or personal use as a main use. The denomination "personal use" stands for commuting to and from work or other private trips. These uses therefore seem possible with a passenger vehicle, and the use of a commercial vehicle has undoubtedly been chosen for the tax advantages it provides. An additional 15% is used for the transport of tools and materials.

In the SDES survey about LCVs, conducted in France in 2010 (and more properly described in sub-section 4.5.1.1), the questionnaire not only required that a primary use be specified, but also made it possible to specify uses one by one. Figure 9 shows how the responses are distributed and how different uses intersect. "People" stands for transportation of personnel or customers, or other travel. "Freight" stands for freight transportation for own or third account. "Tools" stands for transportation of tools, samples, materials or waste material.

We observe that having multiple uses of the same vehicle is common practice for business users. The biggest intersection is on transportation of freight and tools. It is interesting to note that, particularly for the transport of goods, vehicles used for several purposes are more frequent than vehicles intended for this single use.

Also it can be noted that while private uses of the vehicle are rarely the main function of the vehicle, it is frequently permitted in addition to other uses. In small businesses, business owners are often drivers themselves and have the vehicle at their disposal for private use. Boutueil (2015) analyzes different level of rights related to a vehicle that are granted to the employee: if the use of the vehicle is not exclusive, then it is a pool service vehicle. If there is an exclusive use, the employee may or may not have commuting rights on its assigned vehicle. If additionally to the commuting rights, the employee has private use rights, then it can be described as an official vehicle.

Without a surprise, the bigger the vehicle, the less it is used for private trips. Indeed, among the vehicles of less than 2.7 tons of GVW, 29% of the vehicles are used to commute or for private uses, while this figure drops to 16% for LCVs of more than 2.7 tons.

A LCV is often not intended for a single purpose, but is operated in many ways, and uses are overlapping. It is versatile. It transports people and things and

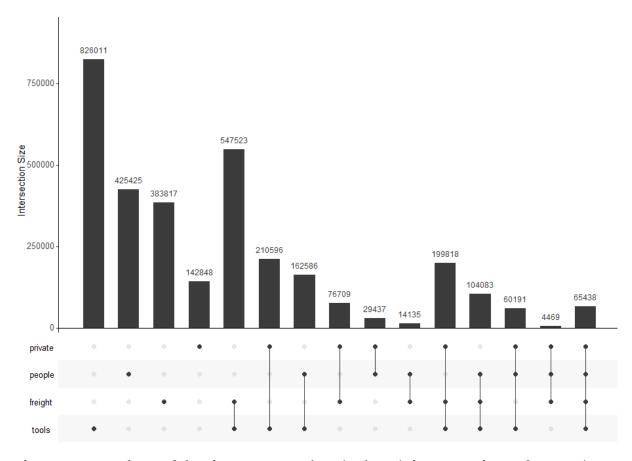


Figure 9 Number of business users by declared intersection of uses (own production on the base of the SDES survey on LCVs, France, 2010)

serves as a toolbox, warehouse, workshop, cloakroom, canteen, office, as an essential tool for professional mobility, as well as for the amateur gardener.

Fruit and vegetable retailers are a good example of this. The vehicle is first and foremost a means of locomotion, which makes it possible to travel to work places. It is also a back-store, which makes it possible to store not only the goods but also the waste, out of sight of passers-by. Sellers in the markets also store their stall material there. Ultimately, the proportion of time the vehicle is used for transport is a minority compared with all these ancillary activities (Camilleri, 2014).

## 2.1.3 Distances driven and age of light commercial vehicles

On Figure 10, the distributions of annual driven distances are represented for different vehicle uses. The median is around 12,000 kilometers a year (roughly 50 kilometers each working day) to 18,000 kilometers a year (roughly 75 kilometers each working day) depending on the category. The graph illustrates the great diversity of annual driven distances and this for all categories of use, which are wide enough to cover diverse and varied activities. It also highlights the extent of the error that is made by taking average distances as a proxy for calculations, for instance of total costs of ownership.

It can be observed that freight for third account stands out by a higher average driven distance (with a median over 18,000 km/year and a mean as high as 30,900 km/year), and more notably, that a significant number of outliers have a very intensive use of their vehicle.

Conversely, transport of tools and materials presents the smallest annual distances, in accordance with the intuition that these business users spend more time for their core business (for instance, their interventions) than driving. The same can be said of transport for own account, with significantly lower driven distances than third-account freight transport.

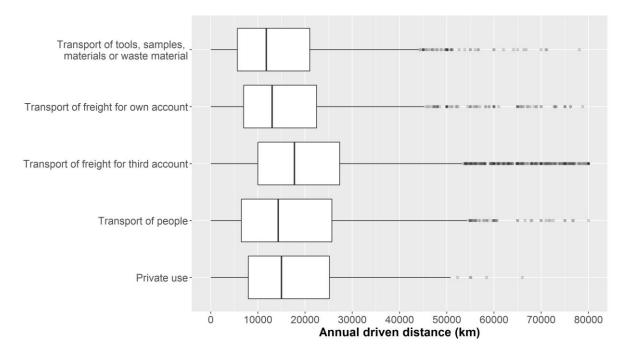


Figure 10 Distribution of annual driven distances for different classes of declared main use (entries with no main use are dropped, own production on the base of the SDES survey on LCVs, France, 2010)

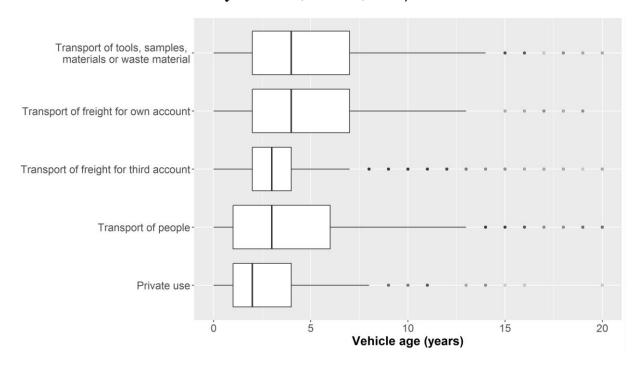


Figure 11 Distribution of ages for different classes of declared main use (entries with no main use or valid purchase year are dropped, own production on the base of the SDES survey on LCVs, France, 2010)

Figure 11 shows the dispersion of the ages of the LCVs on the roads. Again, great variability can be observed, with some vehicles up to more than 20 years of age (the figure is actually cropped at 20 years for better readability).

The categories that have the lowest average annual driven distances happen to be the one with the oldest vehicles in average. Indeed, the less the vehicle is driven, the longer its life expectancy, and this in turn impacts the length of ownership. The age of vehicles mainly used for private uses is the lowest, but no clear explanation has been found for this. Being the category with the least entries, this may be due to more homogeneity of the uses than in other categories.

#### 2.1.4 Link between LCV market and regulations

The choice to use diesel commercial vehicles is not only based on questions of functionality, but also on tax reasons. Two examples illustrate it very well in France: the comparison of passenger cars and passenger car derivatives in France, and the comparison of diesel and petrol vehicles. France has indeed one of the highest commercial vehicle registration rates in Europe (17% of the whole light vehicle fleet), and almost 96% of the LCV fleet is currently fueled by diesel.

LCVs and passenger vehicles share distinct regulations, with for instance separate emission standards and different taxations. Businesses are entitled to deduct Value-Added Tax (VAT) on certain products necessary for their operations.

Considered as working tools, companies are able to deduct the VAT from the purchase price of passenger car-derivatives, while passenger vehicles are excluded from this deduction (with some exceptions, such as taxis, ambulances etc.). In addition, light commercial vehicles do not enter into the scheme of company vehicle tax ("Taxe sur les véhicules de société" (TVS) in French).

Since 1991, diesel for commercial vehicles has also been totally exempted from VAT (while the deduction is only of 80% on passenger vehicles, since 2001). Petrol, on the contrary, has been totally excluded from this VAT deduction (Boutueil, 2015). It will, however, progressively be integrated in this scheme in the future, with a growing share of recoverable VAT on petrol from 2017 on for passenger cars, from 2018 on for LCVs (Code général des impôts - Article 298, n.d.).

The regulation thus discriminates between passenger cars and commercial vehicles and between diesel and petrol, which explains the above

figures. It also confirms the effectiveness of financial incentives to guide professionals' choices.

#### 2.1.5 Variety of fleets and fleet managements

In addition to the diversity of uses of the vehicles, fleet management can take many different forms.

First, the vehicles may not be owned. Ownership has declined for the advantage of long-term rental. The proportion of leased vehicles has increased continuously since 1984, with average growth rates of 15% between 1984 and 1994, 9% to 13% between 1995 and 2001, and 6% in average since 2003<sup>18</sup>. Vehicle rental companies thus gain market shares and allow companies to free themselves from investment in expensive equipment and vehicle maintenance, in exchange of a monthly rent. A multitude of additional options complete the rental for a tailor-made service, such as providing maintenance, damage insurance, replacement vehicles, tire replacements, account management for fuel payments, tolls, etc.

Leased vehicles are generally of good environmental quality. The fleet is renewed on a regular basis, with second-hand vehicles being sold at the most economically convenient time, usually at the end of their accounting amortization.

Within the company, vehicle decision and purchasing processes can take many different forms as well. Nesbitt and Sperling (2001) give a typology of fleet purchasing behaviors, depending on the level of formalization and centralization. Formalization corresponds to the degree to which decisions are governed by defined rules and processes, while centralization measures the number of people and their level of autonomy in decision-making.

They estimate that in the U.S., half of the vehicle fleets (not only light commercial vehicles) have low centralization and high formalization, what they call a bureaucratic behavior. Hierarchical fleets, with a high level of centralization and formalization, represent about a third of the fleets. At last, fleets with a low level of formalization are rarer, and generally smaller.

The nature of the decision process has consequences on the behavior towards alternative vehicle technologies. Authors note for instance that

<sup>&</sup>lt;sup>18</sup> Syndicat national des loueurs de voitures longue durée, www.snlvld.com/site/le-marche-dela-lld/historique-de-la-lld.html., retrieved March 13, 2018

bureaucratic fleets are receptive to clear government rules, especially fleets in administrations or regulated companies. Thus, these fleets are more receptive to mandates than to incentives. In contrast, *hierarchical* fleets are likely to be opposed to mandates if they do not coincide with the organization's preferred vehicle choices, but are more responsive to incentives that reduce the total cost of ownership of alternative vehicle technology.

#### 2.1.6 Defining freight activities

In this dissertation, focus will be given to a specific activity: urban freight. Specificities of this activity will be discussed in length in what follows, and the ability of these users to operate electric vehicles will be discussed in Chapter 3. Given the previous observations on the diversity of overlapping uses of LCVs, this subcategory might be defined in various ways.

Before going on to describe the specifics of these activities, let us give their scope. The preceding sub-sections illustrate the difficulty of having a single definition of freight transport, and since we do not claim that our definition has a theoretical scope, we will confine ourselves to one that is advantageously exploitable. The compromise to be found is to have a definition that is the broadest possible in order to be of practical use, but nevertheless sufficiently homogeneous to allow relevant generalizations. Our aim is to investigate the replacement of conventional vehicles by EVs, and as has been outlined in the previous chapter and by anticipation of the next two chapters, from the user perspective, the main constraints are economic (e. g. cost competition with conventional vehicles) and operational (e. g. range, need for charging).

Therefore, we will only focus on business users, whose approach to vehicle purchase might be different from private individuals. Also, the definition of urban freight should be made from the perspective of the uses (and not for instance of the company main activity), in order to enlarge the scope to activities that we believe share the same operational constraints. When several activities are performed with the same vehicle, all the activities should be taken into account as they are all concerned by a change of vehicle technology.

We finally define the subcategory of *freight activities* as all LCVs used by *business users*, who use their vehicle mainly to carry goods (as opposed to, and therefore excluding, transportation of tools, samples, materials for the own use or waste, and business or private mobility purposes), for *own or third-account*, with no distinction on the company's main activity.

This somewhat fuzzy definition (how exactly can be defined the *main* use of the vehicle) does not aim any theoretical significance (as previously said), but a very practical one, as they allow to derive results directly from the SDES survey on French LCVs, that will be extensively used throughout this work.

Note that the transport of materials (for instance for a building site) only enters in this scope if the materials are subsequently used by a different company or organization. This distinction is somewhat arbitrary but is a direct result of the survey design.

# 2.2 Demand in urban freight

The world's population is increasingly urban. In 2014, 54% of the population lives in cities, compared with 30% in 1950. Forecasts raise this rate to 66% in 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2014). Cities are therefore increasingly dense, the land is becoming scarcer and more expensive, and the mobility of people and goods intensifies.

#### 2.2.1 Urban freight, an industry supporting businesses

To illustrate how freight transport interacts with the urban economy, we will adopt the viewpoint of Savy (2011), who presents transportation as an industrial process. Indeed, transport is too often considered a necessary evil, because it does not affect the morphology of the product. However, a product in one place does not have the same value as the same product in a different place; the availability of the product close to oneself does not have the same value as the availability of the product at a greater distance: the transport impacts the value of use as the exchange value of the good. It can be inferred from this that transportation modifies the physical characteristics of products, just as manufacturing operations change their morphology. What is specific to transport, compared with other industrial processes, is that it cannot be relocated, which makes it particularly visible in cities, where transportation needs are high. In fact, almost all economic activities consume and rely on its services, and last-mile transport represents an important cost for transport chains (which can be as high as one-third of the total logistics cost of a shipment (Dablanc et al., 2017b)).

We will distinguish the terms of *performance* and *quality* of the transport. By performance, we mean the efficiency with which the freight transport system meets customer needs – i. e. cost, quality of service, adaptability, reliability. By quality, we refer to the way in which the transport of goods affects cities. In

addition to its performance, it incorporates all externalities, in particular social and environmental considerations.

The city is a space that concentrates human activities and more particularly the production, distribution and consumption of goods. It is therefore the source and destination of many goods transport flows on which these activities are based.

The performance of urban goods transport therefore conditions the dynamism of urban businesses.

#### 2.2.2 Evolution of the demand

UF is directly dependent on consumption and production practices. Both have evolved significantly in recent decades, and this has necessarily impacted the way goods are transported.

Modes of production had a radically transformation. Just-in-time supplies are now customary, and there is a steady reduction in both plants' and retails' inventories. This leads to a necessary increase in the supply frequency. Freight transport surveys bear witness to these new just-in-time practices and requirements for rapid response to demand (Guilbault & Soppé, 2009). This phenomenon is well illustrated by the comparison of number of shipments and tonnages sent between 1988 and 2004 (for industrial and wholesale establishments with more than 10 employees): the first increases by 160% while the other by only 27% over the same period. There is a strong process of splitting shipments (Dablanc & Routhier, 2009). In addition, this type of management requires, in order to avoid stock-outs, an ever-increasing reactivity to the transport of goods industry.

In addition, there is an increase in the types of goods supplied in stores and on the internet, along with a higher turnover rate of products, which contribute to the increasingly tense flow management and to the growing demand from the retailers (Dablanc, 2013). This fragmentation process also mechanically leads to a reduction in the size of the shipments. The number of bundling/unbundling operations has therefore increased significantly in recent decades and two-thirds of the shipments weigh less than 100 kg. Supply chains tend to become more complex, with an increasing number of stops on logistic platforms, in which logistical services are varied in nature (bundling/unbundling, inventory management, packaging, etc.) (Guilbault & Soppé, 2009). This has also led to lower-volume vehicle requirements for deliveries (especially urban), and

has contributed to an increasing use of light commercial vehicles rather than heavy goods vehicles (Browne et al., 2010).

Consumers are also increasingly using home delivery services, especially with the explosion in e-commerce since 2003, and a continued significant growth: online retail represents 8.5% of total retail in France in 2017, and the actual trend is a 1 point gain each year. The European turnover of e-commerce has amounted to € 540 billion in 2017, with a 13-15% increase since 2015 (FEVAD, 2018). E-commerce has shaken up distribution patterns of goods to individuals. End customers have diversified their acquisition channels and their purchasing process is now multi-channel. 21% of e-commerce customers subscribed to a delivery service in France (FEVAD, 2018). This shift also accompanies the social and demographic evolution. Population is aging due to falling birth rates and longer life expectancy. There is also an increase in the number of single-parent families, or families where both parents work. The argument of saving time and effort with deliveries has more force in these conditions, and perhaps contributes to the development of home deliveries and a change in consumer practices (Ducret & Delaître, 2013).

This increase in home deliveries affects the activity of goods transport and truck traffic in cities. They lead to a fragmentation of the deliveries and therefore an increased number of stops in delivery rounds. Commercial vehicles must circulate in residential streets, which has an impact on the types of vehicles used and questions urban design. These areas are more sensitive to the negative externalities of the vehicle, and the vehicles are highly visible. As a result, they could encourage the use of alternative technologies (Visser et al., 2014). The nature of these changes in traffic intensity is still uncertain today: on the one hand, more vehicles are needed for urban distribution; on the other hand, online shopping makes it possible to reduce the number of trips made by customers to physical stores. E-commerce also causes a significant number of returns, with an average of 20% of products returned after an online purchase in Germany, rising to 40% for fashion items (Morganti et al., 2014b).

The increasing share of Business to Consumer (B2C) deliveries has also led to new dedicated delivery services to end consumers. One of the main problems is the incompatibility between the final consumer's availability (most of the time in the evening) and possible delivery times (during working hours). Failed deliveries have a significant cost for the transport company and the community. Solutions such as deliveries to pick-up points are today well established alternatives to home deliveries (Morganti et al., 2014a), either relying

on a network of physical stores or on an *ad hoc* parcel locker network (Augereau & Dablanc, 2008). Evening deliveries are also developing to alleviate this problem.

Instant deliveries are the latest trend (Dablanc et al., 2017a). More and more e-retailers are proposing same-day deliveries, or even in less than two hours after the act of purchase. They cause already today a significant amount of trips, which are however done mostly by bicycles in France, in order to avoid being forced to register in the national freight transport register. Several companies already closed down due to the strong competition that has emerged in this market, but the market continues to grow and new companies are repeatedly trying to seize this opportunity.

#### 2.2.3 Urban freight demand varies between business activities

Based on the comparison of the results of UF surveys with an original methodology in three French cities (Bordeaux, Dijon, Marseille, between 1994 and 1997), it has been observed that the number of deliveries caused by each type of activity seems to be constant (relatively to the number of jobs) from one establishment to another, as different as their geographical situation may be. Thus, a pharmacy, a bank or a butcher, will generate the same flows, and with similar supply chain characteristics, in a dense city center than a pharmacy, a bank or a butcher of equal size in the periphery or in another city of France (note that this is the fundamental assumption behind the French simulation model FRETURB (Routhier & Aubert, 1999)).

For instance, the same survey in the Paris region raises the ratios of Figure 12, ratios of the number of deliveries (or pick-ups) that a business receives per week and per job. Transport and warehousing cause the most deliveries per week and per job (but this sector concerns only a low share of the overall economic activity in the region), followed by wholesale trade, small trade and industry. Tertiary office activities represent a small consumer of deliveries with only 0.25 deliveries per week per job (but a rather significant share in absolute numbers, as they represent a large share of total economic activities in Paris).



Figure 12 Number of deliveries / pick-ups by job and week, by sector of activity, in Île-de-France (Paris region) (LAET, 2014)

The total number of deliveries per sector therefore depends on the economic reality. In the Paris area, of all the activities, the commercial activity (wholesalers and retailers) is the leading source of UF and accounts for nearly half of the deliveries and pick-ups (LAET, 2014). Despite the low ratio of deliveries per job, the high share of tertiary office activities raises the demand as high as for the industry.

It also underlines how much the nature of the supply chain depends on the type of transported good. UF is characterized by its great diversity: there are as many logistic chains as transported products (Routhier et al., 2002; Dablanc & Rodrigue, 2012). A typology of freight activities has been made by Beziat et al. (2015), which shows how delivery tours vary in frequency, size of the truck, number of stops, length of delivery tour, geographical coverage, consolidation as the very visual representations of Figure 13 demonstrate.

Some sectors are particularly freight consuming: it is the case for the distribution of pharmaceutical for instance, a pharmacy requiring three or four deliveries a day at fixed hours, with an inventory management almost in real time (Routhier et al., 2002).

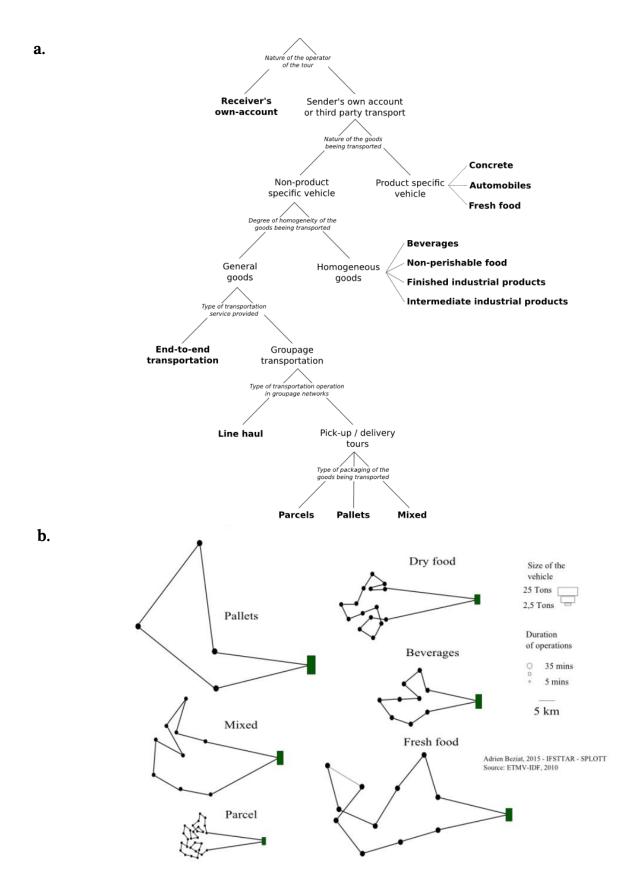


Figure 13 Typology of freight tours and corresponding visual representations (excerpt) (Beziat et al., 2015)

# 2.3 Supply of urban freight

The economic objective of the sector of freight transportation is to deliver at a low cost, while respecting the growing demand of customers for faster deliveries. UF has adapted to all the changes in the urban economy that have been observed in recent decades, and has been able to respond to the needs of urban businesses and individuals (Dablanc, 2013).

#### 2.3.1 Employment and urban freight

Logistics activities, that is to say freight transport and warehousing activities (storing, picking, packaging ... everything that does not affect the morphology of the product), are highly labor-intensive. They generate 313,000 jobs in Île-de-France (not counting temporary workers, who are more numerous than in other sectors of activity). This number rises to 375,000 jobs if counting support activities (such as I.T. in a logistics company) (Graille et al., 2015). It represents 7% of total employment in the region, about half of which is in freight transport activities. Employment statistics specific to urban logistics are difficult to obtain: urban logistics do not correspond to a specific sector in current survey denominations.

The jobs generated by urban logistics are largely unqualified: truck driving, handling, order picking, etc. These occupations can be quite physical, which explains in part the high proportion of young men found there (for instance in the Bouches-du-Rhône, a French department, 87% of hires are men and only 13% are individuals over 45 years old (Cluster Paca Logistique, 2013)). The perceived image of the logistic trades undoubtedly contributes to this strong masculinization, since some trades, such as order preparation, are not particularly physically demanding and do not seem to be predisposed to being occupied by men.

Research from the Cluster Paca Logistique (2013) also identifies that supply and demand do not meet. This observation is still valid, and was recently repeated in a study by the OPTL (Observatory for the future of employment and skills in transport and logistics). According to the OPTL (2017), 35% of short-haul driver recruitments are considered difficult by the employer (53% for road and long-haul truck drivers). The growth of the logistics sector accentuates this tension. While a number of logistics companies report difficulties in recruiting for low-skilled jobs, the number of jobseekers corresponding to these positions is significant. Two possible explanations have been found for this discrepancy (Cluster Paca Logistique, 2013). Logistics facilities are often relegated to the

outskirts of the city, in areas inaccessible by public transport. The scheduling of certain logistical jobs and the reduced mobility of the persons concerned reinforce this lack of accessibility. On the other hand, recruiters face employability problems and lack of appropriate training.

A phenomenon of logistic sprawl has actually been observed, with an increasing distance from the warehouses and terminals to city centers (Dablanc & Andriankaja, 2011), for instance in Paris as shown in Figure 14 (Heitz & Dablanc, 2015).

Finally, the conditions of work in urban freight transport can be extremely demanding. Exacerbated competition and small margins, as well as a significant proportion of undeclared work, sometimes result in disproportionate workloads in deplorable conditions.

#### 2.3.1 Urban freight and road transport

Road transport is unavoidable for urban freight. Freight transport in cities is now essentially done by road, and without entering into the details, it is difficult to conceive of a significant modal shift in the years to come, despite regional policies that pursue this objective (Dablanc, 2013).

In fact, the city is irrigated by a dense road network, whereas rail terminals are rare and often neglected for the benefits of passenger transport. Similarly, river cities can benefit from punctual river terminals, sometimes in the center of cities, but which do not serve the great diversity of origins and destinations of goods.

In any case, the use of another mode requires a transshipment activity, that can be expensive, and which can require large logistical spaces in an urban environment where they are rare and expensive.

Even at a national scale, long-haul road transport is becoming more and more an undisputed mean of transporting goods, with a low and decreasing share of alternative transport means (12% of total tons  $\times$  kilometers in 2016 against 23.2% in 1990). It is therefore relevant to investigate alternative fuel road vehicles as a way to reduce UF's externalities.

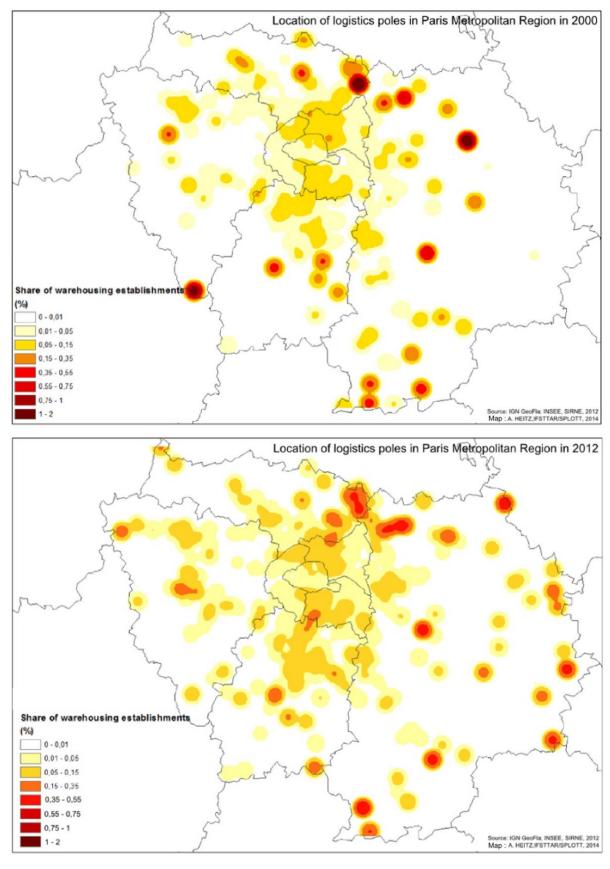


Figure 14 Logistics sprawl in Paris metropolitan area (2000-2012) (Heitz & Dablanc, 2015)

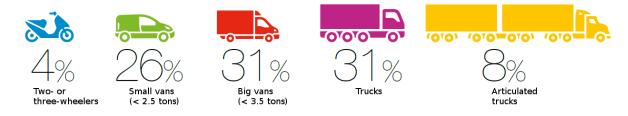


Figure 15 Share of deliveries performed with each size of vehicle in the Paris region (Urban Freight Survey, (LAET, 2014))

Road transport is therefore king in the city. Figure 15 shows the share of deliveries performed with several sizes of vehicles in the Paris region. We observe that 57% of the deliveries are carried out by LCVs. Most probably, this share would rise when getting closer to the city center.

LCVs seem more suitable for city traffic than do heavy vehicles: their size allows for easier driving in a complex environment, and local and national regulations are often more stringent with trucks than with light commercial vehicles. Not only are LCVs dominant in the urban transportation of goods, but their share have been increasing for two decades, by 42% between 1995 and 2013 (CGDD, 2017b). This increase is particularly visible in the courier sector. A cluster of causes explain this trend: increasingly stringent regulations with trucks, increasingly fragmented shipments of ever smaller sizes, and increased express or same-day deliveries (Browne et al., 2007; CGDD, 2017b).

97% of the light commercial vehicle fleet runs on diesel in France in 2016 (ICCT, 2018b), which is particularly regrettable for urban pollution. Local pollutant emissions are significantly higher for an old diesel vehicle than for a petrol vehicle of the same age. Since the Euro 5 standard (in 2011), a significant improvement in fine particles' emissions has been achieved for these vehicles. However, the degree of improvement in actual driving conditions is controversial (see sub-section 1.2.2.2). There are also significant differences in actual  $NO_x$  emissions between diesel and gasoline vehicles of the same age.

#### 2.3.1 Third account and own account

The UF market has low technical and financial barriers to entry. Hence, as explained above, companies whose main activity is not to carry goods can produce transport by their own means and for their own use. It is then called transport for own account. Otherwise, when the merchandise is taken over by a

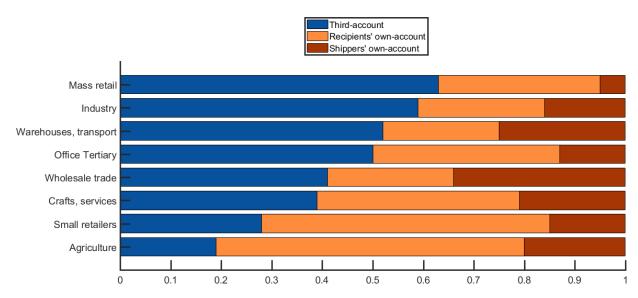


Figure 16 Share of deliveries / pick-ups for third account (in blue), for own account performed by shippers (in red) and own-account performed by recipients (in orange) for different economic activities. Data for France from (Patier, 2004).

company whose core business is freight transportation, and which provides its services on the market, it is called transport for third account (Savy, 2011).

Third-account transport is generally considered of better performance and quality than own-account transport. Indeed, to a certain extent, it enables to reduce geographical imbalances, to share resources, and to use the expertise of the transport company to improve the transport. On the contrary, transport for own account often (but not always) has lower loading rates and a greater number of kilometers traveled without cargo (Cruz, 2010).

Own-account transport is a widespread practice in the urban environment, more than at an interurban scale. In cities it accounts for approximately half of the deliveries (LAET, 2014). In 2007, in Germany, 47% of tons  $\times$  kilometers of journeys within 50 km are transported for own account, and 45% for Great Britain (Cruz, 2010).

Own-account transport is mainly carried out by shippers (with their own vehicle or a rented vehicle), and to a lesser extent by the recipients (e. g. a retailer sourcing from a wholesale market or store). As shown in Figure 16, the share for own account and third account varies greatly according to the sector of activity. Agriculture, small retailers, crafts, services and wholesale trade uses mainly transport for own account, while office tertiary, warehouses and transport, industry and mass retail are essentially supplied through third-account transport.

Some transport for own-account is in every respect similar (in terms of transport quality) with transport for third-account, especially for shippers' own-account, as there is the possibility of polling freight of several customers. This is often the case in the wholesale trade sector, where transport is an essential component of the business, and firms are not far away from specialized transport businesses.

#### 2.3.2 A very competitive environment

Road transport companies evolve in a very competitive environment, especially for generalized transport companies. Margins are therefore reduced to their minimum. In France, the average net operating margin of road transportation companies is around 2.3% (CGDD, 2017c).

Especially, subcontractors in parcel and express transport compete fiercely. At the origin of this competition is the ease of access to the sector. Registration in the national freight transport register does not require significant investments (much less than for long distance freight): a specific training, a financial capacity of €1,800 for the first vehicle, supplemented by conditions such as not to have been sentenced for specific offenses. Thus, many people can become LCV freight carriers quickly, and the rate of business creations in this sector exceeds any other segment of the road freight transport: 1,200 light transport companies were for instance created in the Ile-de-France region in 2014.

At the same time, 1,000 companies were removed from the register of carriers. Despite the small margins of this activity, difficulties of access to employment push job seekers towards this easily accessible business. The result is a high turnover rate. The average life of subcontracting freight companies is 3 to 4 years (Harnay et al., 2014).

There is a significant dependency relationship of the subcontractor and the freight forwarder. Outsourced missions are usually the most complex, either in the densest city centers or in diffuse periphery (Harnay et al., 2014).

Competition through transport is not only present for third-account transport companies. For some own-account activities, transport contributes to a substantial part of the added value in comparison with the "main" activity, and good transport and vehicle management is one of the elements that make it possible to break away from competition. It is for instance the case for fruits and vegetables transportation by in-store or market retailers, for which the good

maintenance of the vehicle to make it last for many years (as it finally runs very little) is seen as a way to stand out from the competition (Camilleri, 2014).

The number of auto-entrepreneurs is growing very rapidly in the transport sector (+64% in 2016) with spectacular growth in the home delivery activity: +271% in 2016 in France, rising from 1,755 to 6,508 in one year (ACOSS, 2018). These auto-entrepreneurs are concentrated in the largest cities, with more than half of them located in the Île-de-France region in 2016. The average annual turnover for these activities is around €3,200, 2.5 times less than for other transport activities, which is partly explained by an activity that is not always carried out full-time (ACOSS, 2018). The couriers have a low average age (26 years old in the company Stuart, in which La Poste has invested) and a large share of them are students<sup>19</sup>.

These auto-entrepreneurs have invested in new markets in full bloom, such as the delivery of meals, but are irremediably stepping into the activities of companies already established in courier activities. The competition is tough. The French national union of light transport (SNTL) accuses these companies of "abusively breaking prices" by "appealing" to self-employed entrepreneurs who are precarious because they are paid by the task, "without any social protection or job security" 19. The safety of self-employed bike couriers is also a real concern.

# 2.4 Quality of urban freight

Urban freight is today an important source of externalities in the city, among which are severe pollution, congestion, noise and safety issues. In this regard, Routhier (2002) describes UF as a materialization of "a friction between economic and urban spheres"<sup>20</sup>.

#### 2.4.1 Pollution

When measured for one ton of transported goods, greenhouse gas emissions are multiplied by a factor of 5 between LCVs and heavy trucks (Cottignies, 2012). The total contribution of LCVs is close to that of heavy goods vehicles in France, with 20% of the emissions attributable to them (CGDD, 2014).

80

<sup>&</sup>lt;sup>19</sup> Steinmann, Lionel. "La Poste Innove Pour La Protection Sociale Des Coursiers De Stuart." Lesechos.fr, Les Echos, 6 Nov. 2017, www.lesechos.fr/06/11/2017/lesechos.fr/030832342581\_laposte-innove-pour-la-protection-sociale-des-coursiers-de-stuart.htm.

<sup>&</sup>lt;sup>20</sup> Author's translation

Emissions (%)	$CO_2$	PM <sub>10</sub>	NO <sub>x</sub>
Île-de-France Region	19.4%	29.6%	29.3%
City of Paris	33.9%	46.4%	51.4%
Urbanized periphery	17.6%	27.8%	26.5%
Rural periphery	6.6%	11.3%	9.3%

Table 1 Share of pollutants in the Paris region related to freight activities (Koning et al., 2017)

The contribution of urban freight to the overall pollution is larger than its actual share in the road transport (in terms of vehicle equivalent  $\times$  kilometer). As we can see in Table , the contribution of urban freight to general road traffic emissions is far from negligible. Results show that the problem is particularly acute in city centers, where local pollution affects most people.

Low emission zones sometimes expressly target LCVs, and thus push the sector to modernize. The transfer of polluting vehicles to the periphery of the low-emission zone may however be problematic (Dablanc & Montenon, 2015).

#### 2.4.2 Congestion

Logistics is in competition with many other public space occupations and is rarely taken into account in urban planning (Conway et al., 2013, 2016).

According to Routhier and colleagues (2002), UF amounts to between 9% and 15% of all trips made in the agglomeration, and from 15% to 20% of the vehicles  $\times$  kilometers traveled (in a private-car-equivalent unit, which takes into account the road occupancy of the vehicles considered). UF vehicles thus contribute to a large extent to urban congestion. This congestion is even more penalizing for the circulation that double parking is a common practice to make urban deliveries, often due to the lack of parking or delivery areas.

Until the 1980s, congestion was perhaps the main concern that led communities to regulate the transportation of goods. In the Paris area, inconvenient parking occurs for more than half of the stops, and increases with the size of the vehicle (except for the minority of articulated trucks) (LAET, 2014). Beziat (2017) notes that double lane parking has an impact on the traffic four times greater for light commercial vehicles and thirteen times greater for trucks than for private vehicles. He measures, according to the type of street, a

collective cost varying from  $\leq$ 0.04 to  $\leq$ 0.32 per LCV for double lane parking in Paris, and from  $\leq$ 0.13 to  $\leq$ 1.03 for a truck.

The parking issues caused by urban freight are not only due to missing delivery bays or parking opportunities, but also result of a commonly accepted practice, with low control and verbalization. In contrast, in Japan, high compliance with parking rules gives industry greater efficiency (Dablanc, 2010).

The problem of congestion is reinforced by the wide overlap of peak hours for UF and passenger transport. Attempts by carriers to make deliveries outside of peak hours are hampered by, among other things, the unwillingness of customers who are not ready to implement special arrangements for receiving the delivery at night, noise (see next sub-section) and some liability issues (Holguín-Veras, 2006; Verlinde et al., 2010). In a multi-actor multi-criteria analysis, Verlinde and colleagues (2010) notice that public support for nighttime deliveries is low.

#### 2.4.3 Noise

Another major problem is noise. According to Giuliano (2013) (citing (Albergel et al., 2006)), freight transport in a French city can cause an increase of 5 dB(A) in traffic noise during morning rush hours. Noise is also an additional barrier for off-peak deliveries, in the evening or at night.

The use of electric vehicles might be the beginning of a solution for night deliveries, as it has much more quiet operation at low speeds. However, noise from operators and handling has been found to be a significant source of nuisance, independently of vehicle technology (Holguín-Veras & Aros-Vera, 2014). The Piek program, which originates from the noise standards for logistics operations (loading and unloading) of the Dutch government, provides a certification scheme for vehicles operating at less than 60 dB(A) (at 7.5 meters from the source) for possible night-time deliveries. These standards have been adopted in Great Britain, Germany, France and Belgium (van Noort et al., 2003). Industry and commerce could at first not comply with these strict standards, and support was needed for the development of new vehicles and work tools (Verlinde et al., 2010).

## 2.4.4 Safety

UF is responsible for a significant proportion of vehicles traveling in the city and thus contributes to traffic accidents. While UF vehicles (often larger in size than private vehicles) are not involved in more accidents than private vehicles (more

the opposite), accidents are generally more severe and the death rate in accidents involving utility vehicles is higher (Giuliano, 2013).

## Chapter conclusion

This chapter highlighted the great variability of uses and activities performed with light commercial vehicles. Light commercial vehicles are used for several, often multiple, purposes, including the transport of tools, materials, freight, passengers or commuting. The vehicles can be used even when not in motion, for example for lunch or as storage space. Their intensity of use and lifespan vary greatly.

Urban freight activities have successfully adapted to recent changes in demand, with increasing fragmentation of shipments. They have enabled and supported the development of e-commerce, home deliveries and instant deliveries.

However, the social and environmental quality of transport sometimes seems to come second to operational performance. LCVs in general and more specifically freight activities, largely contribute to the externalities of transportation, while there appears to be no clear substitute to road transport. Indeed, trends are more towards the multiplication of LCVs than their reduction, especially in cities. Electric vehicles are therefore possibly a first-class solution to mitigate their negative impacts.

The next chapter explores the requirement for the change of conventional vehicles to EVs among urban freight companies, as well as potential effects on business processes.

# 3CONSTRAINTS AND OPPORTUNITIES OF ELECTRIC VEHICLES FOR FREIGHT OPERATORS

In the first chapter, we focused on the battery electric vehicle technology, which constitutes a niche market, but witnessed many changes in the last decade, with more and more supply from car manufacturers and support from public authorities. In a second chapter, we analyzed the market and the use of light commercial vehicles by business users, particularly for freight transportation needs. The review has highlighted the diversity of activities, vehicles and uses.

Freight activity seems (at least on paper) to lend itself particularly well to the use of EVs. However, current market shares do not clearly confirm this and the question of future market uptake is open. To shed light on this question, this chapter proposes to delve more deeply into the intersection of these two ecosystems, and to identify the constraints and opportunities that electric vehicles present for freight users.

The adequacy of the technology with the needs of freight operators appears as absolutely central to the success of EVs. It is therefore their point of view that we wish to explore first and foremost, in order to maximize the chances of successful adoption of EVs.

Numerous experiments with electric vehicles have been conducted with transport companies. Their findings are reviewed and the results are reported according to three categories, which distinguish the origin of constraints and opportunities. First, many constraints arise from *technological differences*, including economic and operational constraints. Secondly, competing with a widely established technology creates an imbalance, in which electric vehicles are disadvantaged by the *novelty of their market*. Thirdly, *regulations* tend to compensate for some of these constraints.

We then explore the conditions under which carriers could accommodate these constraints, in order to identify the conditions favorable to the use of electric vehicles. For example, we explore which organizational changes are tolerable to adapt to the specificities of electric vehicles. We also question the evolution of constraints and opportunities. For this purpose, we conducted interviews with freight operators by drawing on the innovation diffusion theory, well adapted to the analysis of temporal evolutions. The interviews are essentially focused on the transport companies. The question at the center, and which will feed the Chapter 5 model, is to anticipate not the behavior of early adopters, but that of the early majority ( in the terms of innovation diffusion theory), which could drive the market from a niche to a mass market.

The review is presented in section 3.1 and the interviews are analyzed in section 3.2.

# 3.1 Review of experimental projects on electric vehicles and business users

The change in technology brings about many changes in user activity. We have identified three sources of constraints and opportunities for electric vehicles. This categorization results from an *ex post* analysis of the results of the review and of the interviews, but it is presented right away for a more organized restitution of the results:

• First the implications of the **technical specificities of EVs**, which create constraints that did not exist for conventional vehicles, as for instance the limited range, the need for charging, installation of charging infrastructure, matters of weight and volume, auxiliaries, refrigeration, etc. (explored in sub-section 3.1.2).

- A second source of constraint follows directly from the **novelty of the market** for EVs. It includes constraints related to the **adoption process**. It is a challenge to compete against a well established and widely adopted dominant technology: switching to EVs brings freight operators out of their comfort zone (sub-section 3.1.3).
- Finally, *regulations* can affect competition between conventional and electric vehicles. Most often, it favors electric vehicles for its environmental benefits, allowing it to gain in competitiveness and in visibility (sub-section 3.1.4).

#### 3.1.1 Reviewed research projects

Several research projects' reports have been reviewed, which are shortly described here. Some explore all business users, some only one part (urban freight or other), and approaches may differ. In some projects, EVs have actually been experimented, while others gather experience from early adopters in case studies.

The FREVUE project (Freight Electric Vehicles in Urban Europe), as its name states, investigates all sorts of challenges for the use of EVs for urban freight, through 8 demonstrators, involving 70 EVs. The research project, spanning from 2013 to 2017 has been funded by the European Union (Nesterova et al., 2015; Quak et al., 2017).

The North Sea Region electric mobility network (e-mobility NSR) performed an analysis compiling many examples involving the use of freight EVs in several European countries in a project from 2011 to 2014 (Denmark, Germany, Great Britain, the Netherlands, Belgium, Sweden, and Norway) (Taefi et al., 2016).

The SELECT project (August 2012 to June 2015) explored how commercial transport could switch from conventional to electric vehicles, with investigations in Germany, Denmark and Austria, and with some focus on the courier, express and parcel industry and the pharmaceutical transport (Klauenberg et al., 2015, 2016).

The project Infini-drive (2012-2014) provides an in-depth analysis of the installation and management of on-site charging infrastructures for fleets. Bringing together 8 partners, including among others the French Post company and the French electricity distribution network manager, it focused on the successful integration of 100 electric vans into the fleets of these companies (Infini-drive, 2014).

An E-Truck taskforce from Calstart (a member organization dedicated to expanding and supporting a clean transportation) investigated the early business case of using electric trucks (Van Amburg & Pitkanen, 2012), in particular through a survey to North-American early adopters, interested fleet users, and E-Trucks manufacturers.

Papers on potential users or early adopters in commercial transport (Frenzel, 2016; Morganti & Browne, 2018; Pelletier et al., 2014; Trummer & Hafner, 2016; Wikström et al., 2015) have also been reviewed, as well as a white paper on heavy-duty freight vehicles (Moultak et al., 2017).

A report from the TØI (Institute of Transport Economics in Norway) explores not directly urban freight but crafts and service workers (in a project called Crafttrans), which finally exhibit constraints quite close to the freight transport sector. It consists essentially of case studies and mobility analysis based on GPS-based tracking (Julsrud et al., 2016).

The climate group, an international non-profit especially working on ways to alleviate global warming, proposes *a guide to deploying electric vehicles in fleets*, from which some elements are taken (McMorrin et al., 2012).

The ultra-low emission vans study, commissioned by the British Department for Transport and carried out by Element Energy, investigates especially the financial aspects of battery, plug-in hybrid and hydrogen electric vehicles (Alex Stewart, 2012).

### 3.1.2 Implications of the technical specificities of EVs

EVs generally have more operational constraints than diesel vehicles. Among the most critical criteria in this category are costs, limited range, the need to recharge the battery, the maximum weight and volume of goods transported, while comfort and low noise represent some opportunities.

#### 3.1.2.1 Cost

Electric vehicles are known for their high costs, and all reviewed projects identified this as an issue. For instance, electric commercial vehicles' high purchase price is identified in a survey as "by far the most severe" constraint by policy-makers (Barfod et al., 2016), in line with the fleet managers (Van Amburg & Pitkanen, 2012). Another key barrier, ranked third in this last survey, is the difficulty in assessing the cost of ownership. All the projects agree that electric vehicles require public financial support (Alex Stewart, 2012; Julsrud et al., 2016; Nesterova et al., 2015; Van Amburg & Pitkanen, 2012).

Some projects identify possibilities of viable business models, depending on the uses. Different activities offer different prospects of economic assessment, and so the use of EVs is better suited for some companies rather than others. Especially, vehicles need to be driven enough to be financially beneficial, as the fuel savings is the main opportunity offered by electric vehicles, but need to have use patterns suited to the limited range (Klauenberg et al., 2016; Nesterova et al., 2015). An opportunity that has been identified for electric vehicles is its low maintenance requirement (Pelletier et al., 2014).

The cost is one of the two critical operational constraints quantitatively explored by the model developed in Chapter 5. We look at the quantitative economic evaluation of battery electric vehicles in sections 5.1.1 and 6.2.

#### 3.1.2.2 The operational constraint imposed by limited range

Range is also a very common constraint associated with battery electric vehicles. For a good management of limited range, improved trip planning and allocation of resources is essential (Infini-drive, 2014; Nesterova et al., 2015; Taefi et al., 2016). In the Frevue project, adjustment of operational processes was necessary in many cases: change of routes, changes from ad-hoc deliveries to fixed routes to avoid range issues, trips leaving from and returning to company's premises, changes in vehicle size and number, etc.

Operational reliability, including in particular range limitations, is the second constraint considered the most blocking for electric trucks, after high costs, in the Calstart study (Van Amburg & Pitkanen, 2012).

As with costs, range limitations do not affect different companies and activities in the same way. Based on results of the SELECT project, Klauenberg et al. (2016) for instance identify much more favorable use possibilities for the delivery of medicines than for the courier, parcel and express sector.

It should be noted that range and cost are linked by battery capacity. There is therefore a balance to be found between economic and operational constraints. This is true for a certain window of battery capacities, because additional technical problems due to the weight and size of the battery appear for higher capacities (see just below).

#### 3.1.2.3 Weight / Volume

The weight and volume of the battery may affect the payload and possibly the maximum volume of transported goods. One limitation is in particular due to the regulation: gross weight needs, in Europe, to be 3.5 tons or below for the vehicle

to be classified as a LCV. So for big vans having a 3.5 tons gross weight, every additional weight from the battery is automatically lost as payload. A change in the regulatory category would be disqualifying, so it is often a decrease in payload that is observed (Taefi et al., 2015).

A regulatory solution may consist in allowing heavier EVs in the same LCV category. Such a solution is already in effect in Germany, with a policy allowing LCVs with gross vehicle weight up to 4.25 tons (Klauenberg et al., 2016). In Europe a regulatory solution already exists for heavier trucks as well, which can benefit from a weight overrun of up to one ton compared with conventional ones, if they are equipped with a heavier technology using alternative energies (EU, 2015).

In addition to the weight, a loss in available volume might be observed as well. Depending on the goods transported, one or the other may be a limiting factor. According to a survey in Graz questioning 21 freight operators (Trummer & Hafner, 2016), the volume is the most limiting factor (for 7 respondents) and weight is the most important factor for two of them. For these companies, 58% of the trips use the whole volume in average, while the weight limit is reached for 33% of the trips respectively. For instance, the current small vans by Renault provide up to 150 kilograms more payload than their electric versions (800 kg against 650 kg).

#### 3.1.2.4 Vehicle overnight parking and charging space

Charging is another well-known constraint of EVs. Frenzel (2016) analyzed that for commercial users of electric vehicles, only 5% of planned trips actually need recharge during the day, which is a small but not insignificant share. It is noted, however, that for many, recharging during tours is hardly an option. Today, charging takes place essentially overnight and on company grounds, as confirmed by Nesterova et al. (2015). In this configuration, charging might raise several problems:

- Vehicles are generally immobilized for a long duration. The time it takes to charge a vehicle depends on the power of the station and on the capacity of the battery. If any charging problem occurs during night for instance, the vehicle is not usable for an appreciable length of time.
- Managing and supervising the charging process of a whole fleet require adapted and integrated IT tools (Infini-drive, 2014).
- Availability of overnight parking facilities is not systematic. Browne et al. (2007) notice that almost two thirds of the LCVs are taken home by drivers

overnight, and one third are parked off-street at premises, as a result of a study conducted in 2005 in the London boroughs of Southwark and Lewisham. Although old, we believe this study provides data still relevant today. We expect that the acquisition of ad hoc real estate is unlikely, because expensive and complex to integrate into the processes.

- Installation of charging stations might be much more costly than the mere costs of the stations: extra costs can occur due to works, for example to bring the electrical system up to standard. Companies willing to convert to EVs often find themselves surprised in this regard (Taefi et al., 2016; Van Amburg & Pitkanen, 2012). Fire safety regulations can represent a significant financial burden too, especially when facilities are shared and considered as establishment open to the public (Établissement recevant du public, or ERP in French, such as underground car parks).
- An increased fare for the electricity subscription can add up to all this, but can also sometimes be avoided with smart-charging (Infini-drive, 2014).

#### 3.1.2.5 Comfort and noise

After experimentation, drivers are mostly positive about the use of EVs, if no reliability issues have been observed. Electric vehicles have no gearboxes and have thus the comfort of an automatic gearbox on a conventional vehicle. Silent operation and less vibrations are also much appreciated (Nesterova et al., 2015; Taefi et al., 2015).

Exposition to positive reactions from people around (instead of negative ones usually) is also felt as rewarding from the driver's point of view (Taefi et al., 2015).

Silent operation, on the other hand, has been identified as a possible safety issue, as pedestrians, especially for low speeds where the noise of conventional vehicle comes mainly from the engine. The addition of artificial noise at low speeds can compensate for this risk.

#### 3.1.2.6 Specific note on heavy-duty electric trucks

Our research focuses mainly on light electric vehicles. There are several reasons for this. First, electric light commercial vehicles are already marketed by several car manufacturers, while electric trucks are still in their infancy. Then, Renault commercializes only this category of vehicles, and by extension the Renault research department was essentially focused on it. This allowed us to have first-

hand assumptions on light commercial vehicles, whereas assumptions on trucks would have been more speculative.

The distances traveled are on average significantly greater than that of light commercial vehicles: for trucks of 9 to 12 tons, the average annual mileage is 27,200 kilometers (which even rises to 43,200 kilometers for transport for third account), against about 14,000 for light vehicles. On the basis of a survey of commercial vehicles in Germany (Kraftfahrzeugverkehr in Deutschland 2010), the same observation is made by Norman et al. (2016): heavy vehicles are driving on average two to three times the average distance of light vehicles. While average distances are decreasing in large cities, this ratio remains the same.

The challenge of electrifying trucks is therefore twofold: not only does the weight of the truck require greater energy, but the necessary range to cover a large share of the trucks' uses is greater than that of light commercial vehicles. In addition, heavy trucks will require high-power solutions for charging. Innovative charging solutions for heavy-duty vehicle fleets are investigated by the project ASSURED, which started in October 2017 and receives funding from the European Union.

However, the market for heavy electric vehicles might exist in the medium to long term, particularly for urban freight transport. The number of trucks in the cities is far from negligible; medium and heavy trucks make 41% of deliveries and collections in Ile-de-France for example (LAET, 2014). Several successful operations of electric heavy trucks have been carried out, for instance 8 trucks from 12 to 19 tons in the frame of the Dutch Hytruck project<sup>21</sup>.

Norman et al. (2016) note that medium-sized trucks (12 tons vehicle gross weight) have the specificity of having a clearly defined area of operation, which ensures regular daily driven distances, compatible with the limited range of an electric vehicle. However, their economic analysis shows that economic competitiveness is more difficult to achieve for this type of vehicle than for a light commercial vehicle. The need for a big battery imposes high prices, making the vehicle uncompetitive (Quak et al., 2017).

Moultak et al. (2017) investigate three electric technologies for trucks: plug-in electric (with battery), electric with catenary or in-road charging, and hydrogen fuel cell trucks. They qualify this electrification as an "immense challenge". These technologies are investigated at horizon 2030. The study

\_

<sup>&</sup>lt;sup>21</sup> "Eight e-Trucks Complete Hytruck Project." EMOSS, 10 July 2017, www.emoss.nl/en/news-blog/eight-e-trucks-complete-hytruck-project/.

confirms that battery electric vehicles are more suitable to light commercial vehicles for city distribution, and possibly for medium duty regional trucks. The other technologies could be deployed for longer routes and heavier vehicles, under the condition of massive infrastructure deployment.

#### 3.1.3 Implications of the novelty of the market

The current electric vehicle market is rather small and relatively new (compared with the conventional vehicle market). Several drawbacks ensue, that will be detailed in this sub-section: limited supply, poor after-sale services, technological uncertainty, etc.

#### 3.1.3.1 A scarce supply offered by car manufacturers

As it has been already outlined in the first chapter, supply of EVs in general and more specifically of vans and trucks is lacking. This has been confirmed during the projects, and most of the projects do use experimental vehicles. Historical car manufacturers have only started to supply 3.5-ton LCVs very recently (2017-2018).

The Frevue project noted an improvement with time on the procurement of small vans. A lack of information was initially noted, but car manufacturers finally allowed access to more transparent information (Nesterova et al., 2015).

#### 3.1.3.2 Reliability issues

The quality and reliability of the vehicle is obviously an essential factor for companies. Several projects have noted reliability issues (Infini-drive, 2014; Van Amburg & Pitkanen, 2012). Not all vehicles are concerned and some even praised the high reliability of the test vehicle, while others were assessed as completely unusable (Taefi et al., 2016).

These problems are not intrinsic to the technology, but are linked to small series production of vehicles by manufacturers that in some cases are less experienced than for internal combustion engine technologies. Indeed, the Frevue project has observed that small vans are no longer subject to these reliability issues, as they are no longer seen as trial products, but bigger vehicles still need some improvements (Nesterova et al., 2015). The lack of supply leads some companies to experiment pilot vehicles (especially during research projects), often resulting from transformations of ICEVs, and thus more prone to reliability issues.

Electric vehicles are recognized as requiring less maintenance and having lower maintenance costs. However, repair costs in the event of an incident or accident can be very high compared with those of ICEVs (Nesterova et al., 2015).

#### *3.1.3.3 After-sale and maintenance network*

The difficulty of access to qualified mechanics for EV reparation and the lack of availability of spare parts has been observed as an issue as well (Taefi et al., 2015). Downtime for repairs can be long, sometimes because of a lack of experience about EVs by car mechanics.

#### 3.1.3.4 Technological uncertainties

The Caltrans projects' third identified key purchase barrier is about the difficulty in assessing the payback period and the lifecycle costs. In particularly, the battery life expectancy plays a central role in these assessments, and if needed, the possible replacement costs are unknown (Van Amburg & Pitkanen, 2012).

These uncertainties can lead to pessimistic assumptions on depreciation from the potential customers (direct users or lease companies), to reduce their risk. The offer of guarantees by car manufacturers makes it possible to share and thus reduce this risk (Alex Stewart, 2012).

#### 3.1.3.5 Knowledge of electric vehicles

Electric vehicles are not well known by most companies, compared with conventional vehicles, which is linked to their current core activity. However, the SELECT project highlights that a large majority of businesses do not consider EVs to be a temporary trend (Klauenberg et al., 2016).

The possibility to test EVs appears as an important vector for EV adoption. Many studies report how experimentations bring potential users to consider EVs to be an alternative to their conventional vehicles (Julsrud et al., 2016; Klauenberg et al., 2016). Dudenhöffer et al. (2012) confirm this observation for private customers, and claim that shared EVs are therefore the best showcase for the technology.

Wikström et al. (2015) analyze that doubts about the decrease in range in winter leads users to limit their trips in electric vehicles, seemingly unjustifiably because range would allow to maintain the same distances traveled. Measures to improve user confidence in the technology are therefore the key to its optimal use.

Both the Infini-drive project (2014) and the Frevue project (Nesterova et al., 2015) underline the necessity to involve and train users for a successful integration of electric vehicles. It also strongly advises to have a continuous optimization after the vehicle has been installed, emphasizing possible learning and improvements of the processes with experience.

#### 3.1.3.6 Image of an environmentally friendly company

The novelty of the market does not only present disadvantages. It also offers EV users a positive image associated with the technology (Frenzel, 2016), with an innovative and environmentally friendly connotation. The use of EVs fits therefore well into a marketing strategy on environmental consciousness, allowing to stand out from competition. Taefi et al. (2016) qualify this as soft financial benefits. The same observation has been made for craftsmen (Julsrud et al., 2016).

#### 3.1.4 Mitigate constraints with regulation

Public authorities can use a wide range of levers to mitigate the drawbacks of electric vehicles. Leurent and Windisch (2011) propose a typology of public policies in five categories, which we adopt: Command and control policies, economic instruments, procurement instruments, collaborative instruments and communication and diffusion.

A classical approach to evaluating the effectiveness of the support is to monetarize the benefits (including non-monetary ones) and to confront this support to the proportion of sales or ownership of EVs. Fearnley et al. (2015) note a clear positive correlation between monetarized incentives and electric vehicle ownership rates in Norwegian cities. This trend is confirmed for American cities by Lutsey (2015).

Adoption of a new technology and departure from ICEs could require large subsidies and investments as well as a high political commitment (Ramjerdi & Fearnley, 2014), a situation more generally found for environmental technologies (Van den Bergh et al., 2011).

#### 3.1.4.1 Command and control policies

Command and control are often national regulations, with low implementation costs and effort. They act through their legally binding character. This category includes quality or safety regulations, licensing procedures, mandates that

enforce the inclusion of electric vehicles into public sector, or quotas on alternative fuel vehicle sales imposed on car retailers (Leurent & Windisch, 2011). Exempting electric vehicles from restrictive regulations also fall into this category.

Forcing regulations are a common vector of diffusion for environmental innovations (Gasmi & Grolleau, 2003). Julsrud et al. (2016) insist on the opportunity presented by the strengthening of restrictions on ICEVs in urban areas.

Dudenhöffer et al. (2012) identified clear effects on car manufacturers' strategies of the announcements of the Chinese government to more and more restrict the future sales of conventional vehicles. These announcements are about to materialize (after having been delayed by one year) by the introduction of new energy vehicle credits, and a threshold to which car manufacturers must comply from 2019, failing which they will be penalized (the corresponding market share is estimated at 4% of new energy vehicles for 2020) (ICCT, 2018a). The European Commission is following the same path, with the key objective of no more conventional fuel cars in cities in its roadmap for transport by 2050 (European Commission, 2011b) even if binding regulations are still quite rare. Some countries (such as France and U.K.<sup>22</sup>) go a step further and announce the end of fossil-fuel cars by 2040. Beyond these long-term announcements, the first signs of implementation of these policies appear, with, for example, the recent ban on diesel vehicles on certain key roads in Hamburg<sup>23</sup>.

At a local level, low emission zones is a common tool for keeping the most polluting vehicles out of metropolitan centers, particularly in Germany, Italy, Sweden or the Netherlands (Dablanc & Montenon, 2015). However, their primary objective was not always environmental, but sometimes to limit traffic and congestion, especially the urban tolls in Italy. Increasing air quality issues have led to the use of this policy for the discrimination of the most polluting vehicles. They can be implemented with an urban toll (in which case they should

-

<sup>&</sup>lt;sup>22</sup> Ryan, Charlotte, and Jess Shankleman. "U.K. Joins France, Says Goodbye to Fossil-Fuel Cars by 2040." Bloomberg.com, Bloomberg, 25 July 2017, www.bloomberg.com/news/articles/2017-07-25/u-k-to-ban-diesel-and-petrol-cars-from-2040-daily-telegraph.

<sup>&</sup>lt;sup>23</sup> Reiter, Chris. "Diesel Fears Become Reality With First Driving Ban in Germany." *Bloomberg.com*, Bloomberg, 23 May 2018, www.bloomberg.com/news/articles/2018-05-23/diesel-fears-become-reality-with-first-driving-ban-in-germany.

in all rigor belong to the following category) or by a command and control policy. Some low emission zones specifically target commercial vehicles.

#### *3.1.4.2 Economic instruments*

The economic measures are intended to offset the additional cost of electric vehicles. Most commonly, these economic subsidies are direct, with a subsidy or a tax exemption for vehicle purchase and infrastructure installation. Investments in research and development or in public accessible charging infrastructure are indirect public economic incentives. Pricing policies, such as urban tolls, are another possible approach (Leurent & Windisch, 2011).

Most frequently, direct financial incentives are among the best levers (Fearnley et al., 2015).

Norway offers substantial tax exemptions to the buyers of electric vehicles. Electric vehicles are exempted from the registration tax since 1990. The registration tax is very high for passenger cars (e. g.  $\[ \in \]$ 6,000 to  $\[ \in \]$ 9,000 for a Volkswagen Golf), and LCVs have lower tax rates (typically  $\[ \in \]$ 2,000 to  $\[ \in \]$ 2,500 for a small diesel van). Since 2001, electric vehicles benefit also from a VAT exemption, amounting to 25% of the vehicle purchase price. Business users have already full refund of VAT for diesel vans and get no advantage out of this incentive. A reduced annual vehicle license fee adds up to that (Julsrud et al., 2016). There is a significant imbalance in tax exemptions between passenger cars and commercial vehicles.

To cite but a few others, battery electric cars benefit from a SEK40,000 (€3,890) "super green car" premium in Sweden for buying a new battery electric car, and will have a vehicle circulation tax exemption during 5 years (around €600 per year). €4,000 will be granted for the purchase of an electric vehicle in Germany (for vehicles of less than €60,000). This policy lasts for a maximum total of 400,000 cars. Interestingly, car manufacturers abound as much as federal governments, sharing the subsidy. An exemption of car registration taxes adds up to this. The transport companies also benefit from a reduced electricity tax for the operation of electric vehicles. In France, electric vehicles benefit from a €6,000 subsidy, plus a diesel scrappage scheme granting additional €4,000 when replacing an old diesel vehicle 11 years of age or older with a battery electric vehicle (EAFO, 2017).

Local subsidies can add up to that.

Concerning R&D investments, the German government launched in January 2009, for a period of two years, the 'Economic Stimulus Package II',

where electric mobility was addressed by a specific resolution. €500 million has been dedicated to research on electric mobility (Leurent & Windisch, 2011).

#### 3.1.4.3 Procurement instruments

A government or consortium of stakeholders may decide to purchase a set of clean vehicles, to benefit from reduced prices and trigger economies of scale (Leurent & Windisch, 2011).

In France, a group of twenty public and private companies has for instance resulted in the purchase of more than 15,000 commercial vehicles over 4 years starting from 2011.

#### 3.1.4.4 Collaboration instruments

Collaboration instruments aim at managing the collaboration of the different stakeholders, between car manufacturers, researchers, authorities and customers (Leurent & Windisch, 2011).

#### 3.1.4.5 Communication and diffusion

Information and awareness campaigns, electric vehicle specific training, public guides and lobbying activities fall into the category of communication and diffusion (Leurent & Windisch, 2011).

#### 3.1.5 Temporal dynamics

This review highlighted a number of factors that impact freight transport operators when they decide to switch to electric vehicles.

These impacts have been classified into three categories, which bring different constraints both by their nature and by their evolution over time. Different mechanisms can come into play to lift these constraints or open opportunities, as has been already observed in the evolutions of the last decade on specific vehicle segments. A summary of these constraints and an analysis of their temporal dynamics are presented in Table 2.

Constraints and opportunities	Temporal dynamics
Electric vehicles provide a performance below that of conventional vehicles. Technological differences imply often:  • Significantly higher costs  • Limited range  • Weight and volume limitations  • Overnight charging needs  The technology offers also some direct opportunities, especially silent operation and lower maintenance needs.	<ul> <li>Mitigating these constraints essentially involves technological progress, especially on batteries – but not only.</li> <li>Some constraints such as overnight parking requirements would imply an organizational change for some companies</li> </ul>
<ul> <li>The novelty of the market imposes:</li> <li>Limited supply</li> <li>Reliability issues on sometimes experimental vehicles</li> <li>Scarcity of the after-sale network</li> <li>Uncertainties on the future of the technology</li> <li>A learning process</li> <li>However, the technology has a very positive image.</li> </ul>	<ul> <li>If the market grows, these problems are temporary in nature:</li> <li>Many services need a critical mass of users to be developed, while users are waiting for a supportive ecosystem to switch to EVs: it is a well known chicken-and-egg problem.</li> <li>Observations of most developed segments (subcompact cars and small vans) reassures about the market's ability to solve these early issues when market shares increase.</li> <li>The adoption process highlights the existence of a learning curve, which highly depends on communication, and on innovativeness of the actors of the sector. This process can be accelerated through experimentation and communication.</li> </ul>
<b>Regulations</b> deal differently, on environmental criteria, with competing technologies. Electric vehicles benefit from strong regulatory support.	Regulations are dependent on political choices, but also on the technology, particularly when it comes to penalizing conventional vehicles: the acceptability of such a measure is closely linked to the relevance of the alternatives supplied to users.

 $\label{thm:constraints} \begin{tabular}{ll} Table~2~Summary~of~main~constraints~and~opportunities,~with~their~related\\ temporal~dynamics\\ \end{tabular}$ 

# 3.2 Interviews: a slow but promising convergence of supply and demand

Thirty-nine semi-open exploratory interviews have been conducted with transport companies, transport associations and stakeholders from the ecosystem of freight and electromobility. The objective was to judge, independently of the performance of current electric vehicles, which conditions could lead an urban delivery company to adopt electric vehicles. Much has been said about changing and adapting the companies' habits and processes to use electric vehicles. The interviews thus attempt to explore how companies conceive a realistic margin of maneuver regarding these processes.

We want to explore the possible path to the mass market, and to do so we borrow from the *innovation diffusion theory*, which by nature integrates the evolution of adoption over time. The first sub-section will introduce some elements on the framework from this theory that helped us to construct the interview grid and to conduct this exploration.

#### 3.2.1 Methodology

#### 3.2.1.1 Inspiration from the innovation diffusion theory

The innovation diffusion theory, introduced by Everett Rogers in 1962, gives a conceptual framework to the analysis of the evolution of a technological innovation, from the stage of invention to that of wider use (Rogers, 2010).

In particular, a theoretical framework defines five attributes which influence the adoption rate of an innovation, defined as:

- **Relative advantage**: the degree to which an innovation is perceived as being better than its precursor.
- **Compatibility**: the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters.
- **Complexity**: the degree to which an innovation is perceived as being difficult to use.
- **Observability**: the degree to which the results of an innovation are observable to others.
- **Trialability**: the degree to which an innovation may be experimented with before adoption. We add to this category a notion of perceived risk,

defined in (Bauer, 1960) as "a combination of uncertainty plus seriousness of outcome involved".

#### 3.2.1.2 Interviewees

The interviews have been conducted in Germany (15, in Berlin and the Rhine valley), Norway (14, in Oslo), Sweden (9, in Gothenburg) and France (3, in Paris), of which 19 were with transport companies and 8 with freight and retail professional associations. 12 interviews explored the ecosystem (municipalities, academics, etc. see just below). Some companies were already using or preparing to use electric vehicles (8), while others were not interested yet (11). The 12 exploratory interviews were conducted with municipalities or administrations, research project leaders, one software developer and one charging infrastructure operator. The detail of the activity of the interviewed organizations is given in Table 3. We call "couriers" transport companies whose main activity is end-to-end transportation. "Mixed goods, post, and parcels" are companies transporting general goods, post or parcels. The frontier between these activities may be thin, as companies, or even single drivers, may mix both,

Company activity	Number of interviews	
Couriers	6	
Mixed goods, post, parcels	6	
Food and Beverages	4	
Newspapers	2	
Automobile parts	1	
Haulers associations	4	
Retail associations	2	
Electromobility associations	2	
Municipalities and public administrations	6	
Researchers and experts	4	
Fleet management software developer	1	
Charging infrastructure operator	1	

Table 3 Interviewed companies and organizations

so the activity that seemed to be the main activity in terms of time consumption has been chosen.

The format of the interview was about one hour, preferably in person, but for reasons of geographical distance a number of interviews were conducted by telephone (about one third). Interviews were conducted in French in France, in German in Germany, and in English in Norway and Sweden.

The study targeted initially all companies engaged in urban freight transport activities as described in sub-section 2.1.6, including own-account and third-account. In practice, however, the difficulty of obtaining interviews with own-account carriers has led to a refocusing on third-account transport only. In an interview with a retail association, the interviewee was "absolutely certain" that innovation in freight transport would come from the transportation sector, and not from the retail companies operating their own transport. Focusing on third-party transport appears therefore as relevant.

With regard to the diversity of interlocutors, all sizes of company could be questioned from the one-person company to the largest distribution groups. Also, both subcontracting and prime contractors were interviewed. In terms of activity, there is a strong bias towards companies transporting general goods, compared with more specialized transport (for instance no transport of pharmaceuticals, of construction materials, etc.).

At last, there probably is a bias towards the companies favorable to the use of EVs, as the latter may have been more willing to answer positively to my solicitation.

#### 3.2.1.3 Interview form

The interview grid was divided into four parts:

- The first explores the charcteristics of the company, as objectively as possible. It concerns the company's positioning (activities, size, customers, fleet composition), vehicle acquisition practices (purchase or lease, renewal, selection criteria), use patterns (personal use, variability of missions performed, overnight parking), driver training and the use of fleet and tour management softwares.
- The second focused on the assessment of the company's state of mind regarding EVs, as well as its level of knowledge of the technology. Particular emphasis was placed on the anticipation of the future. For instance, elements of interest were whether interviewees had ever

considered this technology for a future use, whether they were preparing for it or on the contrary feared it, whether they were aware of technological developments or what weight they attached to the environmental improvement of their activities.

- Related to the previous part, the question of public policies was then addressed. The aim was to identify how regulatory developments were perceived, and what impact this perception had on the company's activity.
- At last, different activity adaptation scenarios were submitted to the judgment of the interlocutor. In particular, the possibility of mixing a fleet of conventional and electric vehicles, the possibility of using EVs that cover as closely as possible the distances announced in the first part of the interviews (highlighting certain specific needs that the interlocutor had failed to mention in the first place), the idea of using charging infrastructures accessible to the public on the way or the idea of allocating vehicles in advance according to the anticipated routes were explored.

Next sections analyze the results of the interviews.

#### 3.2.2 Perceived relative advantage of electric vehicles

In this section, we define the main drivers for EV adoption, as they appeared through the interviews. Innovation is naturally more attractive when it combines private and collective benefits, in accordance with observations by Gasmi and Grolleau (2003).

First, it can be noticed that the reception of EVs with companies is rather positive, but this observation is possibly biased by the recruiting method. Environmental friendliness was always the first justification for it.

When examining further the possible reasons for purchasing electric vehicles, operational constraints related to (future) regulations limiting ICEVs appeared several times in the interviews.

Electric vehicles also offer drivers better working conditions, and employees are therefore usually favorable to electric vehicles.

However, the operational competitiveness of electric vehicles is much lower than that of conventional vehicles. One exception is notable: companies participating to public tenders were interested in EVs to increase their success probabilities.

These four points are the subject of the following sub-sections.

#### 3.2.2.1 Perception of environmental performance

When asked about the relative advantage, the first element of answer was almost always, and in the same way in the four countries, linked with environmental performance.

In general, associations and companies were very willing to switch from ICEVs to EVs as shows the following quote from the owner of a one person company: "You can believe me, when [the right] range will be reached, I will be the first one to buy an electric LCV"; or stemming from this manager in a newspaper transportation company: "As we have an opportunity [to experiment EVs], we have to seize it".

However, some companies declare not being fully aware of the exact environmental benefits and from alternative technologies in general.

Except this, no significant differences have been identified in the different countries relatively to the environmental benefits assessments. It may be a coincidence, but we observed some weak signals specific to some countries. German companies did more often spontaneously manifest their willingness to install solar panels as a complement to using EVs, and this would be consistent with the lower environmental quality of German electricity. One professional association in Berlin (representing mostly operators of bigger trucks and not light commercial vehicles) questioned the environmental relevance of EVs, arguing that the majority of fine particles were emitted by friction and not exhaust gases. This case is further analyzed in sub-section 3.2.5.1. The events frequently called *dieselgate* (some car manufacturers fraudulently reduced pollutant emissions, NO<sub>x</sub> and CO<sub>2</sub>, from some of their diesel and gasoline engines during certification tests (Air Resources Board, 2015)) have increased the environmental awareness of some interviewees, especially in Germany.

In Norway, hydrogen was mentioned spontaneously as a potential future solution more often than in other countries. This was somewhat surprising in the country where the BEV market is maximal. It may be due to a greater maturity with regard to electric technologies. It also shows that these interviewees do not believe in solutions based on battery electric vehicles when it comes to long range, but rather are seeking for a better suited technology.

#### 3.2.2.2 Adapting to or anticipating regulatory constraints

The companies we met unanimously confirmed that they had not in the past been affected by regulatory restrictions on diesel vehicle traffic (such as low emission zones). The main reason for that is that the transportation companies for third account have recent enough vehicles to not be bothered by these regulations. Moreover, traffic bans, as for example in Oslo in case of pollution peaks, only concerned private vehicles and not businesses. Current regulations were therefore not considered as a strong driver yet.

However, the feeling that the regulations would become more and more restrictive and finally concern business users was a shared feeling in all visited cities. Traffic restrictions for private vehicles in Oslo have been analyzed by a company as "a foretaste of what is ahead of us".

Some companies were anticipating and preparing this. Electric vehicle experiments were a particular element of this anticipation. For national or even international companies, the preparation was all the more intensive, as they have to deal with disparate regulations in cities in which they operate, and solutions must be necessary for any of these cities.

#### 3.2.2.3 Can drivers themselves contribute to the diffusion of EVs?

The question whether employees are a driving force behind the diffusion of electric vehicles is unclear. On one hand, some company leaders were observing certain mistrust from employees to new technologies, but believed that it was only a question of habits. Past problems with reliability of these vehicles were also in cause.

On the other hand, when there were no reliability issues with vehicles, drivers were fully pleased *a posteriori* by driving electric vehicles. At La Poste, the historical French postal company, some drivers were for instance requiring (with medical certificate in support) to have automatic gearboxes on conventional vehicles. Indeed, the numerous stops and starts may cause joint pains. The absence of gearbox and the smooth and silent start of EVs were therefore highly appreciated, and drivers would highly prefer to use EVs rather than ICEVs.

Experimenting larger trucks, the low noise and absence of vibrations was also a big asset for the truck drivers, who declared that they were less tired at the end of the day. The conviction with which the drivers' comments were reported suggests that the benefit is even greater for trucks than for light commercial vehicles ("They are really looking forward to the new electric truck", as it is highly "improving their working conditions").

Freight transportation suffers from a lack of qualified workforce, and one association claimed that once the workforce would be set on EVs, the latter would be an asset to attract the best employees. No company did approve this as

having a notable effect today, but it is possible for the future, when electric vans and trucks are no longer niche vehicles.

#### 3.2.2.4 Often no competitive operational advantage for EVs

As exposed in the three last sub-sections, the market for EVs may be driven by environmental initiatives, anticipation of future regulation and favorable working conditions of the drivers. However, it is more the exception than the rule that these vectors outweigh the additional operational constraints brought by EVs.

The main concern of the interviewed companies and associations is above all to successfully run a business. The vehicle is a tool, for a service up to the customers' needs: highest quality and lowest prices. The urban freight market is fragmented and very competitive, with a massive recourse to subcontracting. The need for flexibility and low costs is therefore at the core of urban freight activities.

#### 3.2.2.4.1 No affordable AND adequate supply for many transportation companies

The consensus is that, for many uses, there is not the right supply of EVs from manufacturers: vehicles must meet operational requirements, but also be affordable (in comparison with ICEVs). For instance, one German courier summarizes well both needs. He needs "at least 350 kilometers range" on his 3.5 tons gross weight van (and he continues: "even in winter!"). "I mean, if the price is right, not for  $\leq 100,000$ ." In short: the right size, the right range, and the right price.

Every company confirmed that two out of three of these elements were not good enough. No replacement of a big truck by two small trucks, or with a truck with a lower range than needed for regular trips is viable.

Big postal companies find workarounds for the use of EVs, when their desired vehicles are not available. Two very illustrative examples exist. UPS converts second-hand conventional 7 tons and 12 tons vans into (tailor-made) EVs. Total cost of ownership computations are thoroughly performed (including for instance training costs) and appear to be equal for these vehicles to new conventional ones, over a use period of 8 years. Deutsche Post DHL Group is also very active in the sector, and has bought a subsidiary company building their own vehicles, StreetScooter, first for their own use, and now also sold to other companies. These solutions are of course not available to all companies, as they require high expertise and high financial capacity.

It should also be noted that the absence of a vehicle on the market also delays companies' interest in the technology and thus future adoption. This idea has appeared several times in the interviews, for instance here by a courier: "I concretely haven't looked at it as there is no supply". Companies who experiment new vehicle technologies are sometimes facing reliability issues. Lack of experience with the technology exposes the company to this inconvenience. A company that has experimented with a delivery truck (5.5 ton payload, three times as expensive as the conventional equivalent truck, with support from a program) deplores lack of reliability, and that the payload is much too low compared with an equivalent conventional truck. Despite their strong environmental commitment, as long as there is "no good commercialized solution" they will keep using bio-diesel instead.

#### 3.2.2.4.2 A competitive environment, with some exceptions

Freight transport is a very competitive activity (see sub-section 2.3.2). However, this competition does not affect everyone in the same way. Competition appears to be inversely proportional to the expertise required for transport, and inversely proportional to the value added of other activities in the total value chain.

Two illustrative examples are the parcel transportation and the fruit and vegetables transportation. Both are very accessible activities, no special license or skills are required (as opposed for instance, to the transport of meat (Camilleri, 2014)), nor is a specific vehicle (anyone can buy an old van and use it for this). Competition for the transport of fruit and vegetables is in turn more intense for sale on the market than for catering (which processes the products and therefore has a greater added value than direct sales).

As a result, these activities are subject to a lot of competition. A subcontractor in the parcel delivery segment told us they had "margins between 1.7% and 5%". EVs more expensive than conventional vehicles "cannot work out". The same was observable for the transport of manufactured goods: retail companies confirmed that retailers were putting a lot of pressure on the transport sector to have the lowest prices.

Some companies evolve in less competitive environments, for instance if they are the biggest actor of their sector. One interview was with Norway's biggest food and groceries transport company. They are responsible both for national-wide transport and local distribution to the end customer. Their dominant position on the market allows them less pressure from the competition and possibly more flexibility in their vehicle choices. This family owned company

was among the most advanced in environmental mitigation. They have as objective to become climate neutral as soon as 2020. As part of this ambition, all 30 warehouses should be covered by solar panel to cover 100% of the energy needed for refrigeration. Biofuels are already in use for their trucks. This strategy requires early experimentation of new technologies, and is further enabled as public administrations represent big clients (school cafeterias and so on), and public tenders tend to become more sensitive to the environmental quality of transport than private companies' contracts, as is highlighted in the next subsection.

#### 3.2.2.4.3 Public tenders as leverage for alternative fuels

Bids for supply contracts rarely favor companies experimenting electric vehicles. One exception lies in public tenders.

Several companies we interviewed (transport of food or newspaper businesses) noticed how the presence of electric vehicles in their fleet would give them an edge for public tenders. This shows how change can be effectively demand-driven.

Very few customers were however willing to pay for it. On the contrary, a parcel delivery company highlighted that the trend was rather towards free shipping for the end customer, including a public administration.

Only one interviewee, a postal, newspaper and magazines transportation company, declared that one private customer was ready to pay more for deliveries with electric vehicles, giving the opportunity for an interesting experimentation.

## 3.2.3 Perceived complexity

While at first glance changing technology may seem like simply replacing one vehicle with an identical one, the use of EVs actually requires the redefinition of a number of processes, which makes its adoption complex. The transition is the sum of numerous (but not insurmountable) process changes, while the ecosystem is under construction.

First, possible charging processes are explored, in link with the desire for *flexibility* by the company. Then, the question of ITs and new skills is raised. At last, the possibility of a mixed fleet with conventional and electric vehicles is investigated.

#### 3.2.3.1 Charging: varying knowledge, various solutions

Throughout the interviews, three possible charging strategies have been identified, and are discussed in this section: charging only during night time, fast charging during long trips (with specific breaks) and integrated charging inbetween trips. To make the link between the characteristics of each charging solution and the specificities of the companies' operation, an 'ideal' company profile is identified for each scheme.

#### 3.2.3.1.1 Charging only during night time

#### A mandatory practice, providing limited flexibility

Charging during nighttime seems absolutely mandatory in every charging strategy. All companies that were using or planning to use electric vehicles were using their own infrastructure, on the company premises or on private grounds. No company was relying on public accessible charging infrastructure (which we will call, somewhat abusively, *public infrastructure*) for overnight charging. In (Frenzel et al., 2015), 69% of business users declare using charging stations on company premises daily, 92% are using them more than once a week. Julsrud et al (2016) analyze that 88% of the vehicles observed (vans of craftsmen and service companies) would not have time problems with slow overnight charging. Four interviewed companies were having night shifts, expecting at least semi-quick charging in order to have full batteries at the beginning of the night operation. For all these reasons, the possibility of charging at night seems to be the first enabler for the use of electric vehicles.

In our interviews, no company was ready to give up any trip that was currently made with conventional vehicles. Electric vehicles, if adopted, are required to fully cover every trip currently made. For companies with irregular or unforeseeable activities, the risk of a loss of a opportunity is unacceptable. Therefore, relying only on night time charging suits a few specific companies.

#### Possible difficulties for installing charging infrastructure

For companies with suitable activity patterns (as presented in the next subsection for instance), this scheme is easy to put into place. It is, in fact, even easier than refueling a conventional vehicle as there is no need to go to a specific place for charging. Being able to have its own infrastructure is also an asset compared with other alternative fuels, like natural gas or hydrogen.

The complexity is met upstream, during the planning and installation phase. It is mainly linked to organizational issues (parking location of the vehicles, private use of vehicles, etc.) and to technical installation difficulties. First, charging infrastructures need a proper access to the electricity network, requiring sometimes expensive additional building works to overcome grid access restrictions. This is especially a problem for large fleets (as for postal and parcel delivery companies). UPS has experimented upgrade works in London, with the support of the European project Frevue (Nesterova et al., 2015), for an additional access for 50 trucks. The process took almost two years for an approximate cost of \$600,000. UPS has chosen a long-term investment. Therefore the dimensioning of the grid access is a bet on the future of electric vehicles, which not all companies can afford.

Among the organizational issues, the use of the vehicle outside of business activities by hired drivers (typically for commute) may increase installation difficulties. The workforce turnover may also question the installation of infrastructure in a place not directly linked to the company. Independent carriers are less subject to this difficulty as they own their vehicle.

More generally, if parking is on the public space, infrastructure installation is not always possible. Sometimes, a solution is to change the parking location, but then it may be to a suboptimal location or may result in significant additional costs for the parking premises. An independent driver (operating one vehicle) had, for instance, a private parking space 15 minutes' walk from home but preferred to park on the street in front of his home to avoid the time loss.

At last, some new processes may be needed. Supervision of charging processes is important, as a charging failure results in the immobilization of the vehicle for the whole day. Charge management enables to reduce the power needs (by not charging all the vehicles simultaneously), in order to make savings on the electricity bill or to allow an increased number of charging positions. Finally, the cooperation between fleet and infrastructure management, two departments that are not used to working together, is an additional obstacle for large companies, as one of them has pointed out in the interviews.

Historical postal companies have the ideal profile for night time charging only

Big parcel and postal companies have been identified in the interviews as the ideal organizations to charge their electric vehicles only during nighttime. First of all, postal companies have their vehicles parked in specific premises overnight, and often inherit many logistics spaces, including in the heart of cities. The very density of their deliveries means that the delivery rounds are, if not identical, very similar from one day to another, so the risk of a loss of opportunity is low.

The historical postal companies also hire a fair amount of their drivers, and the use of the vehicle is exclusively for business activities. This is important because small independent carriers seem to seize any additional mission they can accomplish, even if their main activity is the delivery of mail or parcels.

While adequate EVs for postal distribution (small vans) do exist on the market, there is a scarce supply of larger vans for parcel deliveries, with poor supply and low choice from car and truck manufacturers. However, the organization of the latter is also favorable to the use of EVs with only overnight charging, and it is probably a matter of time before these companies invest in electric vehicles, as postal companies already started to do. It is therefore not a surprise that postal or ex-postal companies (La Poste, Deutsche Post DHL Group, TNT) are today's biggest customers for electric vans.

#### 3.2.3.1.2 Fast charging during long trips

Fast charging is an enabler for many uses, especially for independent drivers, provided there is a high quality of service

Limited battery capacity does not allow doing the longest trips for companies with irregular uses if there are no additional charging possibilities. Fast charging during the trip is one solution and acts as an enabler. It is implied that the driver does not carry out any activity for his company while waiting for the vehicle to be charged. Current business users of electric vehicles are 11% to use charging stations installed on highways or national roads more than once a week, and 25% more than once a month, more frequently than private users (Frenzel et al., 2015).

The need for fast charging has been raised spontaneously by many companies in our interviews. This is not a surprise, as except maybe for additional trip planning, fast charging would not require many process changes to the current refueling practices. For a company declaring daily distances around 250 kilometers daily, "even with 300 kilometers of range, [their future capacity to use electric vehicles] depends on fast charging stations." However, charging time expectations are very high, reaching or exceeding today's most advanced technologies, as for instance Tesla's superchargers (but batteries of vans do not currently support such charging powers today).

However, the use of fast charging requires careful planning of routes and charging stops in advance.

The use of fast recharging leads to a high dependence on service operators

The quality of service is central to the interests of freight transport companies in fast charging. In line with what Morganti & Browne (2018) call *queue anxiety*, the risk of wasting time waiting at the charging station or reaching the station strongly penalizes fast chargers' acceptability.

The geographical coverage of the stations is a concern, outlining again the risk of the loss of opportunities. One company specifically highlighted (and disapproved of) the risk of dependence on public charging infrastructure operators. The company would be helpless in the face of a drop in quality of service (for example because of an increasing demand due to the fast growing EV market). The problem of the reliability of charging infrastructure is regularly put forward by private EV-drivers on the French blog *automobile-propre.fr*<sup>24</sup>. This problem may greatly reduce the acceptability of en route fast charging solutions (and generally all solutions based on publicly accessible charging).

Small independent drivers, even with mostly urban activities, need fast charging solutions

Fast charging seems essential for independent drivers. Indeed, even when the major part of their activities takes place in urban areas, the need for some interurban trips has been expressed during the interviews (see 3.2.4.2).

#### 3.2.3.1.3 In-between trips integrated charging

Integrated processes can lead to substantial benefits

A third charging strategy is to charge the vehicle each time it is parked, between the trips, provided there is adequate charging infrastructure (during lunch, during deliveries, between shifts, etc.). The main difference with the previous scheme is that the stop is not aimed at charging the vehicle, and the driver carries on his normal activity instead of waiting for a certain amount of charge. In that case, the charging event is *integrated* into the companies' processes.

In a context of limited choice in battery capacity, integrated charging may enable to operate an EV despite a range too low. No user relying on integrated public charging has been met. It is not self-evident that if there is a supply in the right battery capacity, this scheme will still be attractive.

-

<sup>&</sup>lt;sup>24</sup> One article among others about a breakdown due to the failure of a fast charging station: Schwoerer, P. "Panne Sèche En Rentrant Du Breizh Electric Tour." Automobile Propre, 8 Oct. 2017, www.automobile-propre.com/panne-seche-breizh-electric-tour/.

The benefit of this additional daytime charging is to be found in the possibility of having a smaller battery. An order of magnitude of the savings can be derived by using, for instance, the monthly rental rates of the battery for small vans (based on Renault Kangoo Z.E. rates). If the company can ensure a daily charge of one hour at a 7-kilowatt charging infrastructure, the economic gain by reducing the battery capacity of 7 kilowatt-hours is around €300. The same charging at a power of 22 kilowatts leads to potential savings of €925 per year and per vehicle. In these simple calculations, we assume that charging takes place without service costs, for example on the company's infrastructure. We can see that these gains can be substantial, even for moderate powers. The assumption of one hour in the day is arbitrary but not unrealistic, it could be a lunch break (in Sweden, a "45-minute lunch break is required by law"), or six ten-minute stops at delivery areas equipped with charging infrastructure. To our knowledge, no city has yet deployed a charging infrastructure network on delivery areas.

#### *Integrated charging requires tailor-made solutions*

This solution provides limited flexibility and requires regular uses, to ensure that daytime charging can be integrated into everyday activity (or it needs irregular uses to be covered by fast charging). One solution that seems of interest is charging during lunch time, even if it may require some organizational changes. It is not uncommon that each driver chooses the time and the place where they want to eat for example (provided they make a real break for lunch, not just a sandwich while driving).

Companies have numerous organization possibilities, depending on their strategies and the transported goods (Beziat et al., 2015) and each organization has different possibilities to integrate charging events. One specific use case seems ideal: companies with several shifts, where vehicles are operated successively by different drivers during the day. This is often the case for companies with night urban deliveries, taking maximum advantage of their fleet by delivering general goods (in our interviews, mostly parcels) during the day. These companies are able to charge in between the shifts: the vehicles are coming back to the premises, where they are parked for some time (there is a change of driver), and sometimes loaded with new freight. There is a real chance to charge the battery during these changes, with very limited inconvenience, as this organization repeats itself on a regular daily basis.

#### 3.2.3.2 EVs may need new software or new skills

Process changes often imply third party companies, who need to develop adapted tools ready to use by the freight companies (charging, fleet and route management, etc.).

The question of software is central. Changing the software of a company (fleet and tour management) is a heavy change and usually does not happen very often. So, if the software does not include EVs, tour management taking the limited range into account is not possible. Experimentations are often carried on with tour management made by hand. If a company happens to have changed its software recently, and the software does not support EVs, then it is unlikely that EVs will be used in coming years.

The initiative must therefore come from software development companies, for which EVs would be currently a niche market. The difficulty also stems, from a software developer point of view, from the fact that electric vehicle feedbacks are not standardized and depend on the brand.

About the new skills, some medium and large companies have their own mechanics that are not able to repair EVs. Initially, repairs can be carried out outside, but mechanics must be trained in the long term. UPS, which appears to be at the forefront of the evaluation and implementation of electric vehicles, integrates training costs into the total cost of ownership.

The use of EVs works also particularly well with eco-driving training, as a less energy-consuming driving style has a positive impact on range.

#### *3.2.3.3* The possible mixed-fleet solution

It would be theoretically possible to introduce a share of EVs in some companies' fleets to cover only the smallest trips, while having conventional vehicles to cover the rest of the trips. This solution, that we call *mixed-fleet* solution, looks promising but has actually a low acceptability for many companies.

Independent drivers are not willing to give up the longest trips, as they are usually the most rewarding. Swapping vehicles between drivers is not feasible either. Indeed, meeting with another driver and switching shipments from one vehicle to the other is too cumbersome. The lack of appropriate tour management software is also a reason (as outlined by two interviews).

This outlines the resistance of companies to process changes. This conclusion is consistent with that of Julsrud et al. (2016) about craftsmen, which calls this solution a "transport redistribution." The authors acknowledge this

solution as "theoretically possible," but note that it "would involve careful planning."

However, some examples show concessions in favor of EVs. The best example is a courier company, which in the frame of the Frevue project guaranteed to its subcontracted drivers a regular activity during the experimentation, thus changing the daily activity with no other purpose than enabling the use of EVs.

#### 3.2.4 Trialability and perceived risk

One company noticed the difficulty to get to reliable information about EVs, arguing that the car dealerships did not know well about this subject. Experimenting directly the technology is therefore the best way to acquire experience and prepare for the future, according to this company.

While the processes for using the combustion vehicle are well established (for example, organizing refueling), small-scale experimentation is the preferred means of gradually discovering and adapting to the specific features of EVs.

The fact that an electric vehicle works mostly on privately owned infrastructure is an opportunity for the trialability of EVs. Indeed, it is not necessary to have a fully developed infrastructure network to launch experimentation, nor a full fleet. Most of the companies that already had (or were having) experience with alternative fuels (among which Natural Gas Vehicles or biofuels) identified the scarcity of the stations was a big obstacle, and would highly complicate the refueling management. Three companies gave up on NGV after having experimented.

#### 3.2.4.1 Risk taking, company size and subcontracting

Bigger companies are used to experiment several technologies, they can afford additional costs for these experimentations, and this does not jeopardize their business because one or two vehicles only represent a small share of their total fleet.

While bigger companies are able to carry out these experimentations by themselves and without a strong impact on the firm's activity, smaller companies can perceive the transition to electric vehicles as a leap in the water. Subsidized experimentations as part of a research project prevent these companies from taking too big a risk.

As has been already outlined, as long as there is no affordable option, small companies do not look further into details of EVs, and so experimentation often starts for real when adequate vehicle supply is offered.

Also, the adoption procedures differ depending on whether the vehicles are driven by employees or independent. Indeed, a company with employees will need an initiative from the company or fleet manager, in a top-down approach, for the adoption of EVs. For this purpose, specific facilities can be designed for electrical technology (mixed fleet, charging infrastructure). When the vehicle is operated by independent contractors, a bottom-up approach is more likely. However, the subcontractor then bears sole responsibility for the use of electric vehicles, and any modification requires negotiation with the contracting company. Change is more difficult to achieve under these conditions.

In one interview with a courier company, however, a manager told us about one independent driver who bought an electric van on its own initiative, limiting himself to urban trips, and with charging breaks during the day. Unfortunately, this driver could not be questioned. For the context, this company also provides bike deliveries and seems to focus on transportation in the dense city-center.

#### 3.2.4.2 Independent contractor and need for flexibility

The position of a subcontractor is very likely to be associated with the need for flexibility. Indeed, diversifying the missions and the clients makes the activity more profitable. One independent driver, for example, carries meal trays and has very regular rounds, but even if long trips are "not the rule," they happen "two or three times in a month, to carry furniture, or whatever." The interviewee told that he was not willing to give up these trips for the use of an EV.

These examples exemplify the main risk linked with limited range: the risk of a loss of an opportunity, which in many cases can be crippling the use of EVs.

It should be noted that many of these independent contractors that are urban couriers (they perform end-to-end transportation inside one metropolitan area) are using small vans, specifically the size of vehicle with the most diverse supply today. However, they don't fit their needs, this time not because of the vehicle size but because of the available range. Indeed, even for regular days driving only in urban areas, couriers can cover distances of 250 to 300 kilometers a day. In this case, urban freight transport does not mean short distances.

#### 3.2.5 Observability

#### 3.2.5.1 Positioning of business associations

Transporters and traders associations have a key role in information and education. First, they inform their members and help them to prepare to new regulatory developments, and train them in the latest innovations, including EVs. For example, an association organized test drives of the latest electric vehicle models for its members, at one of its events.

But the association also has an informative role towards other actors, in particular the public authorities and politics.

A recurring theme that appears in the associations' discourse is that of balance, between support of innovations such as electric vehicles, and constraining regulations on conventional vehicles. This balance varies from one association to the other, much depending on the typology of the members. One retail association claims "not to hinder or push the market" for electric vehicles. Another transportation association, representing mainly small companies, thinks that being able to innovate is an absolute necessity for the long-term sustainability of the sector, and that companies which fail to do so will be penalized in the future. One association representing large companies highlights all the efforts that are being made, while another, whose members own mainly larger trucks, tries to limit as much as possible any penalizing regulation, arguing that there is currently no alternative solution.

Indeed, one clear risk that many associations are raising is that environmental regulations heavily impact companies with vehicles, for which there is no competitive alternative. Associations with members running 7 tons, 12 tons or higher gross-weight trucks were particularly alert to this question. And even if proper alternative solutions are available, the need to be in phase with vehicle renewal cycles is important in order not to put companies in difficulty. The example of moving companies has for instance been given: as they do not drive much, they keep their trucks for many years. The risk of being forced to change the vehicle at a suboptimal time is perceived by many associations as a problem.

Actually, the only interview in which the environmental benefits were really questioned was with an association whose members were using bigger vans and trucks. The interviewee acknowledged that the freight transport sector had a heavy environmental impact, but also argued that a high share of fine particulate pollution in cities was in fact coming from friction rather than

tailpipe exhaust gases. He was aware of the complexity of this question, mentioning the harmfulness of ultra-fine particulate matters from exhaust gases of Euro 6 trucks. The possible load on the electricity network of a rapid mass market for electric vehicles was also a concern. However, in this specific case, EVs were perceived as a risk: the risk of penalizing conventional vehicles under the pretext of this alternative technology, while the markets for trucks of these sizes are at best at a very early stage, if not inexistent. The publication, in a retrospective document on the association<sup>25</sup>, of a text called "Against the Politically Forgotten!" confirms that there is a fear of political decisions not acknowledging these activities.

#### 3.2.5.2 Personal interest in electric vehicles

The interest for electric vehicles does not emanate systematically from company decisions, but rather sometimes from personal affinities. A link between private and business behaviors has been observed at several occasions. Tesla Motors has been mentioned several times in the interviews, despite the fact this company is not supplying any commercial van by now. This company has nevertheless aroused curiosity, a business leader says that "since Tesla came up, [the drivers] want to try" EVs. Julsrud et al. (2016) noted the same for the craftsmen. Frenzel (2016) observed that interest in innovative automotive technology is a strong driver for early adopters of commercial vans.

## Chapter conclusion

Innung Berlin-Brandenburg e. V.

The results from this chapter are summarized in Table 4. Despite the support from public authorities, it would seem that electric light commercial vehicles appeal to only a fraction of professional users. **Currently**, **relative advantage is rather low**, **and complexity rather high compared with conventional vehicles**. In this regard, it seems very unlikely that in the short and medium term, the battery electric vehicle will be able to meet a majority of the transport needs, even in urban areas.

Given this complexity, the most probable scenario is that in the short and medium term, only companies needing only a low level of adaptation of their processes will switch to electric vehicles. Overall, companies were only willing to make small concessions to adapt to the use of electric vehicles. This means that

118

<sup>&</sup>lt;sup>25</sup> Chronik 125 Jahre Fuhrgewerbe-Innung Berlin-Brandenburg e. V. (2012.) Berlin: Fuhrgewerbe-

the range must cover most of the trips, and the cost must be comparable or better than for ICEVs. Solutions such as regular daily fast charging or mixedfleets might come afterwards in our opinion, after companies have gained experience on the technology and new services have emerged.

Penalizing conventional vehicles (for instance through regulatory constraints) is a way to improve the competition of EVs. However, the acceptability of such measures is not certain given that some businesses will simply not have alternatives to ICEVs. It is interesting to note that the acceptability of restrictive regulatory measures for conventional vehicles depends on the competitiveness of electric vehicles.

Next two parts propose to investigate more quantitatively the evolution of the constraints in the short and medium term:

- Given technological progress, how will the operational and economic constraints evolve?
- What share of companies may cope with these constraints with limited additional complexity compared with their current processes and vehicle use patterns?
- How strong is the regulatory mechanism induced by public incentives and how long can be expected, to absorb all current incentives?
- Will car manufacturers be able to supply a variety of electric vehicles, for instance with several battery capacities on the same vehicle segment?

#### Relative advantage

- It is absolutely necessary that the vehicle has the right size, the right range and the right price (two out of three is not enough). Financial constraints are very tight in a very competitive environment. In addition, the absence of supply delays the interest into EVs.
- EVs benefit from a positive image. They are well appreciated by drivers.
- Most third-account transport businesses are currently not affected by environemental regulatory constraints. Some companies are anticipating such future regulations.
- The electric vehicle market is not demand driven, with a notable exception: public tenders. Sum up: Except for some specific activities (postal distribution) the absence of adequate and affordable supply is prohibitive. The other specificities of electric vehicles are rather favorable, but do not compensate for this obstacle.

#### Complexity

- Companies are not willing to concede major organizational changes.
- Switching to electric vehicles requires a multitude of process changes.
- Overnight charging in own premises is the most likely solution. Excellent quality of service is crucial for the possible use of fast charging infrastructures. Ad hoc organisations allowing daytime charging may be relevant for particular activities (e.g. activities with night shifts).
- The use of electric vehicles require new skills and new software (mechanics, tour and fleet management softwares, range management, eco-driving, etc.)
- Mixing conventional and electric vehicles adds a layer of complexity, due to limited cooperation between drivers, and more difficult vehicle allocation.

<u>Sum up</u>: Electric vehicles essentially add new constraints, and require the change of a multitude of processes. **This complexity will only be overcome if there is some compensation.** 

#### Trialability and perceived risk

- Experimentation is the optimal way to gain experience. It is more complicated for small businesses.
- A loss of opportunity is inacceptable. Either there is a solution to cover all the trips, or no EV.
- Bigger companies have less needs in flexibility, and are better able to launch experiments.

#### Observability

- Electric vehicles are in the spotlight. The interviews exhibited relationships with personal mobility and the electric passenger car market.
- Different business associations may have different positions, either doing everything possible
  to ensure that members can adopt electric technology as soon as possible, or by lobbying to
  avoid electric vehicles being imposed when the technology is not mature (or anything in
  between)

#### Table 4 Summary of main findings. Crucial elements are in bold.

PART II – STATISTICAL MODELING OF THE DAILY VEHICLE KILOMETERS TRAVELED AND A MARKET SHARE MODEL BASED ON ECONOMIC AND RANGE CONSTRAINTS

## 4Modeling daily vehicle KILOMETERS TRAVELED

This section discusses the development of an original model.

Knowledge of average or aggregate distances traveled allows a quantitative assessment of the economic constraint of electric vehicles. The constraint of limited range however requires a precise knowledge of the variability of the daily vehicle kilometer traveled (DVKT). Longitudinal data, that is, data collected over a long observation period, provide this information. Unfortunately, these data are very often not available and have to be reconstructed indirectly from inadequate data sources.

Longitudinal data are expensive to collect, as it requires a daily collection (GPS or survey data). When studying commercial vehicles, longitudinal data are rarely available, as the majority of surveys focus on passenger vehicles. In an attempt to overcome the need for longitudinal databases to conduct a constraint analysis, we have been looking for a way to take advantage of partial data from a cross-sectional survey thanks to modeling. To do this, we developed a model able to generate random vehicle use profiles (DVKT distributions) consistent with the data on which the model is estimated. The model is thoroughly presented in this section.

Most of the previous work on DVKT modeling consisted in modeling agents one by one, whereas the originality of our approach consists in modeling

the entire fleet studied. Thus, this fleet is represented, once the model is estimated, with 5 parameters.

To this end, we take the classic approach of considering DVKT distributed according to a statistical law, but rather than estimating it separately for each individual, we consider that the parameters of this law are themselves distributed among the agents to represent the heterogeneity of uses.

By opportunity, and due to the absence of longitudinal data on light commercial vehicles, some explorations are made on the basis of longitudinal data on Indian taxis. The model is then estimated on a cross-sectional base on French commercial vehicles by maximum likelihood.

The results are encouraging because the model is capable of reproducing the data distribution functions on which the model is estimated. However, we note a slight bias: the frequency at which long distances are traveled is slightly overestimated. We deduce from this that in the use we make of the model, i.e. to evaluate whether range covers the majority of uses, the results will be rather conservative.

After the presentation of the main approaches to take into account the DVKT variability in the literature (Section 4.1), the specifications of the model are presented and justified, partly based on the Indian taxis database (Section 4.2 and 4.3). The next section then presents the maximum likelihood estimation (Section 4.4). The model is estimated on the SDES database on Light Commercial Vehicles (Section 4.5), finally the quality of the estimation is assessed (Section 4.5.3).

## 4.1 Literature on statistical modeling of daily vehicle kilometers traveled

## 4.1.1 Fitting agent-by-agent statistical distributions on longitudinal data

The reason we want to model uses is to measure the constraint of limited range. To this end, one variable of interest is the Daily Vehicle Kilometers Traveled (DVKT), defined as the sum of distances of all trips performed on a single day. The limited range of electric vehicles has brought some attention on the distribution of the DVKT across the population (we will interchangeably speak of a fleet of vehicles, or a population of agents, assuming each agent has one vehicle),

and several distributions have been considered to statistically represent the DVKT variations.

The most natural approach for statistical modeling of DVKT, when longitudinal data are available, is to fit a distribution directly on raw data for each agent (we will call this procedure an *agent-by-agent fit*). The validity of assuming the time series of DVKT as identically and independently distributed has been confirmed by Plötz et al. (2017).

This approach is still possible with somewhat aggregated data, if available data per agent is still sufficient to fit a distribution. For instance Greene (1985) proposes to use the Gamma distribution to infer DVKT from the distance driven between two visits at gas stations. In this case, the choice of the gamma distribution is chosen a priori for practical calculation reasons.

The three most common encountered distribution families are the gamma, log-normal and Weibull distributions. The exponential distribution has also been used, as a rough approximation (Traut et al., 2012).

Tamor and colleagues (2013) propose an original mixed distribution to represent trip distances, inspired by the visual inspection of the DVKT distributions of private cars, as well as by the dichotomy of trip purposes. The distribution is a mixture of a normal distribution (representing routine trips), and an exponential distribution for all other trips. This distribution, once fitted, has the merit to give rough information on the trip purposes (for instance the frequency of routine trips). This four-parameter distribution can be completed by a fifth parameter: the average number of trips completed on a given day, in order to sum up to get DVKT.

Plötz and colleagues (2017) explore more systematically the three aforementioned two-parameter distributions on four different datasets from Sweden, Canada, U.S.A and Germany, with different sample sizes and observation times. The two datasets with long observation times enable to compare the best distribution fits according to the sample size. The AIC shows a decreasing score of the log-normal distribution with the sample size, mainly in favor of the Weibull distribution. The authors come to the conclusion that there is no unique optimal choice, but the choice of distribution depends on the purpose of the study and of the data. They however notice that generally, the gamma distribution scores a bit worse than the Weibull or the log-normal distributions. The authors also notice that the log-normal distribution tends to overestimate the frequency of long trips.

On the opposite, Lin et al. (2012) find that the gamma distribution is particularly relevant in the context of a PHEV energy analysis. Dong and Lin (2014) present a stochastic model integrating the trip distribution (a gamma distribution) and the frequency of charging, to show the impact of daytime charging on the feasibility of electric vehicles. They also define a *range comfort level*, as the ratio of the DVKT with the EV range. Considering the range as a random variable following a Weibull distribution (range variations are affected by driving style, traffic conditions, temperature, etc.), they find an explicit formulation for this comfort level. Gamma and mixture gamma distributions are also used to represent the DVKT distribution of taxis from New York (Hu et al., 2018).

Except for the mixture of two gammas, which is bimodal, those distributions are mainly unimodal. Almost all of these studies use longitudinal data to fit their statistical distributions, with some adaptations when data are partial. There is no clear consensus on the most appropriate distribution: the choice of the distribution is very case dependent.

#### 4.1.2 Fleet-wide models

To our knowledge, the approach of Tamor et al. (2015) is the only one that goes beyond agent-by-agent modeling. It introduces distributions of the parameters of the DVKT distribution (which the authors call meta-distributions) to reproduce a whole population of agents. These marginal "meta-distributions" are supposed independent, and they raise a good estimation of the number of days requiring adaptation for a given range. The authors notice the similarity of the uses in different countries, and even propose a way to have rough estimates for a whole population only described by *one* parameter.

This attempt to estimate the days requiring adaptation without full longitudinal data is very similar to our approach.

## 4.2 A DVKT model

## 4.2.1 Model motivation and objective

Our model has been developed to estimate quantitatively the limited range constraint. It is used as an input for a constraint analysis (Section 5.3). We want to be able to quantify for a whole fleet the average driven distance (for TCO computations) and the probability of exceeding a given range that we will call

probability of requiring adaptation at range r,  $PRA_r$ . We want therefore a good estimation of the following function:

$$\omega: (r, p, q) \to Pr(PRA_r \le p, \overline{X} \ge q)$$

Where:

- $\bar{X}$  is the random variable representing the average driven distance of a random agent of the population of interest
- $PRA_r$  is the random variable representing the probability of requiring adaptation of a random agent of the population of interest (with range r).

With longitudinal data, the empirical cumulative distribution function enables an easy estimate  $\hat{\omega}$  provided the number of observations for each agent is high enough:

$$\widehat{\omega}: (r, p, q) \to \frac{1}{m} \sum_{q} \mathbb{1}_{[1-p;1]} \left( F_n^{(a)}(r) \right) \cdot \mathbb{1}_{[q;+\infty[} \left( \overline{x^{(a)}} \right)$$

with:

- $x^{(a)}$  the distribution of distances observed for agent a,  $F_n^{(a)}$  its empirical cumulative distribution function,  $\overline{x^{(a)}}$  its average.
- m: the number of individuals observed, n: the number of observations (which we assume constant for simplification)
- 1 is the indicator function:  $\forall x \in \mathbb{R}, A \subset \mathbb{R}, 1_A(x) = 1 \text{ if } x \in A, 0 \text{ otherwise.}$

We process data from a French database on LCVs (the SDES database on light commercial vehicles, see description in sub-section 4.5.1.1). Data are much less rich than longitudinal GPS data. The database contains only three pieces of information: the frequencies at which DVKT exceed 80 and 150 kilometers, and the average DVKT. This information does not allow recreating with precision a distribution of DVKT for a specific agent.

## 4.2.2 Model concept

We propose a model of the distributions of the DVKT of a population of agents, which statistically represents the variations at two levels:

- First, a bivariate sequence  $(p^{(a)})$  is generated among the population of agents a according to a distribution  $\mathcal{D}_P$ , to account for the *population heterogeneity*.
- Then, the DVKT of each agent a follow a statistical distribution  $\mathcal{D}_{\mathcal{A}}(p^{(a)})$ , representing the day-to-day variations.

This procedure is directly inspired by the work of Tamor et al. (2015). Many divergences can however be noted, in the choice of the DVKT distributions, in the parameterization and especially on the estimation procedure and necessary data for the model to be estimated.

We will use following notations: superscript (a) designates a quantity that refers to agent a, where  $a \in [1, m]$ , with m the number of agents. Subscript i refers to the i-th observation day, where  $i \in [1, n]$ , with n the number of generated observation days. By convention, random variables are uppercase letters, while specific realizations generated from the corresponding distributions are lowercase. The random variable P and its realizations  $p^{(a)}$  will represent the parameter of the DVKT distribution for agent a (accounting for the population heterogeneity, agents are considered independent). The random variable  $X^{(a)}$ , and its realizations  $x_i^{(a)}$  will represent the DVKT of agent a, on observation day i (observation days are considered independent).

The model is written as follows:

$$P \sim \mathcal{D}_P(\epsilon)$$
  $a \in [1, m], \quad X^{(a)} \sim \mathcal{D}_{\mathcal{A}} \circ \Phi(p^{(a)})$  (4.1)

with previously introduced notations, in addition to:

- $\mathcal{D}_P$ : a distribution family, representing the population heterogeneity. We call this distribution the parameters' distribution.
- $\epsilon$ : Parameters of  $\mathcal{D}_P$
- $\mathcal{D}_{\mathcal{A}} \circ \Phi(\cdot)$ : a distribution family representing the DVKT day-to-day variations.  $\Phi$  is a re-parameterization of  $\mathcal{D}_{\mathcal{A}}$ . The parameter of the distribution  $p^{(a)}$  is specific to agent a. We call this distribution the DVKT-distribution.

In this generic model, the parametric distribution  $\mathcal{D}_{\mathcal{A}}$ , as well as the dependence structure of  $\mathcal{D}_{P}$  will be defined *a priori*. Marginal distributions of  $\mathcal{D}_{P}$  and the parameters  $\epsilon$  will be estimated by maximum likelihood.

## 4.3 Justification of the model specification

In this section, we justify our choice for distributions  $\mathcal{D}_{\mathcal{A}}$ ,  $\mathcal{D}_{P}$  and transformation  $\Phi$ . We investigate several distributions and seek to maximize the likelihood of the data under these assumptions.

First sub-section introduces the database used to tune the model specifications (sub-section 4.3.1). The choice of DVKT distribution is discussed in sub-section 4.3.2. The parameters' distributions are discussed after in sub-sections 4.3.3 and 4.3.4.

#### 4.3.1 A longitudinal database on Indian taxis

One of the difficulties encountered during the model specification concerns the evaluation and validation of the model. In principle, it requires the availability of longitudinal data, none of which we had at our disposal for LCVs. No database on light commercial vehicle uses is to our knowledge openly available, all reviewed studies are mainly related to private vehicles. Rather by opportunity than by strategy, the database used is therefore a database on Indian taxis. It is our best guess to look at the uses of taxis, as they share similarities with LCVs. First, they are business users, and as are freight vehicles, they drive for a living, only instead of carrying freight they transport people. The diversity of trips which ensues is assumed to be similar for LCV users and taxi drivers.

The dataset describes DVKT of 318 Indian taxis (obtained from GPS data) in 8 different Indian cities, Ahmedabad, Bangalore, Chennai, Delhi, Hyderabad, Kolkata, Mumbai and Pune. The exploitation of the data mixes all cities. Data has been recorded by the company MapMyIndia. The observation period of each vehicle is at least 40 days, in average 92 days, 56 vehicles are observed on a period of more than 120 days.

#### 4.3.2 Choice of the DVKT distribution

Our model relies on statistical distributions of DVKT for a population of agents. No clear optimal distribution choice stands out in the literature, as discussed in sub-section 4.1.1.

#### 4.3.2.1 Exploring three distributions

The *gamma*, *log-normal* and *Weibull* distributions are explored, for which main characteristics are recalled in Table 5, and which are represented in a specific case in Figure 17. These distributions do not account for days at which

	Weibull	Log-normal	Gamma
Notation	$X \sim Wbl(\lambda, k)$	$X \sim Logn(\mu, \sigma^2)$	$X \sim \Gamma(k, \theta)$

	Scale: $\lambda \in \mathbb{R}_+^*$	$\mu \in \mathbb{R}$	Shape: $k \in \mathbb{R}_+^*$
Parameters	Shape: $k \in \mathbb{R}_+^*$	$\sigma \in \mathbb{R}_+^* \tag{1}$	Scale: $\theta \in \mathbb{R}_+^*$
Probability density function	$\forall x \in \mathbb{R}_+,$ $f_X(x)$ $= \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$	$\forall x \in \mathbb{R}_+, f_X(x)$ $= \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln(x) - \mu)^2}{2\sigma^2}\right)$	$\forall x \in \mathbb{R}_+,$ $f_X(x) = \frac{x^{k-1} e^{-x/\theta}}{\theta^k \Gamma(k)}$
Cumulative distribution function	$\forall x \in \mathbb{R}_+,$ $F_X(x) = 1 - e^{-(x/\lambda)^k}$	$\forall x \in \mathbb{R}_+, F_X(x)$ $= \frac{1}{2} + \frac{1}{2} \operatorname{erf} \left[ \frac{\ln(x) - \mu}{\sigma \sqrt{2}} \right]$	$\forall x \in \mathbb{R}_+,$ $F_X(x) = \frac{\gamma(k, x/\theta)}{\Gamma(k)}$
Mean	$\bar{X} = \lambda \cdot \Gamma \left( 1 + \frac{1}{k} \right)$	$\bar{X}=e^{\mu+\sigma^2/2}$	$\bar{X} = k \cdot \theta$

Table 5 Information about the three compared distributions. erf stands for the error function<sup>26</sup>,  $\gamma$  stands for the lower incomplete gamma function<sup>27</sup>,  $\Gamma$  for the gamma function<sup>28</sup>. (1) Parameters of the log-normal distribution are the expectation and standard deviation of the logarithm of the variable, which follows by definition a normal distribution.

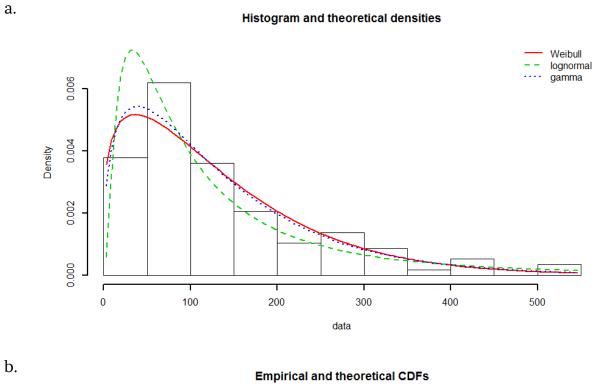
the vehicle is not used (all considered distributions have  $F_X(0) = 0$ ). As such, days at which the vehicle is not used are removed from the data. The number of days per year for which the vehicle is used is treated as a separate variable, considered independent.

Results for these distributions on the Indian taxi database are summarized in Figure 18 in the form of box-plots of negative log-likelihoods (normalized by the number of agents). Next to it are the shares of agents for which each distribution scores the best (minimal negative log-likelihood). The Weibull distribution is a good candidate, while the Gamma distribution is close behind. The Log-normal distribution seems a little bit weaker. We therefore, and in accordance with observations from Plötz et al. (2017), consider the Weibull distribution to be a good possible candidate.

<sup>&</sup>lt;sup>26</sup> Defined as:  $\forall x \in \mathbb{R}_+$ ,  $\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$ 

<sup>&</sup>lt;sup>27</sup> Defined as:  $\forall s, x \in \mathbb{R}_+, \gamma(s, x) = \int_0^x t^{s-1} e^{-t} dt$ 

<sup>&</sup>lt;sup>28</sup> Defined as:  $\forall s \in \mathbb{R}_+, \Gamma(s) = \int_0^{+\infty} t^{s-1} e^{-t} dt$ 



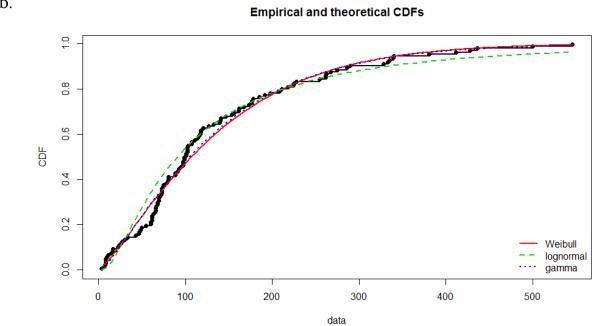
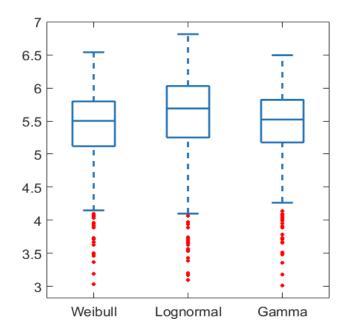


Figure 17 Example of Weibull, log-normal and gamma distributions fitted on the DVKT of one agent (a. density, b. cumulative distribution functions)



Best fit	
Weibull	65%
Gamma	27%
Log-normal	8%

Figure 18 Boxplots of the distribution of the negative log-likelihood (normalized by the number of agents) for three distributions fitted on each agent of the Indian taxi database. In the box, shares of agents for which each distribution scores the best according to the log-likelihood.

## 4.3.3 A reparameterization $\Phi$ to bring up the average

To account for the agent-to-agent variability, we would like to distribute the parameters pair (the usual shape and scale parameters) of the Weibull DVKT distribution across the population.

Rather than distributing these parameters directly, we perform a reparameterization involving the mean of the distribution. The main reason for this is to facilitate parameter estimation. Indeed, introducing the mean distance traveled as one of the parameters allows estimating one marginal distribution directly from the data, i.e. choosing the best marginal distribution family and two parameters out of five. The dimensionality of the likelihood maximization problem is thus reduced to three parameters.

For this purpose, a natural candidate is a reparameterization with the shape parameter and the mean of the distribution:  $(p_1, p_2) = \left(k, \lambda \cdot \Gamma\left(1 + \frac{1}{k}\right)\right)$  (with a Weibull distribution for the DVKT).

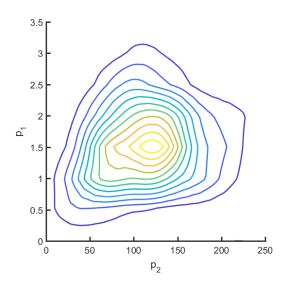


Figure 19 Kernel density function of the joint distribution of the parameters  $(p_1, p_2)$  after re-parameterization.

#### 4.3.4 Choice of the parameters' distribution

We look at the parameters' distribution. The parameters do not look statistically independent (see Figure 19), and to confirm this impression, two tests of independence are performed, based on *mutual information* and on *Spearman*'s *correlation*. The mutual information equals to 0.20, Spearman's correlation equals to 0.23. *p*-values have been computed (for the mutual information, via 1000 bootstrap samples). Both *p*-values would reject an independence hypothesis at level 99%. Independent generation of the parameters seems not sufficient, or the model would make a simplification by doing so. In return, considering the parameters independent reduces the number of parameters to estimate, so we're not immediately ruling out that possibility.

To define the parameters' distribution, we therefore explore the marginal distributions, but also a copula to account for the dependence structure, which is done in the next sub-sections.

#### 4.3.4.1 Marginal distributions

Based on the looks of the parameter distributions obtained on the taxi database and in the literature (e.g. Gamma distribution's shape parameter k, (Lin et al., 2012)), we assume that the two parameters could be represented by right-skewed statistical distributions.

Again, we tested the Weibull, gamma and log-normal distributions as candidates. Table 6 shows that the log-normal distribution for parameter  $P_1$  and Weibull for parameter  $P_2$  stand slightly out. Second choices are a Gamma distribution for  $P_1$  and a Gamma distribution for  $P_2$ .

	Weibull	0.99
	Log-normal	0.9
Distribution for $P_1$	Gamma	0.91
	Weibull	5.2
Distribution for $P_2$	Weibull Log-normal	<b>5.2</b> 5.3

Table 6 Negative log-likelihoods of different parameters' distributions  $D_{\mathcal{P}}$  (divided by number of agents), with the Weibull distribution as DVKT distributions  $D_{\mathcal{A}}$ . In bold are the best fits.

#### 4.3.4.2 Dependence structure

Among most common parameterized copulas, we are looking at a minimal parameterization of the dependence (always with the aim of keeping a small number of parameters). We therefore looked at the class of the bivariate Archimedean copulas (Frees & Valdez, 1998), which allow modeling dependence with a unique parameter.

Three families have been tested in addition to the independence of the parameters: the Frank, Clayton, and Gumbel copulas. These copulas are fitted using maximum likelihood estimates with the *copula* package for R, with lognormal and Weibull distributions as marginal distributions respectively, as found in the previous sub-section. The Akaike Information Criterion (AIC) is adequate, as now the considered models have different numbers of parameters.

The Clayton copula stands out as a clear winner (Table 7). Figure 20 shows the parameter pairs of individually fitted DVKT distribution, and the generated equivalent side-by-side (with Clayton copula, Weibull marginal distribution for the mean and lognormal distribution for the shape). We observe that, even if the data are not perfectly reproduced, the Clayton copula avoids

	AIC
Gumbel	3882
Clayton	3856
Frank	3878
Independence	3896

Table 7 Akaike Information Criteria (AIC) for the Gumbel, Clayton, Frank and independent copulas applied on parameter pairs  $(p_1, p_2)$ , with log-normal and Weibull marginal distributions respectively.

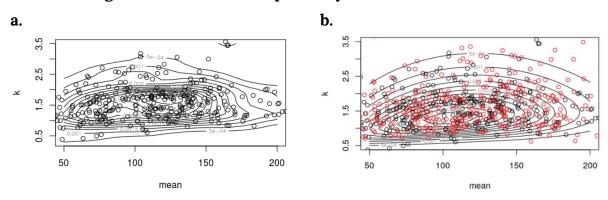


Figure 20 Parameter pairs of individually fitted Weibull distributions and its kernel density (a.), and corresponding Clayton copula based density with generated pairs in red (b.)

creating inconsistent profiles with high means and low shape parameters (unlike an independent generation, which would generate very long unrealistic trips).

## 4.3.5 Wrap-up

Given the previously obtained results, we choose a *Clayton copula*-based parameters' distribution. This choice has an interpretation: it avoids the creation of usage profiles with unrealistic distances traveled (great variability and great average distance traveled). For this reason, we decide to transfer this result from taxis to light commercial vehicles.

The first marginal distribution represents the heterogeneity of the sample. One can imagine that the distribution family may vary according to the

sample observed (e.g. what disparity of activities). The second marginal distribution is the average distance traveled, which can be estimated directly from the data. Thus, we decide to let these distributions free and integrate their choice into the model estimation.

We choose the Weibull distribution as the DVKT distribution  $D_{\mathcal{A}}$  with parameters  $(\lambda, k)$  and a transformation  $(p_1, p_2) = \Phi(\lambda, k) = \left(k, \lambda \cdot \Gamma\left(1 + \frac{1}{k}\right)\right)$ . Since this distribution of DVKT has already been found relevant in the literature, and to avoid too many possible distribution combinations to estimate, we choose to transfer this distribution to light commercial vehicles.

General model specification (equation 4.1) can thus be rewritten:

$$\begin{cases} P_{1} \sim D_{1}(\epsilon_{1}, \epsilon_{2}) \\ P_{2} \sim D_{2}(\epsilon_{3}, \epsilon_{4}) \\ \forall (u, v) \in [0, 1]^{2}, Pr[P_{1} < F_{1}^{-1}(u), P_{2} < F_{2}^{-1}(v)] = C_{Clayton}(u, v; \epsilon_{5}) \end{cases}$$

$$\forall \ a \in [\![1,m]\!], \qquad D^{(a)} \sim Weibull \left(\frac{p_2^{(a)}}{\Gamma\left(1+\frac{1}{p_1^{(a)}}\right)}, p_1^{(a)}\right)$$

The nature of  $D_1$  and  $D_2$ , as well as the parameters  $\epsilon_1$ ,  $\epsilon_2$ ,  $\epsilon_2$ ,  $\epsilon_4$ ,  $\epsilon_5$  have to be estimated on the data. Considered distributions for  $D_1$  and  $D_2$  are Weibull, gamma or log-normal distributions.

We will next present the fitting procedure, before assessing the performance of this DVKT model.

## 4.4 Maximum likelihood fitting procedure

The next step shows how the model can be estimated on partially available data. The model is estimated on data about the vehicle uses with maximum likelihood. The idea is to find the nature of the two marginal distributions and the five parameters of the model for which the observed statistics are the most likely to occur.

We will detail here the procedure on the SDES database. The estimation methods for fitting the model on longitudinal data can be found in appendix (Appendix 2). Many other data formats could be used instead to estimate the model, but will not be detailed here. To give but one example, the model has been successfully estimated on the average and maximum distances traveled.

The SDES database is presented in detail in sub-section 4.5.1.1.

#### 4.4.1 General setting

It is assumed that for each agent  $a \in [1, m]$ , information about q descriptive statistics  $(s_1^{(a)}, s_2^{(a)}, ..., s_q^{(a)})$  of the DVKT distribution are known (in practice when no longitudinal data are available, q = 2 or q = 3).

We will use i for indexing the different observations and n for the total number of observations (which we consider identical for all agents to simplify notations, but which is not required by the procedure). The superscript (a) will index the different agents, and m the total number of agents. k will be used to index the statistics, total number of statistics is denoted q.

The likelihood function can be written as follows:

$$L\left(\left(s_{k}^{(a)}\right)_{a,k};\epsilon\right) = \prod_{a} f_{S|E}\left(\left(s_{k}^{(a)}\right)_{k} \middle| \epsilon\right)$$

$$= \prod_{a} \iint_{\mathbb{R}^{2}_{+}} f_{S|P}\left(\left(s_{k}^{(a)}\right)_{k} \middle| p^{(a)}\right) dF_{P}\left(p^{(a)} \middle| \epsilon\right)$$

$$(4.2)$$

Then, the negative log-likelihood is:

$$-LL\left(\left(s_{k}^{(a)}\right)_{k,a}; m\right)$$

$$= -\sum_{a} \log \left(\iint_{\mathbb{R}^{2}_{+}} f_{S|P}\left(\left(s_{k}^{(a)}\right)_{k} \middle| p^{(a)}\right) dF_{P}\left(p^{(a)} \middle| \epsilon\right)\right)$$

$$(4.3)$$

where  $f_{S|E}(\cdot | \cdot)$  and  $f_{S|P}(\cdot | \cdot)$  denote the conditional probability density functions of the statistics obtained from the model, given the value of the model parameters or the DVKT distribution parameters respectively. Sums, products and index of sequences over i and j are implicitly for  $a \in [1, m]$ ,  $i \in [1, n]$  and  $k \in [1, q]$ . Second line of equation 4.2 involves the law of total probabilities.

The integral will be approached by a Monte-Carlo method. The explicit computation of the factor under the integral is detailed in the following subsection for the specific setting of the SDES database.

## 4.4.2 SDES setting

We have three pieces of information on the uses of the LCVs in the SDES database. The first one is the average distance traveled, the second and third ones are the frequency with which distances of 80 and 150 kilometers are

exceeded. An additional difficulty is that the database only tells whether they are inside given intervals (5 days per week or more, 3 or 4 days a week, 1 or 2 days per week, 1 to 3 days per month, never or less than one day per month). The frequencies are set to the interval [0; 1], considering 5 working days a week and 21 working days a month.

We note  $r_1 = 80$  and  $r_2 = 150$  the two ranges. For an agent  $a, a \in [1, m]$ , we know:

$$1 - F_n^{(a)}(r_1) \in \left[ s_{1,inf}^{(a)}, s_{1,sup}^{(a)} \right]$$

$$1 - F_n^{(a)}(r_2) \in \left[ s_{2,inf}^{(a)}, s_{2,sup}^{(a)} \right]$$

$$s_3^{(a)} = \underset{i \in [\![1,n]\!]}{mean} \left(x_i^{(a)}\right) = n^{-1} \sum_{i=1}^n d_i^{(j)}$$

We do not know precisely the number of days on which the observations are estimated by the respondents. We assume they responded based on about a year's experience, or n = 250 working days.

Then, for a given  $a \in [1, m]$  (that we omit in the notations for more clarity):

$$f_{S|P}((s_k)_k) = Pr(1 - F_n(r_1) \in I_{r_1}, 1 - F_n(r_2) \in I_{r_2} \mid X = s_3, p) \cdot f_{\overline{X_n}}(s_3 \mid p)$$
(4.4)

We note  $\mu_X$  and  $\sigma_X$  the mean and standard deviation of the distribution of X. We also note:

$$\overline{X_n} = \frac{1}{n} \sum_{i=1}^n X_i$$

$$Y^{(r)}=\mathbb{1}_{X>r}$$

$$\overline{Y_n^{(r)}} = \frac{1}{n} \sum_{i=1}^n Y_i^{(r)}$$

Note that  $\overline{Y_n^{(r)}}$  is related to the random empirical distribution  $F_n(r)$  by:

$$\overline{Y_n^{(r)}} = 1 - F_n(r)$$

and therefore has average 1 - F(r). It also has variance F(r)(1 - F(r)) ( $I_{X>r}$  the outcome of a Bernoulli trial).

The central limit theorem gives the following convergence in law:

$$\sqrt{n} \left[ \left( \overline{Y_n^{(r_1)}}, \quad \overline{Y_n^{(r_2)}}, \quad \overline{X_n} \right) - M \right] \stackrel{\mathcal{L}}{\to} \mathcal{N}(0, \Sigma)$$
(4.5)

where:

•  $\Sigma$  is the variance–covariance matrix of  $X, Y^{(r_1)}$  and  $Y^{(r_2)}$ , equal to:

$$\begin{pmatrix} F(r_1) \Big( 1 - F(r_1) \Big) & F(r_1) (1 - F(r_2)) & \Big( 1 - F(r_1) \Big) \Big( E[X]_{r_1} - E(X) \Big) \\ F(r_1) (1 - F(r_2)) & F(r_2) \Big( 1 - F(r_2) \Big) & \Big( 1 - F(r_2) \Big) \Big( E[X]_{r_2} - E(X) \Big) \\ \Big( 1 - F(r_1) \Big) \Big( E[X]_{r_1} - E(X) \Big) & \Big( 1 - F(r_2) \Big) \Big( E[X]_{r_2} - E(X) \Big) \end{pmatrix}$$

- M is the vector of means  $(1 F(r_1); 1 F(r_2); \mu_X)$
- $[X]_r$  represents the at r left-truncated Weibull distribution with same parameters than X. Closed formulae of the moments of the truncated Weibull distributions can be found in (Crénin, 2015).

For the computation of equation 4.4, we make the approximation of using the asymptotic form (equation 4.5). Equation 4.4 can then be simplified to:

$$f_{S|P}((s_k)_k) = \iint_{s_{inf}}^{s_{sup}} f_{\mathcal{N}}([s_1, s_2]|\overline{X_n} = s_3, p) \, ds_1 ds_2 \cdot f_{\overline{X_n}}(s_3|p)$$
(4.6)

where  $f_{\mathcal{N}}(\cdot | \overline{X_n})$  is the (multivariate normal) distribution of  $\overline{Y_n^{(r1)}}$  and  $\overline{Y_n^{(r2)}}$  conditionally to  $\overline{X_n}$ . The first term is then a bivariate Gaussian cumulative distribution function, directly available in numerical calculation tools such as Matlab. The expression of the conditional multivariate normal distribution can be found in (Do, 2008).

The final result is finally obtained by combining (4.3) with (4.6).

#### 4.4.2.1 Optimization algorithm

The solution to this optimization problem is approached numerically with Matlab2013b fmincon function, for non-linear constrained minimization, with an interior-point algorithm (Byrd et al., 2000). To facilitate the convergence algorithm  $\epsilon$  is normalized by the initial point, to have variables with the same order of magnitude.

In practice, we fitted the best marginal distribution on the observed average distance traveled, getting  $\epsilon_1$  and  $\epsilon_2$ . We then started a 5-parameter optimization process, but allowed only small variations ( $\pm$  5%) to the parameters already estimated. The choice of the marginal distribution of  $p_2$  is done by

estimating the model with different candidate distributions (Weibull, gamma, lognormal), and choosing the one that raises the maximum likelihood.

# 4.5 Model estimation on the SDES database about light commercial vehicles in France

In this section, the model is estimated on a database about light commercial vehicles in France.

### 4.5.1 Database and pre-processing

#### 4.5.1.1 The SDES database on LCVs

The database used is the SDES database. It is a survey performed in 2011 on light commercial vehicles (less than 3.5 tons of vehicle gross weight), which have been registered in France. The survey was carried out by the statistical service of the Ministry of the Environment. The sampling plan results from a stratified drawing resulting in 38 strata, based on the crossings of five variables: the gross vehicle weight, the year of first circulation, the status of the users (business or private users), if applicable the activity of the company and the type of fuel used. Freight transport activities are deliberately over-represented in the sampling design compared with other activities.

This database contains information on the vehicle (age, gross vehicle weight, fuel, etc.), on its ownership status (year of acquisition, mode of acquisition, etc.), on its use (annual distance traveled, distribution by type of journey, frequency of trips of more than 80 and 150 km, etc.) and on the business activity. It has the advantage of being a relatively large base (15,093 entries).

However, beyond the approximate frequency of daily trips exceeding 80 or 150 kilometers, little information on the *variability* of the uses is present.

#### 4.5.1.2 Database pre-processing

The database has already been statistically processed, resulting in the weighting of entries to be representative of the French fleet, as well as imputation of some partial non-response. In addition, since the scope of the survey goes beyond the scope of our study (for example, we are only interested in the new vehicle market), we pre-processed the database. We apply following filters:

• We keep only the vehicles that have been used at least once during the year of survey (2011).

- We exclude the privately-owned LCVs, as they would require different TCO computations (different taxes). The private cars transformed into LCVs (private car derivatives) are kept however as they benefit from the same taxation (the fact that their purchase price may be slightly different is less relevant, as it is the *price difference* that matters, and not the absolute price). For the same reason, transformed vehicles are kept in the database. After this step, there are 12,687 remaining entries.
- The database is representative of the vehicle fleet, while we are interested in the new vehicle market. To be representative of this market we keep only the vehicles that have been bought new (or used with less than 5,000 km odometer reading). We filter three suspicious entries with declared average daily trips of more than 1,500 kilometers. After this step, there are 6,311 remaining entries.
- Uses may differ between time of purchase and a few years laters, therefore only vehicles bought the year of the survey and the year before are kept. Implicitely, the vehicles for which the purchase date is not given are filtered. After this step, there are 2,159 remaining entries.
- We keep in the first place vehicles with gross weight less than 2,500 kg, that we define as the small van segment (1,349 entries). The average distances for bigger vans (between 2,500 kg and 3,500 kg gross weight, 810 entries) will also be used to show how they are relatively more difficult to electrify.

Due to a high partial non-response on the fields relative to the usual daily driven distance, the annual driven distance and the frequencies of use of the vehicles (around 20%), these variables have been adjusted by the statistical services. Note that these are specifically the features we are using to fit our use model. However, in the adjustment, unlikely combinations of these variables have been produced. For instance, a vehicle that exceeds 80 kilometers very rarely should not be able to travel 300 kilometers per day in average.

To eliminate these false entries, entries with likelihoods under a given threshold have been removed. The threshold has been chosen by visual inspection of these entries. This final procedure discards inconsistent data, to arrive at our final base. This base is composed of 1,020 small vans (329 entries filtered in this last step). As for bigger vans, the resulting database has 608 entries.

In addition to this non-response adjustment, it can be observed that some entries are repeated several times. Most likely, a fleet manager who received multiple questionnaires completed them all identically. This observation raises the question of stated data accuracy.

Additionally, some variables have been worked on:

- Annual distances of vehicles purchased in 2010 are adjusted in proportion to their running time in days (if a vehicle is purchased halfway through the year, the annual driven distance is multiplied by a factor 2).
- Distances traveled on private sites were assimilated to distances driven in urban environment, given the probable low speeds.
- The survey asks for the frequency in number of exceedance days per month of 80 km and 150 km distances. Five frequency classes are proposed in response. The frequency classes are transformed into an upper and lower probability of exceeding 80 and 150 kilometers a day.

#### 4.5.2 Model fit

Resulting parameters and distributions from model estimation are given in appendix. Figure 21 compares, for the average driven distance and the frequency at which 80 and 150 kilometers are exceeded in a single day, the cumulative distribution functions resulting from the model with the raw data.

We observe that the maximum likelihood estimation leads to a model that is perfectly consistent with the observed data, for both the average distance traveled and the PRAs.

These are encouraging results: the data on which the model is estimated was not easy to exploit. The information on the variability of the trips is rough (data by frequency classes, for only two distances, 80 and 150 kilometers), the recovery of partial non-response leads to inputs that are not exploitable, and inputs are weighted with large weight variations, etc. Nevertheless, the model makes it possible to estimate, whatever the range considered, the joint distribution of the average driven distance and the probability of requiring adaptation of a whole fleet of vehicles.

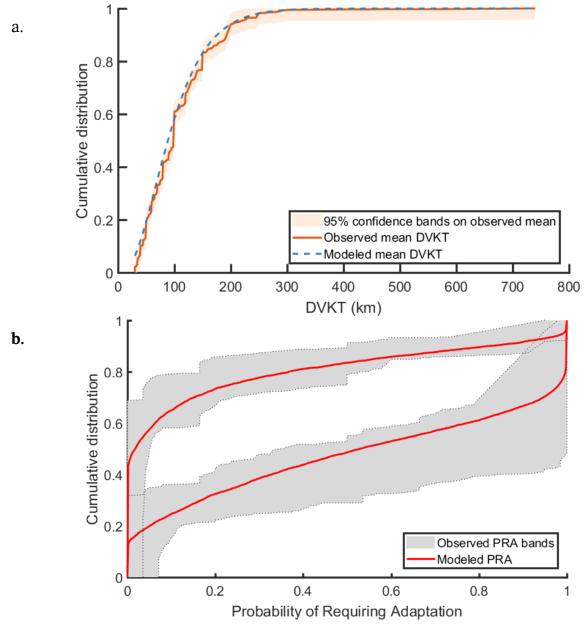


Figure 21 Comparison of observed and modeled average distances traveled (a.) and probabilities of requiring adaptation with range 80 km and 150 km (b.)

## 4.5.3 Assessing the goodness of fit of the model

So far we have introduced a DVKT model and its fitting procedure, modeling a DVKT distribution for each individual across a population. The model has been successfully fitted on a database about light commercial vehicles.

This section aims at assessing the model performance for its use with the electric vehicle market forecast model of Chapter 5. The different sources of uncertainty are identified and their order of magnitude evaluated.

#### 4.5.4 Identification of the error sources

Before quantitatively assessing error of the model, different error sources are identified:

- Statistical uncertainty on the data
  - Each agent's vehicle uses are observed on a limited number of days.
     So the statistics of interest are estimations, and have standard errors (which is the standard deviation of the estimation).
  - o In the same manner, the limited number of observed agents, representing a small subset of the whole population, is another source of uncertainty.
  - In our case, the sample is assumed to be representative (it has been subject to statistical adjustment), but can generally be an additional source of bias
- Uncertainty on the output of the model
  - Specification bias: the model is a simplification of real world mechanisms, and real data does not follow exactly the distribution of the model.
  - The model propagates the uncertainties of the input data.
  - An irreducible error arises from all factors that are not observed,
     but which may influence the observations.

The remainder of this section is intended to provide a quantitative assessment of the error made by estimating the DVKT model on data.

# 4.5.5 Statistical uncertainty on the data

First, let us explore uncertainties introduced by the sampling of the agents. We assume that the sample is representative of the whole population, and that there is no selection bias.

First, the central limit theorem gives a pointwise estimate of the uncertainty, with following convergence in law:

$$\forall t \in \mathbb{R}, \quad \sqrt{n} \big( F_n(t) - F(t) \big) \stackrel{\mathcal{L}}{\to} \mathcal{N} \left( 0, F(t) \big( 1 - F(t) \big) \right)$$

with:

- $F_n$ : empirical cumulative distribution function of  $(x_i^{(a)})_i$
- F: real distribution function of X

Alternatively, it is interesting to look at the confidence bands from the empirical cumulative distribution function (ecdf), obtained by the Dvoretsky-Kiefer-Wolfowitz inequality:

$$\forall \epsilon > 0$$
,  $Pr\left(\sup_{x} |F_n(x) - F(x)| > \epsilon\right) \le 2 \exp(-2n\epsilon^2) = \alpha$ 

where  $F_n$  is the ecdf, F the exact distribution function, n the size of the sample,  $\epsilon$  the size of the confidence band, and  $\alpha$  the confidence level. Thus:  $\epsilon = \sqrt{\frac{1}{2n} \cdot \ln{\left(\frac{2}{\alpha}\right)}}$ 

We finally get the lower and upper confidence bands:

$$L(x) = \max(F_s(x) - \epsilon, 0)$$

$$U(x) = \min(F_s(x) + \epsilon, 1)$$

In Figure 22 are presented the order of magnitude of  $\epsilon$  according to the sample size, at level 0.05, 0.2 and 0.4. We observe that for small samples (less than 100 individuals), the possible error on the empirical cumulative distribution function is substantial.

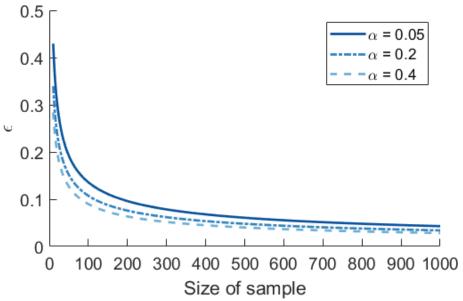


Figure 22 Size of confidence bands (at level 0.05, 0.2 and 0.4) of the empirical cumulative distribution function, according to the size of the sample (number of agents)

# 4.5.6 Inspection of the marginal distributions

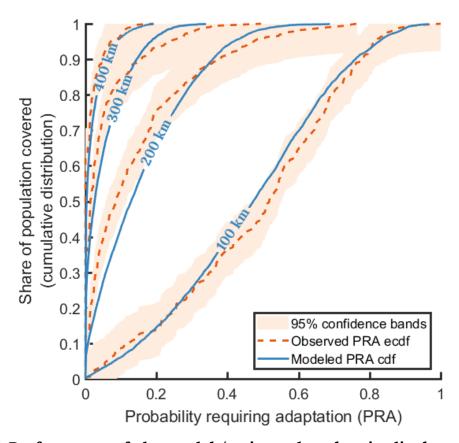


Figure 23 Performance of the model (estimated on longitudinal taxi data) on the prediction of the PRA with 100, 200, 300 and 400 kilometers of range

To assess the relevance of the model we compare the marginal distributions of the average distance traveled, and the PRA with several ranges. The good fit of the average distance traveled can already be appreciated on Figure 21 (a.) for the light commercial vehicles, and works equally well on the taxi data, so we will focus on the PRAs.

Figure 23 represents PRA distribution functions (observed and modeled) on the taxi data, with the model estimated on longitudinal data, for different considered ranges. The graph reads like this: the share of vehicles having a PRA inferior to 20% (0.2 in abscissa) with 100 kilometers of range is 15%. This figure rises to 75% with 200 kilometers of range. To put the differences into context, the 95% confidence bands on the empirical data are also represented. They take into account the number of agents sampled (but not the limited number of observation days).

This figure shows the specification error: differences up to 10 points are visible. The model seems to overestimate the frequency of exceeding the range for rare trips (i.e. low PRAs seem to be somewhat overestimated). However, we

note the **model's robustness across different ranges**, which was a strong requirement. We anticipate that our range constraint will be somewhat conservative.

# 4.5.7 Size of the sample and fitting procedure

We showed a good match between the model and the data on which it is estimated. We will now study sample and estimation uncertainties.

For this purpose, we create artificial samples directly generated from the model. PRA classes are extracted from this sample, in order to reproduce the available information from the SDES database. The model is then estimated on this information, and the result is then compared with the original model from which the sample is generated. Alongside, we also evaluate the longitudinal and agent-by-agent procedures.

As the fitting and assessment procedures are computationally demanding, only one specific example is investigated, with following distributions and parameters:

$$D_1=\text{Log-normal}; D_2=\text{Gamma}$$
  $\epsilon_1=1.63;\ \epsilon_2=1.63;\ \epsilon_3=3.03;\ \epsilon_4=32.8;\ \epsilon_5=0.748$ 

We test this distribution on two different sample sizes, one with 1,000 agents and 250 observation days (which represent conditions similar to our estimate based on SDES data) and one with 200 agents with 30 observations days each. Three estimation methods were assessed, the maximum likelihood method on disaggregated longitudinal data (which we will call longitudinal estimate), the agent-by-agent method on disaggregated longitudinal data (which we will call agent-by-agent estimate), and the maximum likelihood method on aggregate data in the same manner as in the SDES data (which we will call SDES estimate). The longitudinal estimate was not performed on the largest sample, because the way we implemented the procedure was provoking a memory shortage.

We assess a distance between the estimated model and the original model by using a bivariate Kolmogorov-Smirnov statistic<sup>29</sup> (Justel et al., 1997) for the pair (mean distance, necessary range). The necessary range is defined as the range r needed for an agent such that  $PRA_r = 1/250$ , or put differently the last 1/250-quantile of the DVKT distribution of each agent.

-

<sup>&</sup>lt;sup>29</sup> The Kolmogorov-Smirnov statistic is the maximal absolute value of the difference between the empirical and theoretical distribution functions:  $D_n = \sup_x |F_n(x) - F(x)|$ .

a. 1000 agents with 250 observations each							
	1	2	3	4	5	KS-stat mean	KS-stat std
Long							
ABA	0.018	0.022	0.029	0.020	0.056	0.029	0.016
SDES	0.050	0.15	0.051	0.091	0.060	0.080	0.042
b. 200 agents with 30 observations each							
	1	2	3	4	5	KS-stat mean	KS-stat std
Long	0.13	0.12	0.082	0.042	0.087	0.092	0.034
ABA	0.15	0.12	0.28	0.17	0.046	0.16	0.085
SDES	0.28	0.13	0.25	0.40	0.049	0.22	0.13

Table 8 Bivariate Kolmogorov-Smirnov statistics of the estimated model compared to the original model from which the data are generated, for different estimation procedures, and different sample sizes. Long = longitudinal estimate. ABA = agent-by-agent estimate. SDES = SDES estimate. Std = Standard deviation.

To compute this statistic, two samples of 30.000 agents (one for each model) are generated and compared. This size of sample has been found (manually) as a good trade-off between computation time and standard error. The order of magnitude of the standard error on the Kolmogorov-Smirnov estimate is then around 0.01. The procedure is launched 5 times for each sample size. The results are presented in Table 8.

First, we observe for the biggest sample (Table 8 a.) that the agent-by-agent performs very well, with an average Kolmogorov-Smirnov statistic of around 0.03. The error on the SDES procedure is worse, but remains moderate, with a Kolmogorov-Smirnov estimate of 0.08 in average. The observation of the cases for which this statistic is the worst (cases 2 and 4) give some explanations. Compared to the original model, these cases present errors of opposite signs for the parameters of the marginal distribution of the shape parameter ( $\epsilon_1$ ,  $\epsilon_2$ ) on one side, and the parameter of the Clayton copula  $\epsilon_5$  on the other side. Despite the rather poor results of the bivariate Kolmogorov-Smirnov statistic, marginal distributions fit well. This suggests that the data on which the model is estimated do not allow clearly dissociating the respective impact of these parameters. **The** 

dependency structure through the Clayton copula thus improves the specification on longitudinal data, but increases estimation error on the SDES data.

When inspecting the second part of the table (Table 8 b.), we find that the longitudinal estimate produces the best results for smaller samples, significantly better than the agent-per-agent estimate (Kolmogorov-Smirnov statistics of 0.09 and 0.16 respectively). The problem of the agent-by-agent estimate comes from the two-step estimation procedure: having only 30 days of observation degrades the DVKT distributions fits in the first step, and creates outliers to which the parameter distribution estimate is sensitive in the second step. The longitudinal estimate does not have this issue. We note that the order of magnitude of the Kolmogorov-Smirnov statistic for the longitudinal estimate is consistent with the empirical errors reported in Figure 22.

The SDES estimate is the worst. Working on data with degraded information on the uses comes at a cost: to have a quality estimate, the amount of data must compensate for the low-quality information.

# Chapter conclusion

The use model has been developed in order to be able to conduct a disaggregated study on the range and cost constraints of EVs. Many studies take the shortcut of looking at average uses rather than to a distribution of uses: this leads to systematically highly biased and overoptimistic results for BEVs and PHEVs.

However, a proper disaggregated study usually requires a lot of data. If working directly on raw data, then the requirements of the range constraint may be increasing with the number of observations, which is not satisfactory (uneven numbers of observation is difficult to handle as well). One approach is to fit a specific distribution on each agent. It is then necessary to have enough observations per agent to be able to fit a distribution on the DVKT variations. This limits disaggregated approaches to specific geographical scopes, or agent types, depending on availability of data.

Our proposition is a statistical model representing the DVKT variations by parametric statistical distributions. It also reduces the need for input data, enabling to estimate the model without longitudinal data, for instance only with average and maximum driven distances, which can be stated by the user in a one-time cross-sectional survey. This is especially relevant for the exploration of smaller markets, for which data are scarcer.

We have observed that some specification error is made by fitting the model. This is a margin of progression for the model. Perhaps other distributions could give better results. In the meantime, we will consider that the results are slightly conservative for the limited range constraint analysis.

Furthermore, we also identified that when the baseline data are aggregated, the estimate did not always converge well to the best model, even for large sample sizes. These estimation problems seem to stem from the fact that this data format does not clearly distinguish the impact of a variation on the Clayton copula from the impact of a variation on the marginal distribution of the shape parameter. Simplification of the model while maintaining a dependency structure should be possible. For example, prior definition of what a *realistic* profile is and filtering unrealistic profiles could be a way to free oneself from the copula without generating inconsistent profiles.

# 5ELECTRIC VEHICLE MARKET SHARE MODELING

In this chapter, we construct a model for evaluating potential future market shares of electric vehicles. The model aims to construct of time series of market shares, to account for rapidly evolving technology. Particular emphasis was placed on sensitivity analysis in order to identify limitations and draw robust conclusions from the results.

As ambitious environmental objectives have been set for the medium term (cf. sub-section 3.1.4), electric vehicle is part of the solution for reducing local and global pollution. It is therefore essential for the authorities to understand the temporal dynamics to take the most appropriate and targeted actions to achieve these goals.

On the one hand, technological development offers interesting prospects, while on the other hand electric vehicles today need significant subsidies to be competitive. The question of the future of battery electric vehicles, in our case of light commercial vehicles for business users, remains therefore open.

This model is based on both economic and operational constraints. These constraints have been identified as the most critical to the success of electric vehicles and it is essential that both be lifted for the effective development of electric vehicles (Chapter 3). The limited range calls for small

driven distances, while on the contrary economic competitiveness is better for long distances traveled, by maximizing the fuel displacement. They therefore call for contradictory behavior. This makes them particularly blocking, and it is therefore essential to study them jointly.

The core of the model is a constraints analysis. It first generates real use profiles for a complete fleet. Economic and operational constraints are then assessed for each agent, and then aggregated over the whole population. Economic assessment is done through a Total Cost of Ownership (TCO) calculation. The constraint of range is assessed by the frequency at which the range is exceeded, that we call probability of requiring adaptation (PRA). On top of that, technological scenarios and a simple consideration of the diffusion of electric vehicles finally allow the construction of time series.

Our model meets an essential requirement for assessing the operational constraint: the heterogeneity and individual variability of uses. Uses are modeled according to the method presented in Chapter 4, allowing the market potential model not to be dependent on costly longitudinal data. A reference scenario will be constructed and analyzed in Chapter 6. This chapter is focused on the methodological aspect.

The first section (5.1) reviews several methods in the literature for the quantification of the economic and operational constraints, and highlights the difficulty in predicting market shares. Many approaches have been applied to assess the market potential of electric vehicles, or to make market forecasts. However, these market forecasts are highly variable, reflecting the difficulty of such an exercise. The second section (5.2) gives a general overview of the model, followed by a focus on the decision model, which sets the acceptability criteria for electric vehicles (section 5.3). Section 5.4 deals with the transition from market potentials to market share time series and section 5.5 details the sensitivity analysis.

The model described in this chapter led to the development of a Matlab tool, allowing the evaluation of one or several alternative technologies with the conventional technologies, and to browse the results graphically. This tool is used by Renault's research department as a decision-making aid to determine the most promising technology or technologies on which to invest the most resources.

# 5.1 Constraints quantification and market forecast methods

In this section, we are interested in the quantitative measurement of electric vehicle constraints in the literature, first the economic constraint (sub-section 5.1.1) and then the limited range constraint (sub-section 5.1.2). Some methods allow market potential or future market share scenarios to be calculated. After noticing the difficulty of the exercise (sub-section 5.1.3), the main methods are explained (sub-sections 5.1.4, 5.1.5 and 5.1.6).

# 5.1.1 Quantifying the economic performance

One conclusion of Part 1 is that economic competitiveness is critical for the success of electric vehicles for business users. This sub-section explores the quantification of this economic barrier in the literature, which is mostly done through total cost of ownership (TCO) calculations.

#### 5.1.1.1 The total cost of ownership as a way to assess the economic performance

Some transportation companies perform advanced evaluations through total cost of ownership. There is not one uniform rule behind economic competitiveness, as each company has its own evaluation and decision processes and its own assumptions. Those depends on the scope of the evaluation (an isolated experimentation and a full fleet change will be assessed differently), on the uncertainties surrounding the technology (how much range will I have during winter with a fully loaded vehicle?), or on the knowledge of the precise uses of the vehicles. From the perspective of a given company, the competitiveness assessment also depends on projections, regarding criteria such as coverage of publicly accessible charging infrastructure, or fuel prices.

TCO computations can thus be very case dependent. It is therefore essential to make a thorough sensitivity analysis, and to challenge the robustness of input parameters.

#### 5.1.1.2 Total cost of ownership analysis for freight in the literature

TCO computations have been conducted for light commercial vehicles in several countries and with several assumptions.

Total cost of ownership is a financial estimate of the direct and indirect costs of a product over its life or ownership. The TCO accounts only for the financial costs supported by the *customer* (and as such does not account for

costs of externalities borne by the society). It is computed as the sum of a sequence of discounted cash flows:

$$PV = \sum_{t} \frac{1}{(1+p)^n} \cdot A_t$$

with:

• *PV*: Present Value

•  $A_t$ : Amount of costs at year t

• *p* : Discount rate

• n: Time, in number of years

The discount rate is the minimum required rate of return, and the higher the risk, the higher it is (Jain, 1999). It takes into consideration the fact that the same amount earned today has more value than earned tomorrow (and oppositely for spent money).

Several studies investigate the TCO of electric vans and trucks. The results are highly variable with several parameters: the type of vehicle that is evaluated (vehicle size, battery capacity), the context in which it is evaluated (vehicle taxes, fuel, subsidies or tax exemptions for electric vehicles, etc.) which can change over time, and the assumptions and parameters that were chosen (evaluation period, usage, infrastructure cost, etc.).

Lee et al. (2013), Van Amburg and Pitkanen (2012) and Davis and Figliozzi (2013) have investigated the US case for medium-sized trucks (around 7 tons gross vehicle weight). Lee et al. (2013) use a statistical distribution of numerical hypotheses to take into account uncertainty, and find (in the baseline) a TCO distribution centered around zero, which shows that electric vehicles are competitive in some scenarios even without subsidies. The total cost of ownership is computed over the vehicle's lifetime, considered to be 240,000 kilometers. Van Amburg and Pitkanen (2012) insist on the potentially surprising high costs that can occur for installation of charging infrastructure, due to electrical works, and the need to carefully plan in advance the deployment of further vehicles. Hidden costs linked to the infrastructure affect large fleets in particular, as upgrade works may be necessary for the electrical installation. Davis and Figliozzi (2013) present a model that integrates and combines routing constraints, speed profiles and vehicle ownership costs.

There are European studies as well. Lebeau et al. (2015) consider a wide range of different small vans. TCO calculations are made for the Belgian market, with €5,000 subsidies. In general, the results put electric vehicles between their diesel counterpart (cheaper) and their petrol counterpart (more expensive, provided 7,500 kilometers or more are traveled per year. In France, Crist (2012) studies the TCO and societal cost of three electric vehicles, including one LCV (the Renault Kangoo). The research shows that he difference in TCO between conventional and electric vehicles is smaller for professional users (with almost comparable TCO between conventional and electric LCVs after only three years) than for private individuals. However, assumptions are rather optimistic for the professional user given the range of the vehicle at that time (90km/day for 260 days a year are assumed, which is flirting with the maximum range of the considered electric vehicle every working day: it is the most optimal use profile a company can have for using electric vehicles). It also finds negative overall balance for society, mainly due to a loss in government revenue on fuel taxes and the expense for the subsidy of electric vehicles with an additional cost over the vehicle lifetime of almost €7,000.

In the Frevue project (Quak et al., 2017), a TCO assessment is made on several van and truck sizes. Small vans with 60km/day appear to have a similar TCO than conventional vehicle after only 2 years (with a €5,000 subsidy), and 4 years without subsidy. These encouraging (and compared with ours, optimistic) results are mostly due to supposed substantial savings on maintenance (around €5,000 in the first five years). For medium-sized vehicles (from 3.5 to 7.5 tons gross vehicle weight), the balance is more mixed, with a break-even point at 7 years with subsidies, 10 years without subsidies. For bigger trucks, electric vehicles do not break even with conventional trucks within 10 years, even with subsidies.

In the project Infini-Drive (2014), presented in section 3.1.1, the study focuses mainly on charging and infrastructure optimization, but TCO are computed as well. Three results caught our attention: the optimization of the use of the electric vehicles in a mixed fleet (i.e. with use of both conventional and electric vehicles) makes it possible to save 3% to 7% compared with the same fleet without optimization; an estimation of 3% savings made possible by charging optimization in the most favorable case; and as in Van Amburg and Pitkanen (2012), a high variability and uncertainty of charging infrastructure costs, that range from 5% to 15% of the vehicle TCO.

The Observatory of Company Vehicles (Observatoire du Véhicule d'Entreprise (OVE, 2015)) presents a TCO study for France, which is specifically aimed at companies, mainly about conventional LCVs but with a section about electric vehicles. At last, we can mention tools available online for businesses willing to calculate TCO within their own operational conditions: the tool from Van Amburg and Pitkanen (2012) where a user can enter their own data, or the I-Cvue decision support model (I-Cvue n.d.), which has preloaded data for several European countries and several car models, including LCVs, and which gives also other information, e. g. CO<sub>2</sub> emission reductions.

Plötz et al. (2012) investigate the TCO of private battery electric vehicles (alongside hybrid and plug-in hybrid vehicles). What is interesting is that they use real-world driving profiles from Germany rather than an average profile, and quantify how many vehicles are concerned by the favorable or unfavorable economic comparison. They find that economic competitiveness is inexistent for battery private cars (from small to large cars) until 2021. Then, a niche market grows until 2030, where electric vehicles are competitive starting from 50 km/day.

We can conclude from these studies that electric vans can have at best, a similar TCO as ICE vehicles, and that they are in general a bit more expensive. Medium and large trucks are significantly more expensive than conventional ones. Also, the results are very sensitive to the uses and to public financial support. It is widely admitted that the more intensive the use, the more competitive electric vehicles.

# 5.1.2 Quantifying the operational performance

As mentioned in previous chapters, many operational differences exist between electric vehicles and conventional vehicles, but many of them are not easily quantifiable or generalizable within a model. To give but one example, the extent of the difficulties for the installation and use of a charging infrastructure is hard to grasp, because of the multiplicity of the possible constraints, of the high dependence on local settings and organizations (each case almost requires its own study), and of lacking data on companies' parking behaviors and premises. Some of these operational constraints have nevertheless already been discussed qualitatively separately in Chapter 3 (especially in sub-section 3.2.3). These factors will not directly be included in the constraints quantification (other than by uncertainties in the TCO inputs, on the infrastructure installation costs for instance), because of lack of data.

There is however one central operational constraint that can be approached in a quantitative way: the range limitation. Indeed, the limited range is the most notable and influential difference between electric and conventional vehicles, and a central preoccupation for businesses.

To account for this constraint, measuring the variability of the trips of each vehicle is fundamental. A commonly made, but erroneous, simplification is to take the average driven distance (Plötz et al., 2017). This looks convenient, as it uses only the distribution of the average daily driven distances of a vehicle fleet (usually widely available data), but the validity of this approach can be easily proven deficient: these data contain very little information on long trips and their frequency. Pearre et al. (2011) stress out the need for monitoring long periods to be able to assess the range constraint, and that neither the average driver nor the average travel profile is sufficient.

The necessity of accounting for the variability of the daily traveled distances for each vehicle (we will use the abbreviation DVKT for Daily Vehicles Kilometers Traveled) is also important for the evaluation of hybrid technologies, where working with average distances leads to overestimating the traveled distance on the first (usually electric) system, especially when the average DVKT is close to the vehicle's electric range (Lin & Greene, 2011).

#### *5.1.2.1 Range variations*

A first important remark is that the range of an electric vehicle has not a constant value, it varies with many parameters. It can cause difficulties for communicating about electric vehicles (some car manufacturers made the mistake of communicating on the range on test benches, much larger than the range in real driving conditions, and generating disappointed customers). This variability should be kept in mind.

Among the most important parameters impacting the range: (i) the driving profile, which depends both on the context (consumption in cities will be less than on highways), and the driving behavior (an aggressive driving style will consume more than a relaxed one, the latter will in addition benefit from regenerative braking); and (ii) the temperature, the colder the weather, the higher the fuel consumption, mainly due to increased rolling resistance but also to the use of heating. Indeed, auxiliary equipment is often powered directly on the traction battery. The heater is by far the most consuming auxiliary component and in addition, contrary to conventional vehicles, it does not benefit from the recirculation of heat from the engine. For instance on the Kangoo Z.E.,

an electric van marketed by Renault, online simulations (provided by Renault) demonstrate a decrease in range from 260 km at 20°C to 180 km at -5°C with heater on (at 50 km/h), i.e. 30% less.

Heater consumption depends on use time, not on distance (Helms et al., 2010), and is thus especially disadvantageous in traffic jams. Solutions exist to minimize overconsumption and the lack of predictability of the range, for example an additional fuel heater or pre-heating scheduling as the vehicle is still charging (Taefi et al., 2016). While the first generation of Renault's Kangoo Z.E. was equipped with demanding conventional heaters, the new generation can optionally be equipped with more sober heat pumps.

For vehicles that make regular rounds (for instance delivery rounds for freight activities), these seasonal range variations limit the maximal possible route to the minimal range (reached during winter, with the heater on, and with the worst driver).

The maximum available capacity of the battery is also variable and depends on many factors including the temperature. The state of health of the battery is having a non-linear decrease over time, depending on the solicitation. Car manufacturers generally ensure a state of health of at least 75% of the initial battery capacity.

#### 5.1.2.2 Range criteria or metric, days requiring adaptation, range anxiety

The vocabulary used to qualify the adequacy of the range with the uses in the literature varies, but all refer to the same quantity: a measure of the number of days on which range is insufficient, with possible variations about what "insufficient range" means. Dong and Lin (2014) speak of "feasibility" of electric vehicles, when a given "comfort level" is acceptable. Pearre et al. (2011) question the compatibility of electric vehicles with "gasoline-enabled driving habits", by looking at the number of "days requiring adaptation" or "adjustment days". Tamor and colleagues (2015) qualify this metric as a "metric of acceptance". On our side, we will use the terminology "days requiring adaptation", abbreviated DRA, or "probability of requiring adaptation", abbreviated PRA, which have the advantage of clearly describing the criterion they name.

When working on raw longitudinal data, a common range metric is the number of days at which the range is not enough to cover the DVKT. Pearre et al. (2011) explore the annual use (one to three years of observation) of 484 vehicles from the Atlanta, Georgia greater metropolitan area. Data were generated by data acquisition hardware equipping the vehicles. Results show that even if most

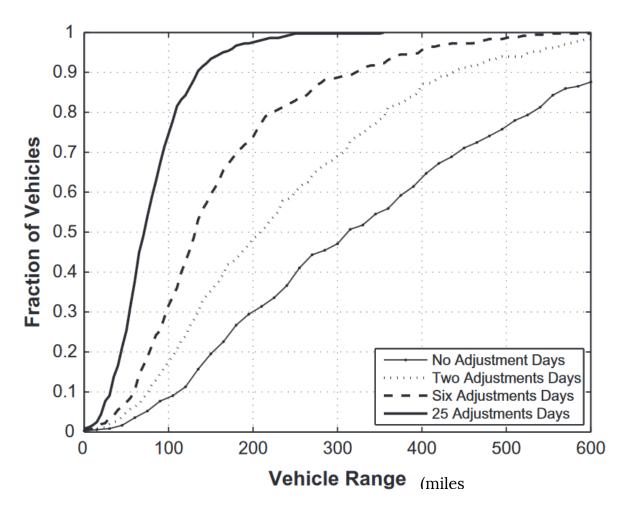


Figure 24 Fraction of private vehicles that can be replaced with EVs as a function of the vehicle range and the number of allowable adjustments days (data on private vehicles from the region of Atlanta) (Pearre et al., 2011)

of the mobility needs of a household are covered by electric vehicles, the measurement of the range constraint varies greatly with the acceptable number of days for which the distance traveled exceeds the range. For a range of approximately 320 kilometers (200 miles), 30% of vehicles could be replaced by electric vehicles without any adjustment day or DRA (i.e. when the range is sufficient to cover each and every day of use), which rises to almost 50% with 2 DRA, and to almost 75% with 6 DRA in the year. Figure 24 shows that the fraction of coverage of a vehicle with a given range is as sensitive to the number of acceptable adjustment days as to the range itself.

This study emphasizes that the requirement that a vehicle would cover most of everyday trips – for instance 90% of the trips (or even the *average* driven distance) –, is not at all the same than a solution that covers *all* the trips, allowing unchanged mobility patterns. The results of our interviews (Chapter 3) suggest

that it is this second option that companies are expecting. To our knowledge, no such study has been conducted for business van users.

Adaptation can have different means: it can signify giving up some trips (which, for a business user, can mean refusing a client or a mission), charging during the day or trip, or finding another way of doing the trip (use another vehicle, rent a vehicle, use public transport, etc.). It can be noticed that freight operators do not have, for the vast majority of their trips, any alternative to road transport (as outlined in sub-section 2.3.1). One potential solution is to substitute ICEVs to EVs for these specific trips, in a *mixed fleet* solution (discussed in subsection 3.2.3.3).

Shi et al. (2017) explore battery range needs for taxis and private vehicles in Beijing, using GPS data, with observations of over three weeks for the taxis and nine months for the private cars. It is considered that charging is allowed when the vehicles are parked nearby a public accessible charging station. If the users accept to give up 1% of their longest trips, the coverage of the fleet of an EV with 125 miles of range (considering only the range constraint) rises by 11 points for the taxis, and by 14 points for the private users.

Another facet of the acceptability question is linked to range anxiety, explored for instance by Dong & Lin (2014). Indeed, contrary to the previous examples, they do not only investigate the necessary number of adjustment days, but also explore variable safety margins, accounting for a possible range anxiety, which is the fear of having insufficient range to reach the destination.

These studies and the vocabulary used illustrate how closely the question of range is linked to the question of acceptance. They all note that the parameters representing the acceptability of a solution, like the frequency of trips exceeding the range or the amount of range that the user is actually willing to use, have both significant impacts on the possible success or feasibility of electric vehicles. As discussed in Section 3.2.3, limited range adds complexity (in the sense of the innovation diffusion theory), which is acceptable only to the extent that it is otherwise compensated.

## 5.1.2.3 Charging and use patterns in feasibility studies and statistical modeling

When in possession of relevant longitudinal GPS data, it is possible to assume charging possibilities during parking time. For example, Shi et al. (2017) consider a scenario where a vehicle parked at a service range of two miles or less of a publicly accessible charging station could have charged there (taxi or private car).

Dong and Lin (2014) have another approach to evaluate the charging possibilities without having localized travel data. In their statistical modeling, they evaluate the availability of charging stations by the number of trips (there can be several trips in the same day) between two charging events: it is considered statistically distributed using a Poisson law and fitted on observed data. Given the statistical distribution of the trip distances, it leads to the probability of being able to do a full day's activities (that is of course higher than without charging opportunities).

# 5.1.3 Variability and optimism of market forecast methods

This sub-section and the following study electric vehicle market forecast models in the literature. Future market modeling is a complicated task. As a consequence, the results of these studies show quite different conclusions, depending on the assumptions and the method used. It is therefore difficult to form an opinion.

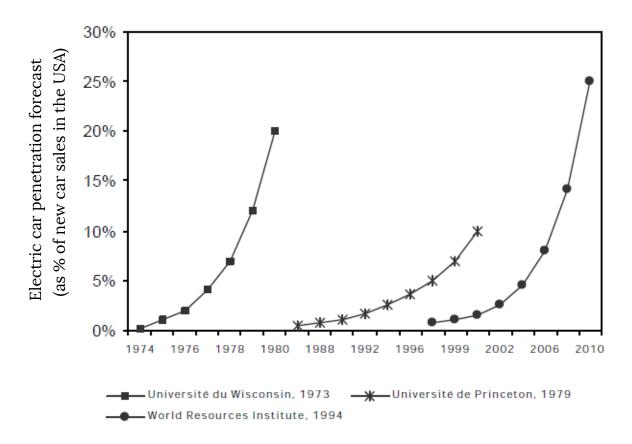


Figure 25 Example of optimistic forecasts for electric vehicles, from (Fréry, 2000)

For the review, we rely in particular on the review of Al-Alawi and Bradley (2013), which presents different electric vehicle market penetration studies, for battery, plug-in and non-plug-in electric vehicles. The methods are catalogued into three main categories that we adopt as well: agent-based models (sub-section 5.1.4), stated preference and discrete choice models (5.1.5), and diffusion models (5.1.6).

Fréry (2000) outlined the permanent excess of optimism that has been observed for many years in studies forecasting an exponential growth of electric vehicle markets at many different times. The author highlights the gap between the "indisputable" failure of the substitution of conventional vehicles throughout the twentieth century, and the recurring forecasts of exponential diffusion of electric vehicles. He qualifies this anomaly as an "eternally emerging" technology. Figure 25 illustrates three of such studies that span a 25-year window, and for which history has shown how far they diverged from reality.

The literature review performed by Al-Alawi and Bradley (2013), presents and compares methods, applied on different databases and resulting in many different market forecasts. Even for one specific method category, forecasts may vary dramatically. For instance, forecasts for non-plug-in hybrid electric vehicles are represented on Figure 26.

In general, authors of predictive models run several context scenarios and assumptions, and observe that output EV markets highly depend on the chosen scenario, e.g. (Becker et al., 2009; Sullivan et al., 2009). Under these conditions, interpretation of the results is difficult. The accumulation of small

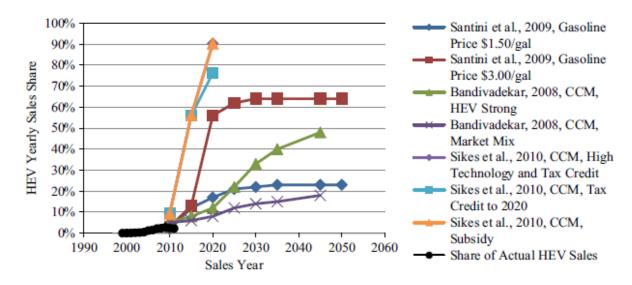


Figure 26 Share of actual and estimated hybrid electric vehicle penetration rate using consumer choice method studies (Al-Alawi & Bradley, 2013)

variations in the most important inputs can lead to significant differences. Extracting robust conclusions that hold over time is therefore challenging.

# 5.1.4 Agent-based models

Agent-based models are numerically simulating behaviors and interactions between different agents, who may or may not take action according to a specific decision process. Agents can represent potential consumers, but can be extended by adding car manufacturers, policy makers and fuel suppliers (e.g. Sullivan et al. (2009)). An agent-based model can represent complex individual behaviors and sophisticated distributions of characteristics (including gender, age, income, lifestyle, budget, driving needs etc.), based on data-driven or theoretical assumptions. It can represent the spatial dimension, integrating, for example, the effects of density and geographic proximity on interactions (Eppstein et al., 2011). Results can be aggregated over all agents to facilitate analysis.

Different categories of models can interface, for example, the agent decision-making can be a discrete choice model (Cui et al., 2010).

The link that leads from individual mechanisms (especially the interaction mechanisms) to aggregated results is often not easily readable, because of their intricateness and complexity. The authors of the review acknowledge the fact that when agent-based models are used to forecast market share, there is generally a sensitivity analysis to the numerical assumptions, such as fuel prices or vehicle prices. However, they deplore regular absence of sensitivity analysis to the modeling methods and to the data. As a result, the quality of the results is difficult to assess.

#### 5.1.4.1 Individual rule-based decision model

Some agent-based studies do not integrate interactions between agents, but only model individual decision-making, often with a rule-based decision model (which may or may not include social and cognitive factors). The models assume that agents' technology decisions follow pre-determined rules. By dropping the interaction term, the diffusion phenomenon across agents over time is lost, and the model gives a steady asymptotic picture. Actually, most of these models do not claim to compute market shares but market potentials. This approach has several names in the literature, e.g. constraints analysis (Windisch, 2014) or niche exploration (Greene, 1985).

The individual decision model can be more or less complex. Very common criteria for the use of electric vehicles are the constraint of limited range and an economic criterion. For electric vehicles, the main assumption is very often that the agents will not change their travel patterns.

Social factors might be included as well. For example, Plötz et al. (2014) developed a model for which, in addition to the economic and limited range constraints, parameters accounting for EV user acceptance are integrated. With socio-economic data about the vehicle users, different adopter groups are defined according to the innovation diffusion theory (Rogers, 2010), and each group has a different willingness to pay for electric vehicles (based on a survey). Furthermore, the limited supply of EVs is taken into account, with a forecasted supply of vehicle models based on announcements by car manufacturers on future model commercialization. In case of a brand not offering a given model, the agent may either change its brand under a certain probability, or choose its second best option. At last, the model integrates the variability of the use profiles based on the German Mobility Panel survey database, and the REM2030 Driving Profiles collected by the authors with GPS trackers on commercial passenger car users. This decision model is then integrated into a stock model for future stock predictions.

Windisch (2014) applies a constraints analysis based on the French private cars use profiles, with conditions on the vehicle usage (differentiated according to whether the household has only one or several vehicles), on charging possibilities (availability of private parking at home or at work) and on TCO comparison. Data are based on the French national travel survey (Enquête Nationale Transport Déplacement, 2007–2008).

# 5.1.5 Stated preferences and discrete choice models

A second common approach to electric vehicle market forecasting is consumer choice modeling. Discrete choice models model choices made among a finite set of alternatives, depending on these choices' attributes and the attributes of the person or entity making the decision. Preference of consumers can be assessed in matters of vehicle technology, range, cost, make, class, or other characteristics of the alternatives in the choice set. They can integrate a wide range of consumer characteristics, and including possibly variables on social influences (Axsen & Kurani, 2008), or on attitudes by integrating a latent variable model (Glerum et al., 2013).

They are most of the time regression models, estimated using vehicle past sales data when available. Otherwise, especially for niche markets like BEV or PHEV markets for which regressions on past data may be hazardous, results can be derived from surveyed stated preferences.

Fernández-Antolín et al. (2018) explore vehicle choices, with a range of different segments and technologies (diesel, petrol, electric). Three policy scenarios are explored: a *do-nothing* scenario, a *tax* scenario (increase in registration tax and fuel price) and a *technological innovation* scenario (decrease in the purchase price and increase in range of electric vehicles). Electric vehicle market shares in 5 years are estimated for each scenario, by classes of income.

Discrete choice models may be applied on agent's choices, but also on specific agent groups. Diamond (2009) uses already aggregated USA state-by-state market shares of HEVs sales to derive effects of tax incentives and gasoline prices in a macroscopic model. Other state characteristics, as car dealership availability, are also taken into account.

Consumer choice modeling is appreciated for the possible direct interpretation of the link between declared or stated behavior and observed characteristics. The major drawback identified by Al-Alawi and Bradley (2013) is the limited availability of the data.

#### 5.1.6 Diffusion models

The third main model class provides quantitative insights on the diffusion dynamics. These dynamics have been introduced qualitatively in the first place with the innovation diffusion theory (Rogers, 2010), but they have soon involved time series models.

Diffusion and time series capture the life cycle of innovations over time, implicitly integrating and summarizing all parameters influencing the rate of adoption. They are the quantitative pendant of the qualitative innovation diffusion theory: the models parameterize the famous S-shaped curve associated with the rate of an innovation's adoption (the S-Curve of Adoption (Rogers, 2010)). Authors identify three widely used model classes, the Bass, Gompertz, and logistic models. The difference between these models lies essentially in the mathematical function used to represent the diffusion process, a function that reproduces the S-shaped curve. The upper limit of the sales per time period (or maximal potential of the innovation) is given as an input to the model.

The Bass model for instance explicitly incorporates a behavioral rationale, summarized in a simple assumption by the author of the model (Bass, 1969): "the probability that an initial purchase will be made at T given that no purchase has been yet been made is linear function of the number of previous buyers". This raises a mathematical description of the diffusion process.

These methods are often based on the concept of successive vehicle generation for more fine-tuned time-series. They either need historical trends to be fitted on, or parameters from another study about a similar object. They are also easy to implement. However, they are dependent on market potential estimates, and do not address competition between several technologies. The Norton-Bass model (Norton & Bass, 1987) is for instance an extension of the Bass model presenting successive technological generations. Newer generations are absorbing former generations' market share, and increase the maximum potential. For the electric vehicle market, the notion of successive generations may be somewhat blurred as more and more car manufacturers enter the market, so that technological progress appears more continuous over time.

Becker et al. (2009) use a bass model to forecast battery electric vehicle market shares for private vehicles. The forecasts are optimistic, with a penetration rate of 45% forecasted for 2025. The maximum potential market share is computed using a range constraint applied on the 2001 National Household Travel Survey in the US: profiles with less than one trip exceeding 80 miles per month are considered qualifying.

So, several models are available to assess electric vehicle markets, a few of which have been presented based on a categorization from Al-Alawi and Bradley (2013). The authors identified several gaps in current models, among which are the lack of modeling of vehicle supply and of actions by automakers. They also insist on the necessity of a thorough sensitivity analysis.

# 5.2 Overview of the model

Based on these results, and given the available data, we have chosen to develop our own model, which we present in the remainder of this chapter.

# 5.2.1 Motivation for the methodology

The aim of the model is to capture the adequacy of current and future electric vans to the needs of transportation companies. Particular emphasis is placed on anticipating technological developments and temporal dynamics. After having

observed a large variability in the results of future market share models, we looked out for a stabilizing mechanism, which we found in the possible evolution of public subsidies.

The specificities of the market deserve to be recalled. First, it is an emerging market, so current users are early adopters. The perceived relative advantage of the technology is relatively small, so the complexity of the solution makes it unattractive for transport companies (and professionals in general) (sections 3.2.2 and 3.2.3). The technology has a very positive image and strong public support. Most transportation companies are convinced of the virtue of electric vehicles over conventional vehicles (3.2.5). Regulations are favorable to electric vehicles, with heavy subsidies, which will probably not last forever (3.1.4). These subsidies are critical for economic competitiveness.

As exposed in the first section, several methods are possible to pursue this objective. Given the poor availability of data, the approach has to be possible with a relatively small amount of data. The model must in particular be able to cope with the absence of *ad hoc* survey data or longitudinal data. Secondly, since this work was carried out with the research department of a car manufacturer, an explicit link between the technical characteristics of the vehicle and market potential was required, so that the model would be an actual decision support system. In particular, the model must be able to quantify the impact of a change in range, cost, or diversification of supply on the market.

A discrete choice model approach was eliminated, due to the lack of an adequate dataset, or means to proceed to an adequate survey. These are demanding to obtain.

A multi-agent system with interactions seems less well suited to this particular study, given that it was found that information circulated relatively well among professionals, and that the main obstacles were essentially in matching requirements with the service provided by electric vehicles. In addition, interactions are complex, with large groups responsible for a significant share of the commercial vehicle market and variable fleet sizes. For lack of quantitative data, and in order to avoid hazardous hypotheses on these interactions (especially since validation is not easy in an emerging market), this method was rejected as well.

Diffusion models are interesting insofar as they do not require detailed data but raises two critical issues. The first is the difficulty of estimating the model on current data. Given the early state of the market, all three parameters (ultimate number of adopters, coefficient of innovation and of imitation) would have to be guessed. The second problem is that this model does not allow evaluating finely different scenarios, and in particular cannot accurately address subsidy variations, or specific technological evolutions, making it unsuitable for a decision support tool.

An individual rule-based decision model or constraint model (sub-section 5.1.4.1) appears to be a good candidate. First, it requires information on the use of vehicles and not specific to electric vehicles, allowing the use of databases for purposes other than the study of EVs. However, the model still requires disaggregated data. On the other hand, the impacts of all technical specificities are explicit. Therefore this type of model provides a sound basis for evaluating different technologies, and offers decision support in the development of alternative technologies. Its weakness is that it integrates neither diffusion dynamics, nor the behavior of users as finely as a discreet choice model would. The decision-making process is in this case expert-based.

Section 5.3 presents how we treated these limitations.

#### 5.2.1 Model architecture

The model we have developed allows us to anticipate changes in market share for electric vans. It takes various input parameters:

- The estimated parameters of the statistical usage model presented in Chapter 4 for the fleet investigated. As mentioned, these parameters can be obtained from different sources, but can be estimated with much less detailed data than longitudinal data.
- Economic and operational assumptions for calculating the TCO (fuel prices, infrastructure prices, residual value, maintenance costs, share of highway, vehicle consumptions etc.). These parameters can be fixed values, but also probability distributions for uncertain parameters.
- Assumptions on the evolution of the supply of electric and conventional vehicles, in the form of successive generations of vehicles. This requires assumptions to be made about the price evolution of batteries and vehicles; the optimal battery capacity is then calculated by the model.
- A low assumption and a high assumption on the maximum budget that the public administrations are prepared to put for the subsidy of electric vehicles.

On output, the model gives an expected market share (or range of expected market shares), and its evolution over time in the short and medium term. The

evolution of the supplied battery capacities and plausible future public subsidy scenarios are obtained as a by-product. It also lets sensitivity analysis measure the impact of input parameter uncertainties on the result. Sensitivity analysis can be performed graphically or more systematically with total Sobol indices.

The model deals with *new vehicle market shares*. The consequences on the composition of the stock will therefore inevitably be delayed by vehicle renewal time, and could be deduced with a stock model.

Figure 27 and Figure 28 present the model architecture. Figure 27 shows the constraints analysis. The constraints considered in it are simple: we consider an economic constraint, evaluated using Total Cost of Ownership (TCO) computations, and an operational constraint due to limited range, evaluated through the probability of requiring adaptation (Section 5.3). It is an agent-based model (each agent choses its preferred technology), without interactions, based on a simple expert-based decision model or as we called it previously, a constraints analysis. The agents are statistically generated using the model presented in Chapter 4.

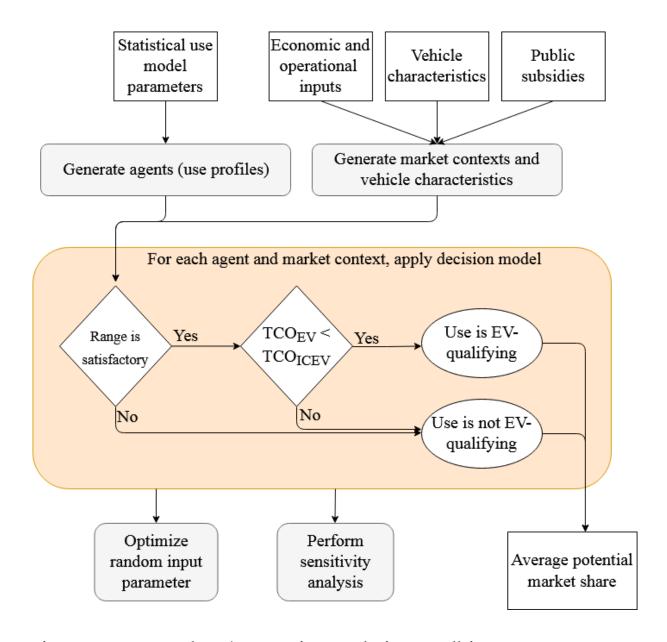


Figure 27 An agent-based constraints analysis. Not all input parameters are exogenous to the model: some are solutions of an optimization problem or an equation. See Figure 28.

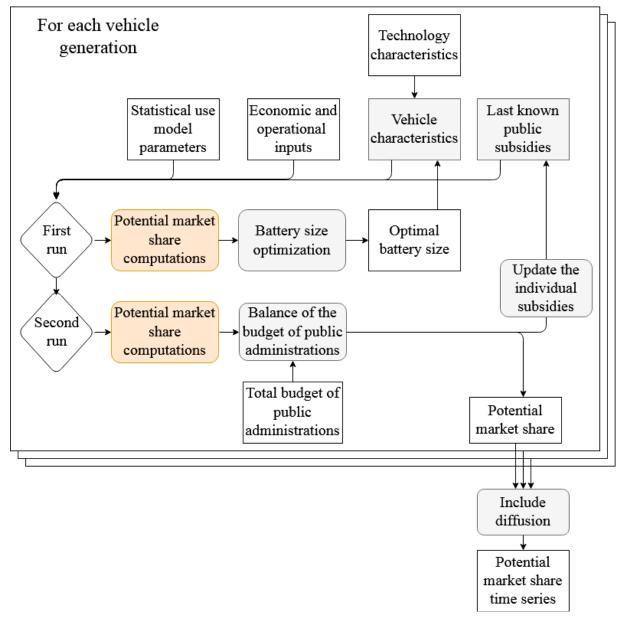


Figure 28 Whole model architecture: the orange boxes correspond to the constraint analysis as shown in Figure 27.

#### Possible inputs of the model are:

- the estimated parameters of the use-model introduced in Chapter 4. The model could work with a longitudinal database as well (in this case, the data would be used to replace generated agents).
- Economic and operational data (such as diesel and electricity prices, share of distance driven on highways, road and city environments, vehicle resale values, infrastructure costs)
- Vehicle and technological information, on several successive vehicle generations (e. g. vehicle prices, battery capacities, battery costs, vehicle consumptions, charging efficiency)
- Subsidies from public administrations for the purchase of an electric vehicle.

The model can run with fixed or statistically distributed parameters. Despite relatively simple constraints, we noted that small variations in parameters could lead to large variability in the results of the decision model. On the other hand, some parameters are difficult to estimate independently of others, such as subsidies and battery capacities available on the market.

We therefore took advantage of the possibility of having random parameters as inputs of the constraints analysis to obtain these two parameters as the numerical solution to an optimization problem and a budgetary equation, making them endogenous to the model. Figure 28 shows the total architecture with the encapsulated constraints analysis model.

Major evolutions to the mere constraints analysis are:

- The inputs are estimated and the constraints model is run for several successive vehicle generations. This allows time series to be obtained on the market share of electric vehicles. Diffusion mechanisms are included by delaying the time series (sub-section 5.4.3).
- A first model run enables to calculate the battery capacity that optimizes the market share of electric vehicles. To do this, a wide range of battery capacities is given as input of the constraints analysis, with projected battery prices per kilowatt-hour. The analysis of the average market share as a function of the battery capacity thus makes it possible to pick the optimal capacity (sub-section 5.4.1).
- A second model run enables to estimate the amount of subsidies from public administrations for the purchase of an electric vehicle. It is

therefore an equation that is solved numerically: we look for the maximum amount of individual subsidies that leads to a market share that respects the public administrations' budgetary constraint. In the same way as before, this is obtained by presenting as an input range of possible subsidies, and by analyzing as an output the total expenditure as a function of the amount of individual subsidies. This dynamic value of the subsidies gives a lot of stability to the model (sub-section 5.4.2).

• If the entire market is explored, then by construction, knowledge of the total budget of the public administrations and individual subsidies makes it possible to estimate the market for electric vehicles (which is simply the total budget divided by the individual subsidy). If a subgroup of the entire market is explored, a third launch of the model with previously estimated parameters allows access to market shares.

In addition to the market share time series, most critical uncertain factors can be identified thanks to sensitivity analysis. Some iterations are possible to refine the most critical input factors. See section 5.5.

# 5.3 The decision model

We begin by describing the core of the model, which is the individual decision model. We choose a simple decision model that addresses two of the most critical constraints: operational and economic performance for the company. Each of these constraints is the subject of a complete sub-section.

In Figure 29, an elementary two-step decision model is proposed to assess a market potential. If a given use of the vehicle, with given market and technology assumptions, pass the decision model, we will say that the use is EV-qualifying.

The two steps represent two first-order concerns of companies related to electric vehicles:

- Are electric vehicles suited for my operational needs? The range will be the criterion to segregate interesting uses.
- Are electric vehicles economically more competitive than diesel vehicles?
   The total cost of ownership of the considered technologies will be compared with equivalent diesel vehicles.

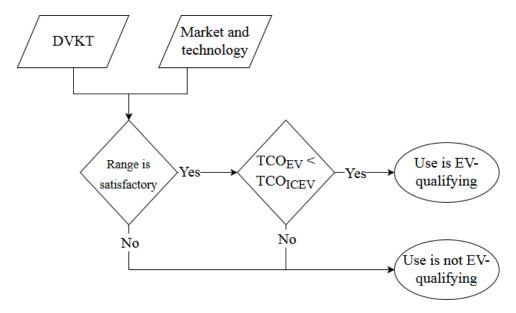


Figure 29 Decision model for one individual (excerpt of Figure 27)

If both of these constraints are met, environmental benefits, pressure from public authorities, comfort of use and other factors, which are considered to have less weight than the ones presented above, will push companies to purchase EVs.

Despite its apparent simplicity, this model offers already much room for various analyzes as we will try to prove throughout this work, in particular in Chapter 7.

# 5.3.1 Explicit computation of the probability of requiring adaptation

The range condition we use translates in everyday language into: the probability of exceeding the range for a given agent needs to be less than an acceptable threshold.

For a given agent, which DVKT are following a Weibull distribution of scale parameter  $\lambda$  and shape parameter k (as in our model presented in Chapter 4), we have the following probability of exceeding a range r on a given day:

$$PRA(r; \lambda, k) = 1 - F_{Weibull}(r; k, \lambda)$$
$$= e^{-(r/\lambda)^{k}}$$

r denotes the range

- $PRA(r; \lambda, k)$ : is the probability that the DVKT exceed r (the probability of requiring adaptation with range r), for an agent which DVKT are parameterized by a Weibull distribution of parameters  $\lambda$  and k.
- *PRA*<sub>limit</sub> is a threshold fixed *a priori*, and depends on the *acceptability* of having trips not covered by range by the potential customer, which is very low for the investigated businesses according to our interview results (Section 3.2).

The range is actually a random variable. It depends on energy consumption (and thus on the speed), on the use of auxiliaries (heater, air conditioner) and on the outside temperature (cold weather induces higher rolling resistance). In practice, we approximate this variability: we consider two running conditions for the vehicle, an extreme weather condition, which occurs only a few times in the year, and where the range is degraded; and a normal or average working condition, with an average available range.

For each weather condition, we compute an average range, depending on battery capacity, share of distance driven on three different route types (highway, road or urban) and the corresponding specific consumptions (numerical assumptions are presented in section 6.1.6.2, and in Appendix). The approximation gives:

$$E_R\left(PRA(R;\lambda,k)\right) = f_e \cdot PRA(r_e;\lambda,k) + (1 - f_e) \cdot PRA(r_a;\lambda,k)$$

with same notations as previously, plus:

- R: a random variable representing the range, and  $E_R$  the mathematical expectation relatively to R
- $f_e$ : the frequency of extreme weather conditions
- $r_e$ ,  $r_a$ : the ranges on extreme and average weather conditions respectively.

This refining of the constraint accounting for range variations allows to model country specific vehicle specifications.

In France for instance, extreme weather conditions could be at -5°C, and range at this weather would integrate the consumption of the heater (which actually also depends on the temperature). Average weather conditions may be at 20°C, without heater or air conditioner. Mostly, coldest temperatures are the most extreme because of the high consumption of the heater. However, in some hot countries, most extreme conditions may be rather the hottest temperature, with the air conditioner on.

Finally, we can define that a given electric vehicle is an acceptable alternative under the condition:

$$E_R(PRA(R; \lambda, k)) < PRA_{threshold}$$

The use of a probability (*PRA*) is not totally equivalent to the use of a number of days (*DRA*). The conversion from one to the other depends on the numbers of observation days where the vehicle is driven. This choice has been made first because of the available data. Since the database we use does not contain information on the number of days per year the vehicle is used, it is convenient to use probabilities instead. Also, the probability does not depend on a specific time frame (whereas the number of days is usually given per year). Finally, using a probability threshold implies that users using the vehicle less frequently will find a given number of days requiring adaptation less acceptable than somebody using its vehicle frequently (in an extreme illustration, somebody using its vehicle once a year will not accept one adaptation day per year). This choice should not significantly affect the outcome of the study.

# 5.3.2 Explicit computation of the range

This sub-section describes the computations of the range that has been used for the modeling. We consider the range in km is given by:

$$r = (1 - b) \cdot \frac{C}{m}$$

- A battery capacity *C* in *kWh*
- A consumption m in  $kWh \cdot km^{-1}$
- A security buffer b, expressed as a share of the total battery capacity (typically, (1 b) = 0.9)

The battery capacity is the usable battery capacity, which does not include the technical buffer the car-manufacturer can keep out for technical reasons.

The factor (1-b) is a safety margin accounting for several possible factors. First, it accounts for a possible loss of capacity of the battery due to ageing. (Actually, car manufacturers that are renting the battery are ensuring a state of health of the battery of 75%. Given the fact that the vehicle is considered new and the time spans are relatively smaller than the life span of the battery, we do not consider such a low state of health for the range computation.) Also, the precise distance that is driven on a trip is not precisely known by the user beforehand, so he may by security round it to a higher value.

Consumption varies also with diverse parameters. We simplify the continuous scale of possible consumptions into a discrete scale of three values: one for urban trips, one for the road, and one for the highway. The use profile of a user will then be described by the respective shares of the mileage driven on each of these road types.

In the model, the three share parameters are not entered directly. Instead, two parameters *Highway* and *pUrban* are used: respectively the share of distance driven on highways, and the share of the *remaining distance* driven in urban environment (and not the total distance). This way, it is ensured that the sum of *Highway*, *Road* and *Urban* shares is always equal to 1, even with randomly generated parameters. Mathematically, this gives:

$$Urban = pUrban \cdot (1 - Highway)$$
  
 $Road = (1 - pUrban) \cdot (1 - Highway)$ 

For example, in the case of a distribution of 33% of the distance driven in urban environment, 33% on roads and 34% on highways, the values to be used are Highway = 0.34 and pUrban = 0.50.

# 5.3.3 Modelling the uses

To compensate the absence of a comprehensive database on the uses of the investigated population, a stochastic model was developed to represent the distribution of DVKT for each individual across the population, presented in details the Chapter 4. In this model, a specific statistical distribution of DVKT is generated for each vehicle, thus taking into account both the variability of the DVKT of each agent, and the heterogeneity between agents. These distributions are precious information, as they allow computing with precision the PRA for any given range.

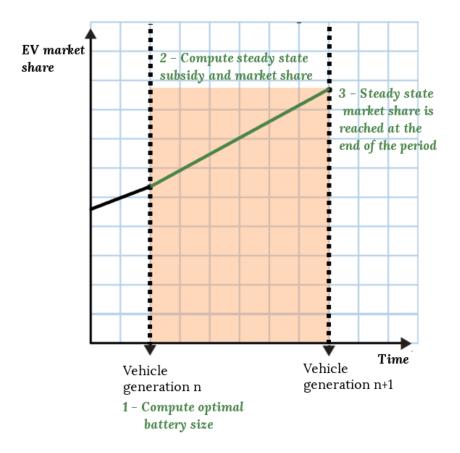


Figure 30 Schematic representation of the 3 steps to compute market share time series

# 5.4 From static potentials to market share time series

Several steps lead from the static electric vehicle potential to actual market share time series, as exposed in Figure 30. For each new vehicle technology, the first step is to determine the battery capacity of the new generation of vehicles (sub-section 5.4.1). The second determines a steady state market, for which the public administrations do not exceed a maximum total budget (5.4.2). Finally, this steady state market is reached at the end of the period in order to take into account a diffusion time (5.4.3) (we consider periods of 5 years, at the end of which a new generation of vehicles is introduced).

# 5.4.1 Successive vehicle generations and battery capacities

Technological evolution scenarios need to be established. Technological developments are presented in the form of successive vehicle technologies, with new models supplied at regular time intervals. In our case, we assume that a

second generation of vans appeared in 2017, and then a new generation will be marketed every 5 years.

For instance, the battery capacities and prices, the vehicle prices, the vehicle classes that are available need to be defined. In the reference scenario, only one battery capacity is considered for each vehicle generation. A scenario with two different supplied battery capacities is explored in sub-section 7.1.2.

We consider the battery capacity on each new vehicle generation as an endogenous parameter, computed depending on potential market shares. To do this, we run the model a first time, with a large range of battery capacities, and define the car manufacturers' choice as the capacity which maximizes the market share.

$$C_{opt} = \max_{C} (p(C))$$

with:

- $C_{opt}$ : Optimal battery capacity chosen by car manufacturers
- p(C): Market potential as a function of the battery capacity C

This car manufacturer decision modeling is quite basic of course. It does not take into account competition, which would require game theory given the oligopolistic nature of the automotive market.

#### 5.4.2 Public subsidies

Most market parameters are estimated prior to the model runs, and are therefore considered independent on the actual market shares of electric vehicles. It is for instance the case for the price of energies (price of diesel and electricity). Residual values are also assumed beforehand, even if they are in fact are influenced by the supplied vehicles on the market and the actual success of electric vehicles at the time of sale of the second hand vehicle.

We chose to consider public subsidies, however, as directly dependent on the electric vehicle market size. The variable specified beforehand is the total budget the public administrations are willing to invest for the support of electric vans.

#### 5.4.2.1 Incentives

Incentives are calculated according to a regulatory mechanism that ensures that the total amount of the total budget remains constant. This is an equilibrium amount, solution of the following equation:

$$p(inc) \cdot inc = B$$

#### where:

- p(inc): potential market share as a function of the incentives (in number of vehicles)
- inc: amount of incentives (in €/vehicle)
- *B*: total public budget allocated to the support of electric LCVs.

This can be represented graphically, by plotting the projected potential on one hand, and the amount  $\frac{B}{inc}$  on the other. Intersection of both curves gives the equilibrium point. The first curve moves with technological progress, the second one is fixed under the constant total budget assumption.

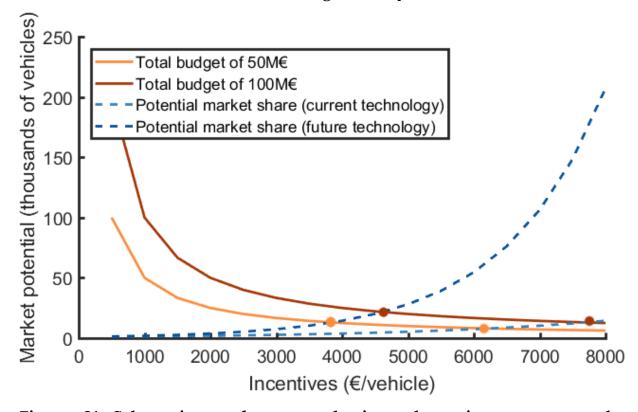


Figure 31 Schematic regulatory mechanism: the points represent the equilibrium points for which demand (blue lines, modeled by exponential functions) causes expenditures that exactly respect the budget of public administrations (orange lines).

Figure 31 shows schematically the mechanism at play. We notice that in this configuration, a technological improvement, which has a significant impact with unchanged incentives per vehicle (observed by comparison of the two exponential blue curves), is for the most part absorbed by a decrease in subsidies per vehicle, rather than by an increase in market shares (observed by comparison of the same-colored dots). This phenomenon happens regardless of the total amount of the budget allocated to the support of electric vehicles, and explains why this mechanism adds much stability to an otherwise very sensitive model.

Obviously, this does not mean that the market itself is independent of the subsidies granted to electric vehicles. Red dots, corresponding to the equilibriums with a public budget twice as big as for the orange dots, offer a significantly increased demand, but not a significantly increased growth between generations.

One additional mechanism that could intervene and that does not appear in this graph is that the demand at time t (current technology) has an influence on the technological evolution, and thus on the position of the demand curve at time t+1 (future technology). This has not been included in the model, because it is the world market, and not only the French market, that has the capacity to provoke this.

# 5.4.3 Integrating diffusion

Consideration was given to using the Norton-Bass model to integrate diffusion. This model indeed needs a market potential as input, which is specifically what we computed (it is often determined by an "informed judgment", which opens the possibility of a bias "in the direction of over-optimism" when investment funding are at stakes (Bass, 2004)). In addition, clear successive generations driven by the leading car manufacturers can today be identified, and the market potential grows with each generation. However, two problems hindered us from using it:

- First the potential computed in our model changes with time, as energy prices and incentives evolve. If an increase in potential is easily implemented in this model, it is hard to catch what occurs with a *decrease* in potential.
- As our potential computations already integrate the costs of the innovation, it does not totally represent a broad medium-term potential as needed in the Bass models, but instead a close fit to the current market share. As such, high diffusion rates would be found, on very short

observations periods. So the diffusion rate would be probably very optimistic.

We therefore opted for a simpler diffusion model with linear approximations. First, different successive vehicle generations were defined with gaps of five years between generations. The maximum potential market share was computed for each vehicle generations as detailed in the previous sub-section. The Bass model tells that after a sufficiently long period, the market shares will eventually reach this maximum potential in a steady state. We consider that this steady state is reached at *the end* of each period, at the time of introduction of the next vehicle generation. This is a way to include a macroscopic diffusion process across potential customers. For simplification, we interpolate linearly the market shares between two successive vehicle generations. This mechanism is a rough imitation of the Norton-Bass model, with a guessed characteristic time (but precise maximum market potentials).

Mathematically, the maximum size of the market  $m_i$  of generation i is reached at time of introduction of the next generation  $\tau_{i+1}$ :

For 
$$t \in [\tau_i, \tau_{i+1}]$$
,  $S(t) = m_{i-1} + (m_i - m_{i-1}) \cdot \frac{t - \tau_i}{\tau_{i+1} - \tau_i}$   
With: 
$$\begin{cases} m_0 = 0 \\ m_i = p_i(\tau_{i+1}), \ \forall i \ge 1 \end{cases}$$

With:

- S(t): sales at time t
- m<sub>i</sub>: ultimate market potential of generation i
- $\tau_i$ : time of introduction of generation i, fixed beforehand.
- p<sub>i</sub>(t): market share computed for generation i at time t

# 5.5 Sensitivity assessment

# 5.5.1 Individual variability and volatile parameters

To be able to assess the level of uncertainties that the prospective results entail, stochastic modeling enables to do a thorough sensitivity analysis. We chose to do this analysis both in a graphical way, or by computing Sobol's total order sensitivity indexes (Saltelli et al., 2010).

Model input random variables can be random for two purposes. The sensitivity of these two variable types needs to be addressed separately.

First, they allow us to represent the heterogeneity of the uses among the vehicle fleet, e.g. the individual distributions of daily driven distances. This heterogeneity is inherent to the system, and its analysis gives us insight about the impact of the use profile on the relevance of the investigated alternative fuel.

Second, random variables are used to represent uncertainties on input variables, due to their volatile nature, or measurement or forecasting difficulties. Future diesel price projections are one example. They are extrinsic variables, and their sensitivity analysis can be seen as a risk analysis. So in what follows, methods have been adapted to avoid mixing them up.

In mathematical terms, if we denote A the set of random variables representing individual heterogeneity, and B the set of random variables representing volatile and uncertain parameters, we get a market potential expectation  $\bar{p}$  and variance  $\sigma_p$  as follows, with q(a,b) the decision model, which gives for inputs a and b if the vehicle is EV-qualifying:

$$p(b) = E_A(q(A, b)|b)$$

$$\bar{p} = E_B(p(B)) = E_{A,B}(q(A, B))$$

$$\sigma_p = V_B(p(B))$$

The first line expresses that for a given set of volatile and uncertain parameters b, the market share is obtained by averaging over the random variables representing individual heterogeneity A. The *expected market share* is then averaged over the random variables B, and simplification shows that this amounts to averaging q on all random variables without distinction.

However, this is not the case for variance, as the third line shows. The computation of the variance of the market share relatively to the possible uncertain and volatile parameters requires knowledge of the intermediate variable p(b).

Calculations were therefore made by nested Monte-Carlo simulations. First, a set of uncertain and volatile parameters is drawn, and for each element  $b_i$  of this set,  $p(b_i)$  is computed over the set of random variables representing individual variability (always the same, it is drawn once). This allows to compute  $\bar{p}$  and  $\sigma_p$ .

This method is probably not the least computationally demanding method to compute these quantities, and could be improved. However, given the relative low number of random variables, the computation times and memory requirements remained acceptable and we have not pursued this lead. Pseudorandom Halton sequences have been used for number generation to reduce without any additional computational needs the variability of the results. Results in Chapter 6 and 7 are presented with 2,500 draws for each category of random variables.

# 5.5.2 Graphical sensitivity

Much information can be drawn from graphical representations. The way the market share is computed allows investigating easily the impact of volatile parameters.

First, an output distribution can be represented with a histogram (for instance, the total cost of ownership, or the potential market share).

One output parameter, usually the potential market share, can also be represented as a function of one or two input parameters (such as in Figure 39 and Figure 43). The output parameter is then averaged other all input except this one (resp. these ones). For instance, if output p is represented relatively to random variable(s) (the output is noted as a function of A, B and I), the function which is represented is a conditional expectation:

$$f(i) = E_{A,B|I}(p(A,B,I)|I=i)$$

In the case of one input parameter, uncertainties intervals can represent the variability of the output parameter. In the case of two input parameters, the averaged output variable is represented in a heat map.

# 5.5.3 Sobol's global sensitivity analysis

To analyze more quantitatively the sensitivity of the market potential to input parameters, a variance-based global sensitivity analysis is used. The aim is to identify factors or group of factors, for which additional precision leads to the greatest reduction in the variance of the output. It will also help to make the most relevant scenarios, when additional precision is not achievable due to the prospective nature of the inputs. For this, the Sobol's total order sensitivity indexes appear to be very relevant.

Let us introduce a generic model:

$$Y = f(X_1, \dots, X_n)$$

where Y designates an output, and for  $i \in [1, n]$ ,  $X_i$  are the inputs. We assume that each input is a random variable, independently distributed over given spaces. The idea of the total order indexes is to quantify the contribution of the variance of an input  $X_i$  to the variance of Y, including all variance caused by its interactions with other random variables. The total order sensitivity indices are defined as follows:

$$S_i = \frac{E_{X_{\sim i}}\left(V_{X_i}(Y|X_i)\right)}{V(Y)}$$

where:  $E_{X_{\sim i}}(.)$  is the conditional expectation, taken other all inputs but  $X_i$ , with  $X_i$  fixed and equal to  $x_i$ . The resulting indexes are all between [0,1] and their sum over all inputs exceeds 1 (due to the total variance formula, see (Saltelli et al., 2010)).

Sobol's sensitivity analysis also offers the possibility to investigate interactions between inputs. Saltelli claims that first and total order indexes (the latter including all possible interactions) allow a thorough and computationally acceptable analysis. More information can be found in (Saltelli et al., 2010).

# Chapter conclusion

Based on current market forecast models for electric vehicles, and on experience gained with the interviews, a disaggregated model has been developed that is both simple and sufficiently rich to explore different scenarios.

This model, based on an expert rule-based decision model applied to each individual in a disaggregated approach, explicitly integrates the issues of cost and the constraint of limited range, which allows the impact of technological developments on these factors to be finely assessed.

It is based on the statistical model of the uses introduced in the previous chapter. Therefore, it works with limited available data.

In order to make the model dynamic over time, the evaluation covers several successive generations of electric vehicles, and an implicit diffusion phenomenon is integrated in order to approach a calculation of market share rather than market potential.

The strategies of public authorities and car manufacturers have also been integrated. The public authorities subsidize each purchase of an electric vehicle within the limit of a constant total budget: an increase in market shares

therefore leads to a reduction in subsidies per vehicle. Car manufacturers choose the battery capacity that optimizes the potential of the new generation of electric vehicles. Individual subsidies and supplied battery capacities over time are therefore a by-product of the model.

The purpose of the next Part is to explore the results we can draw from this model.

PART III - MODEL RESULTS AND DISCUSSIONS

# 6 ELECTRIFICATION SCENARIOS FOR LIGHT COMMERCIAL VEHICLES

The challenge of forecasting success or failure of electric vehicles is to integrate the complexity of individual behaviors while keeping an overview of the underlying assumptions and how they influence the results. Our simulations directly integrate the diversity of uses into input parameters, and then aggregate indicators of electric vehicle relevance for the whole fleet (Chapter 5). In order to exploit a database with partial usage data and to avoid the need for a heavy longitudinal database to integrate usage data, a model has been developed for a synthetic representation of this diversity (Chapter 4).

In this chapter, we apply the methodologies introduced previously to the French market for electric vans. We develop a reference scenario, in which we first detail the assumptions made for the TCO calculations (Section 6.1). Then, the costs of LCVs currently on the market are studied: the analysis will focus on two types of van, a small van (around 2 tons gross weight) and a larger van (3.5 tons gross weight) (Section 6.2). Given the surprising results for larger vans, and the uncertainty about future projections for these vehicles, the remainder of the analysis focuses on the smaller ones.

The model is validated by being confronted to past market shares (Section 6.3). We then apply our model to simulate the future evolution of the

electric vehicle market (Sections 6.4). Different business activities are explored (Section 6.5) and most likely customers are described (Section 6.6). We believe that a 15-year forecast is the most ambitious attempt that we can make with this model, given the amount of uncertainties.

# 6.1 Total cost of ownership computations and input data

First, let us introduce the details of the economic evaluation. As mentioned earlier, it is carried out by a consumer-centered total cost of ownership comparison between BEVs and ICEVs.

We decompose the TCO into cost item categories: vehicle costs, infrastructure costs, battery costs and fuel costs. The TCO results in the sum of these items.

Input numerical data are given in appendix. Results depend on a wide range of numerical parameters, which define the space on which the stochastic model is run. For uncertain parameters, a reference value is given, and the standard deviation of a Gaussian distributed uncertainty (or uniformly distributed if stated so). These variables are considered independent (unless stated otherwise).

## 6.1.1 Model parameters

Two different approaches are possible for the choice of a study period: over the lifetime of the vehicle (with no residual value for the end-of-life vehicle), or over the ownership time of the vehicle before purchase on the second-hand market (the TCO then takes the residual value into account at the end of this period). The electric mobility system can be broken down to three independent systems, namely the vehicle without battery, the battery, and the charging infrastructure. As each has its own life cycle, and as we perform a business-centered analysis, we chose to make the analysis on the ownership period.

The number of years on which the study is made is chosen equal to 4, as it is a common period for accounting depreciation of LCVs run by businesses, and many companies seize the opportunity of the end of this period to change their vehicle.

We choose – a bit arbitrarily – a discount rate of 7%. This discount rate has however relatively low impact on the results as the structure of costs between a BEV with battery rental and an ICEV are rather similar (see Section

6.2). This discount rate is rather high, to penalize upfront investments for companies that have a tight cash flow due to low margins in many transport professions.

We subsequently use  $\tilde{n}$  as a mathematical shortcut to account for discounted yearly expenses, that we will call *number of years with discount*. It is defined as follows:

$$\tilde{n} = \frac{(1+p)^n - 1}{p(1+p)^n}$$

Indeed for a yearly cost c, the total discounted costs over the study period n are (by simplifying the sum of terms of a geometric series):

$$tot = \sum_{i=1}^{n} c \cdot \frac{1}{(1+p)^{i}} = c\tilde{n}$$

The parameter  $\tilde{n}$  is always inferior to the number of years n (or equal when the discount rate is zero). With a discount rate p = 7%, over n = 4 years, we have  $\tilde{n} = 3.39$ .

#### 6.1.1.1 User acceptance and expectations

Two parameters allow us to modulate range and economic constraints respectively.

The first is the PRA threshold beyond which limited range is seen as a crippling barrier ( $PRA_{threshold}$ ). According to interview results, this threshold is low: there are few alternatives when electric vehicles are not suitable, and companies are not ready to abandon some clients or missions. We therefore set this threshold at 0.04, which corresponds approximately to 1 day per year for a vehicle that runs every working day.

Concerning the economic evaluation, we add to the calculation of the TCO of electric vehicles a normal variable, centered on 0, and of standard deviation 1000, to take into account both the uncertainty that the carrier could have at the time of the evaluation of the vehicle, and the heterogeneity of the willingness to pay for electric vehicles.

#### 6.1.2 Vehicle costs

The vehicle costs refer to the costs of purchase of the vehicle, possible purchase incentives, the depreciation of the vehicle after four years of use, and maintenance costs. The battery and infrastructure for EVs are treated independently.

We have:

$$TCO_{veh} = veh_p + veh_{inc} - \frac{veh_p \cdot \text{dep}_0 \cdot (1 - dep_t)^n (1 - dep_k)^d}{(1 + p)^n} + \tilde{n} \cdot veh_m \cdot d$$

With:

- *n* : Study period in years
- *p* : Discount rate
- $\tilde{n}$ : Number of years with discount (as introduced in previous section)
- *d* : Total annual driven distance
- $veh_n$ : Vehicle purchase price
- *veh*<sub>inc</sub>: Vehicle subsidies (if negative) or penalty (if positive)
- *veh*<sub>m</sub>: Vehicle maintenance costs (per kilometer)
- $dep_0$ : Depreciation at purchase
- $dep_t$ : Depreciation rate with time
- $dep_k$ : Depreciation rate with mileage

#### 6.1.2.1 Residual value

We model the residual value as the product of three terms: a loss of value at purchase, a loss of value with time, and a loss of value with the driven distance.

We choose a residual value equal in euros for ICEVs and EVs, and given the uncertainties, we assume a standard deviation of the residual value of more or less 5% for EVs. ICEV residual value data are derived from averages on used vans sold by the Renault network in France in 2015.

Under this assumption, the only difference between ICEVs and EVs is the above-mentioned 5% uncertainty, so the exact absolute value of the resale value does not matter much, the right order of magnitude is however interesting for the sensitivity analysis. As the vehicle prices move with time, we therefore choose to adapt the residual value in percent to stay constant in euros.

#### 6.1.2.2 Vehicle price

Current purchase prices for conventional vehicles are based on Renault vans. For 2017, they are based on a Renault Kangoo Express Comfort dCi 90 model (ICEV) and a Renault Kangoo Z.E. Comfort model (EV). They are among the most sold LCVs in their respective segment in France and in Western Europe<sup>30</sup>.

At the time of writing this thesis, alongside the Iveco Daily and the Gruon Electron II, the Renault Master Z.E. is one of the few 3.5 gross weight vans on the

<sup>30</sup> http://ccfa.fr/, accessed 14 June 2018

EV market (released on February 2018). The prices in our investigation are based on a Renault Master Z.E. Comfort L1H1, and a conventional Renault Master Comfort L1H1 dCi 130 E6.

Future prices are based on two assumptions:

- The price of ICEV will increase as more and more stringent regulations will require more demanding air-pollution treatment devices.
- The price of EVs will decrease (excluding batteries), driven by economies of scale and technological progress.

In the reference scenario,  $\leq$  500 additional costs for ICEVs and a  $\leq$  500 cost reduction for electric small vans are considered for each new introduced van generation (in 2022 and 2027).

Vehicle maintenance is put to zero for both technologies (which in practice amounts to considering them identical since we are interested in the TCO difference). If in theory electric vehicle maintenance should be lower, not enough evidence has been found to give an order of magnitude of the savings.

#### 6.1.3 Incentives

Financial incentives are a critical factor for the economic competitiveness of EVs. In France, significant public subsidies support them. Since 2008, financial incentives have been offered through a bonus / malus system, based on carbon emissions. In July 2012, the bonus was raised from  $\leqslant$  5,000 to  $\leqslant$  7,000. It then dropped to  $\leqslant$  6,300 at the end of 2013, but a "super-bonus" with an additional  $\leqslant$  3,700 scrapping premium is introduced in April 2015, under the condition (among others) of scrapping an old diesel powered car. Today, a  $\leqslant$  6,000 bonus is still in force (since January 2017), which goes up to  $\leqslant$  8,500 with the super-bonus. For simplicity, changes are reported at the beginning of the nearest semester in the simulation.

The tax exemption of company cars does not apply in our context, as there is already an exemption for LCV-users, regardless of the motorization.

In addition to the national bonus and super-bonus, some local authorities add their own subsidies. The most notable is in Paris, where the municipality offers to small companies (less than 10 employees) an additional subsidy of  $\leqslant$  3,000 for small vans,  $\leqslant$  6,000 for 3.5t gross-weight vans, and  $\leqslant$  9,000 for trucks. Many regions offer some subsidies for infrastructure or vehicle purchase.

The scrapping premium and local subsidies are hard to take into account in our disaggregated study. Indeed, they are subject to conditions (for instance sometimes the same company cannot apply for several subsidies) local incentives are usually limited in time and (by definition) in geographical coverage.

Future public incentives are computed according to the rule presented in sub-section 5.4.2. The lower assumption takes into account only the national public bonus which led to expenditures of a bit less than  $\leq$  40M euros for LCVs in 2017. Assumptions are made for the total budget of public administrations allocated to the support of electric vans. As the bonus has been maintained, we assume that the public administrations are approximately ready to increase to a total expense between  $\leq$  50M and  $\leq$  60M in the reference scenario. Other scenarios are explored in section 7.2.2.

We consider the LCV-market size and the distribution of vehicle sizes on these markets to be constant over time. Market sizes (including passenger car derivatives) are taken from 2017<sup>31</sup>, with 202,000 small vans and 235,000 big vans.

#### 6.1.4 Battery costs

Battery costs are integrated separately through battery rental costs. If it is not obvious which business model will dominate in the future between battery rental and battery sale, today different car manufacturers do one or the other. At Renault, batteries are mostly leased and subject to a monthly rent, even though recently the batteries have been opened to purchase with the vehicle<sup>32</sup>.

The choice of a battery lease is made for several reasons. First, the financial difference between the two business models is minimal, as the battery rents should be proportional to the battery price, and so variations in the latter may affect the TCO independently of the business model. Furthermore, this allows us to use current rental rates. Then, the separation between vehicle and battery price is very clear this way. Furthermore, we assume that the car manufacturers have already accounted for the battery price and billing, battery's second life value, battery ageing with time and mileage, battery replacement costs when it becomes unsuitable for automotive use. Taking these values as a

-

http://www.statistiques.developpement-durable.gouv.fr/donnees-ligne/r/immatriculations-vehicules.html, accessed 14 June 2018

<sup>&</sup>lt;sup>32</sup> TORREGROSSA, Michael. "Renault Ouvre L'achat Batterie Sur Ses Utilitaires Électriques." Automobile Propre, Automobile Propre, 1 June 2018, www.automobile-propre.com/renault-ouvre-lachat-batterie-sur-ses-utilitaires-electriques/.

reference avoids the need to make assumptions by ourselves, by relying instead on the assumptions of the car manufacturers.

In fact, the model can easily be adjusted to represent direct purchase costs, by adding the battery upfront costs to the vehicle purchase prices  $(veh_p)$  and setting the rent to zero. The depreciation rate of the vehicle would need to be changed accordingly, but analogies with conventional vehicles would then be more hazardous, because of the uncertainties surrounding battery ageing.

The cost of the battery is computed as follows:

$$TCO_{hatt} = \tilde{n} \cdot 12 \cdot r_{hatt}(d_{el})$$

With:

 $\tilde{n}$ : Number of years with discount (as introduced in previous section)

 $d_{el}$ : Annual distance driven

 $r_{batt}(\cdot)$ : Monthly rental rate for the battery depending on distance driven

In practice, we will use a piecewise linear function, as Renault charges the battery to its customers today, with a minimum rental rate  $r_{floor}$ , for the first annual kilometers  $d_{floor}$ , and then a kilometric cost  $r_{km}$  per kilometer:

$$r_{batt}(d_{el}) = \max(r_{floor}, r_{km} \cdot (d_{el} - d_{floor}) + r_{floor})$$

With:

 $r_{floor}$ : Minimum rental rate

 $d_{floor}$ : Annual distance paid for in the minimum rental rate

 $r_{km}$ : Rental rate per kilometer

The minimal rate can be explained by the need for the manufacturer to get back the money invested in the battery in "reasonable" time. In reality, the most *energy* is drawn from the battery, the more the battery wears, and energy needed for one kilometer driven at high speed differs from one kilometer driven at low speed. Equalization over all customers, who in turn pay an average price, allows using the driven distance as a proxy.

Costs in 2017 are based on Renault rental rates. The latter are presumed to be directly proportional to battery capacity  $\times$  battery cost per kilowatt-hour, which is an approximation because technology and price actually depend on power, energy, and their ratio. Battery costs in 2022 are set according to a  $8 \pm 8\%$  decline (Nykvist & Nilsson, 2015) between 2017 (release date of the last Kangoo Z.E. generation) and 2032.

The choice of the battery capacities of next vehicle generations are justified in sub-section 6.4.1.2, they are the result of the maximization of the EV-potential assuming there is only one battery capacity supplied on the market.

#### 6.1.5 Infrastructure costs

EVs need specific infrastructure installations for the vehicle to be operational. The infrastructure may last longer than the vehicle, so not the entire expense needs to be put on the study period. As for the vehicle, we suppose there is an upfront installation cost, and a (discounted) residual value at the end of the period. Unlike the vehicle, infrastructure will not depend on a second-hand market, so we assume a uniform decline in value over its lifetime.

$$TCO_{infra} = infra_p + infra_m \cdot \tilde{n} - \frac{infra_p(1 - n/infra_n)}{(1 + p)^n}$$

With:

n: Study period in years

p: Discount rate

 $\tilde{n}$ : Number of years with discount

 $infra_n$ : Infrastructure upfront purchase and installation costs

 $infra_m$ : Annual infrastructure maintenance costs

 $infra_n$ : Expected lifetime of the infrastructure (in years)

We choose upfront and installation costs uniformly distributed between  $\leq$  1,500 and  $\leq$  2,500, and  $\leq$  200 yearly maintenance costs. Prices are in the range to those of level II AC public infrastructure (Schroeder & Traber, 2012) and in line with the testimonies in our interviews. Network reinforcement works, if needed, for instance for big fleets, could add up a significant cost (Van Amburg & Pitkanen, 2012).

#### 6.1.6 Fuel costs

$$TCO_{fuel} = \tilde{n} \cdot infra_{eff} \cdot meancons \cdot F \cdot d$$

With:

 $\tilde{n}$ : Number of years with discount

 $infra_{eff}$ : When applicable, the charging efficiency of the infrastructure (else, 1)

meancons: Average consumption

F: Fuel price

d: Annual driven distance

The charging efficiency of the infrastructure  $infra_{eff}$  accounts for the loss of energy during charging of the battery. This efficiency is around 85%.

#### 6.1.6.1 Energy prices

Diesel price series are computed as follows. Past time series are data from the Comité National Routier<sup>33</sup>. Variations of crude oil prices (in \$/bbl) are taken from the World Bank Commodities Price Forecast released October 26, 2017 (World Bank, 2017). As crude oil prices accounts for approximately 30% of the VAT-free Diesel prices in France, the trends can be reported to the prices at the pump. We correct the results with the additional tax of  $7.9c \le /L$ , effective since January 1, 2018.

Given the volatility and the difficulty to forecast Crude oil prices, a high uncertainty is applied on the Diesel price assumptions. We use a normal distribution, centered on the forecasted price, with a standard deviation up to 10% of the forecast.

Past electricity time series are obtained from the Pégase<sup>34</sup> database, from the SDES (Statistical services from the Minister of the Environment). They are taken with the off-peak fair, as our main assumption is mainly nighttime charging. Future time series are extrapolated by linear regression of data between 2011 and 2017. A normal distribution centered on the forecasted price, with a standard deviation of 5% of the price, accounts for uncertainties on electricity predictions.

For a given time, the electricity or Diesel costs are averaged over the study period in the TCO computations. All energy prices are taken VAT-free.

#### 6.1.6.2 Consumptions

Consumptions are computed by crossing the share of distances driven in different environments (urban, road or highway) with reference consumptions on these environments.

 $meancons = Highway \cdot cons_{highway} + Road \cdot cons_{road} + Urban \cdot cons_{urban}$ 

<sup>34</sup> www.statistiques.developpement-durable.gouv.fr/donnees-ligne/r/pegase.html, accessed 12
March 2018

<sup>33</sup> http://www.cnr.fr/, accessed 12 March 2018

#### with:

- *meancons* = average consumption of the vehicle
- $cons_{environment}$  = Consumption in the given environment (urban, road or highway)
- *Highway*, *Road*, *Urban* = Share of distances driven in the respective environments. Sum must be equal to 1.

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 (Tietge et al., 2015). EV consumption rates are based on Renault's real world range evaluation tool<sup>35</sup>, on the Renault Kangoo ZE (300 kg of load, 20°C). Worst range is obtained with the same tool at -5° with heater on. Worst consumptions are only used for the range, so they are not required for ICEVs. Worst consumptions in winter are all the more penalized for bigger vans, as the volume to heat is significantly increased.

For the first generation of Kangoo Z.E., a 15% penalization has been applied, as the efficiency of the motor was not as good as today.

#### 6.1.7 Use variables

In addition to the statistical use model (estimated in section 4.5), other use parameters can be fitted on the same database to describe the nature of the trips: urban environments, roads or highways. We recall that these characteristics are encoded by two variables, the share of highway on total driven distance, and the share of urban uses on the remaining distances (so as to ensure that the sum is 1). We have made the assumption of independence between these variables and with other input variables (in particular the average driven distance) to simplify the inputs. In practice, we have fitted separately two beta distributions on each of these inputs, observed in the SDES database (values are in appendix).

198

<sup>&</sup>lt;sup>35</sup> https://www.renault.fr/vehicules/vehicules-electriques/kangoo-ze/autonomie.html, accessed 12 March 2018

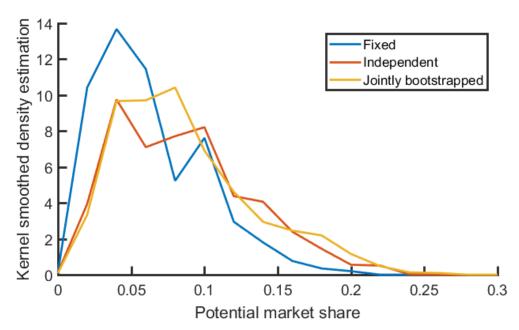


Figure 32 Difference in potential market share distributions with different assumptions: 1- constant shares of distance driven on highway and in cities ('Fixed'), 2- independently distributed use variables ('Independent') or 3-jointly distributed use variables (jointly bootstrapped average driven distance, share of distance driven on highway and in cities).

To confirm the validity of this independence assumption, we compare three model runs in Figure 32. To be able to generate jointly bootstrapped use variables, given the absence of longitudinal data, we were forced to assume the shape parameter independent of the mean of the distribution, resulting in a simplified version of the usage modeling (or reformulated, the copula parameter is set to 0). The distributions of the output potential market share (with assumptions for 2017) are compared in three setups:

- with fixed input variables on the nature of the trips (fixed to the average),
- independently fit variables (with fitted beta distributions),
- jointly bootstrapped distributed variables (average distance, share of highway, share of urban uses on the remaining distance)

We see that the assumption of independence does only affect weakly the distribution of the market potential. However, considering the parameters as constant significantly reduces the market potential. This can be explained by the fact that it imposes a fraction of highway on all agents, penalizing the many vehicles that are in reality only driving in urban environments.

To fit the beta distribution, we need values in the open-interval ]0, 1[. To deal with values equal to 0 and 1, we simply apply the transformation suggested

in (Smithson & Verkuilen, 2006) before the fit (with x the sample to fit on, N the size of the sample):

$$x' = \frac{x \cdot (N-1) + 0.5}{N}$$

Thus, all variables corresponding to uses were estimated from the SDES database.

#### 6.1.8 Note on PHEVs

For hybrid vehicles, two vehicle running phases can be distinguished, the depleting phase and the sustaining phase. During the depleting phase, the battery (that we call system 1) has enough energy to power the traction chain and the battery discharges. Depending on the technology, the additional system (that we call system 2) may or may not also operate during this phase, in addition of the battery, or for specific running phases (as for instance at high speeds or during acceleration phases).

Once the battery is empty, or reaching a predetermined state of charge (SOC) threshold, the sustaining phase is initiated. Then, the additional system is providing the traction power. The battery can be further used thanks to regenerative braking, but is stabilized around its SOC.

Therefore, for hybrid vehicles, the range is computed slightly differently and represents the range on *depleting* mode.

$$r = (1 - s) \cdot \frac{C}{m}$$

Where s is a predetermined state of charge level at which the system management switches to sustaining mode (typically s = 0.1 for hybrid electric vehicles).

We can define the driven distances  $d_{\rm dep}$  and  $d_{\rm sus}$  which are respectively the annual driven distances on depleting and sustaining phases with a hybrid system. The TCO equations can then be rewritten by replacing the distance traveled by the appropriate combination of  $d_{\rm dep}$  and  $d_{\rm sus}$  (for example, battery ageing or electricity consumption can only be considered as dependent on  $d_{\rm dep}$ , while the residual value depends on the sum).

# 6.2 TCO exploration

The TCO explores successively small vans in sub-section 6.2.1 (less than 2.5 tons of gross weight) and 3.5 tons gross weight vans in sub-section 6.2.2. In reality,

car manufacturers have at least three (sometimes four) segments of LCVs, with intermediate models between the smaller and the bigger LCV. We reduce to two segments for simplification.

#### 6.2.1 Small vans

#### *6.2.1.1 Are electric vehicles economically competitive?*

This question alone makes not much sense: the cost of electric vehicles is, as has been repeatedly proven throughout this dissertation, very variable from one potential customer to the other.

The aim of the previously introduced disaggregated study is specially to include this variability into the competitiveness assessment, so the right question that should be asked is: for whom and for how many potential customers are electric vehicles competitive?

In Figure 33 are represented the average TCO as a function of the annual driven distances, for EVs and ICEVs, where different expenditure items are distinguished.

First, we note new expenditure items for BEVs (upper left subfigure (a.)), infrastructure costs and battery costs, which are absent from ICEVs' total costs (upper right subfigure (b.)). Infrastructure costs are far from being negligible. Overall, depreciation costs have very similar profiles for both technologies, and so do the fuel compared with the battery costs (rental and electricity). So in the first order, the savings made on diesel are approximately compensated by battery rental costs. For short annual distances traveled, the minimum battery rental rate can be observed.

In the third subfigure (c.), the distribution of the annual driven distances (all small vans, France) are superimposed to the total TCO curves. The computations are done with current assumptions (2017) for small vans in France. We observe that the average TCO of EVs is in average higher than the TCO of ICEVs. They are however close enough so that their confidence bands are overlapping, allowing exceptions to this observation: especially when the annual driven distance is high, but it is also where limited range becomes the more critical.

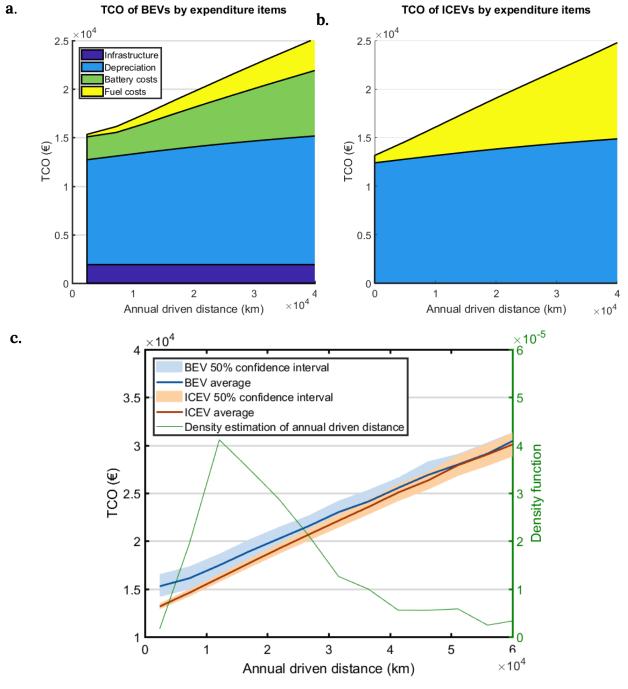


Figure 33 TCO comparison for electric and conventional small LCVs, by expenditure items (a. and b.) and total (c.), assumptions of 2017. Confidence bands are at 50 %.

The amount of depreciation may seem high, due to the discount of the resale value. Indeed, with a 7% discount rate, only 75% of the resale value is actually integrated in the total cost of ownership, as the money is recovered only at the end of the four-year period.

#### 6.2.2 Big vans

We refer to *big vans* as vans with a gross vehicle weight of 2.5 to 3.5 tons. In practice, the vehicles considered have a gross weight of around 2.8 tons. In Figure 34, three major differences can be noticed with the small van market:

- The price difference between combustion and electric vehicles is significantly higher than for the small van market (both in absolute and relative terms). This may be a consequence that the market is in its infancy, with only few available vehicle models.
- The variable costs are different as well. The high consumption of ICEVs leads to more than twice the kilometric costs of small vans. For EVs, electricity costs are higher, but also and especially battery costs, as the wear of the battery is roughly proportional to the energy drawn from it.
- With the same battery, the range of big vans is much smaller than for small vans (average range estimated around 90 kilometers in real life conditions).

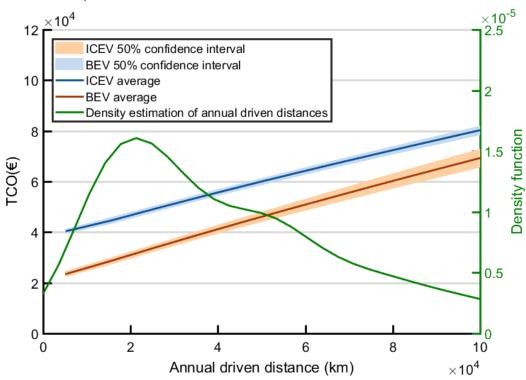


Figure 34 TCO comparison for electric and conventional bigger LCVs, assumptions of 2018.

Figure 34 shows that this bigger van is clearly not competitive, as things stand at present, with an equivalent conventional van. Even for high driven distances (which is virtually impossible to achieve given the vehicle's reduced range), fuel savings would not refund the difference in cost at purchase at all. As a result,

there is very little chance that this first generation will find a market outside cities that prohibit the use of conventional vehicles.

This finding suggests that the fear of some companies that city centers will be closed to ICEVs is justified: without even counting the operational difficulties, the additional cost of switching to EVs may be considerable. Similarly, without even considering the need for range improvements, car manufacturers are confronted with an additional cost of over €10,000 that has to be reduced to make electric vehicles somewhat competitive.

The evidence we have does not allow us to adequately assess whether these objectives are realistic, and if so for what time frame. The vehicle prices may be artificially high. We have not identified any structural reasons in our research why the price differential between electric and diesel vehicles (excluding batteries) is greater for large vans than for small ones. The high price of the vehicle surprised at the time of its release <sup>36,37</sup> and it is not unlikely that it is due to low competition and development costs rather than critical technical causes. Competition in the segment is weak, and these manufacturers could benefit from the closure of city centers to diesel vehicles, and the willingness to pay more for environmental innovations by *innovators* (as the very first adopters are called in innovation diffusion theory). The development of the vehicle undoubtedly required investments in research, as well as in industrial equipment, which also explains the high cost. No future scenario will therefore be evaluated, but we guess that it will probably remain a niche market for many years to come.

This would suggest that prices could fall rapidly at first, nuancing the above statements, but this is highly speculative. Rather than making these speculative assumptions, we will rather analyze the small van market, bearing in mind that the large van market should have the same dynamics with several years of delay.

204

\_

<sup>&</sup>lt;sup>36</sup> Lara, Hugo. "Essai Renault Master ZE : Ce Cher, Très Cher Fourgon Électrique." Automobile Propre, 28 Feb. 2018, www.automobile-propre.com/renault-master-ze-cher-tres-cher-fourgon-electrique/.

<sup>&</sup>lt;sup>37</sup> Leone, Gabin. "A Quoi Joue Renault Avec Son Master Électrique?" Le Mobiliste, 23 Feb. 2018, http://lemobiliste.com/a-quoi-joue-renault-master-z-e/

# 6.3 Market potential and past market shares

We do not pretend that our model is able to compute precise year-by-year market shares. However, a retrospective evaluation of the model based on past data confirms its relevance and outlines its limitations

To our knowledge, it is very difficult for a model to forecast the market in such early stages (for a model that has not directly been fitted on past data). The reasons for that are multiple:

- La Poste, owner of the worldwide biggest electric van fleet, has bought since 2012 approximately 1,700 electric vehicles per year. Thus, past time series have been heavily affected by the strategic choice of a single economic actor. As such, it is a challenge to guess from past time series any information about the rate of diffusion.
- Among the buyers of electric LCVs, a significant proportion probably are companies making experimentations: the economic pressure is then somewhat relieved. Experimentations can in addition be externally funded, for instance by research projects.
- It is difficult to estimate how much the vehicle and the charging infrastructure were subsidized, between the bonus, the possible superbonus, many possible local incentives spread in space and time, research projects, all applying an unknown number of conditions.
- Incentives have undergone several readjustments, upwards or downwards, whose effects on the diffusion of the innovation are unknown in the short term. Indeed, the announcement of a raise in the subsidies may cause a temporary postponement of the purchase, or oppositely with a planned decrease of the financial subsidies.
- As market shares are small, a small absolute error can lead to a major relative error.

To account for possible additional incentives between 2011 and 2017, we choose a lower scenario with only the national bonus (which changed several times during this period), and an upper scenario with additional €1,500 in average for each vehicle (which could correspond to additional local incentives). The computed potential market shares are represented in Figure 35, for small vans only. It has been considered that all electric LCVs sold until now are small vans.

We observe that:

- The order of magnitude of the computed potential is consistent with the actual market shares. With only the bonus, the market shares are underestimated. Local subsidies are, according to the model, essential to the competitiveness of the first generation of electric vans.
- The market share potential estimation is very sensitive to changes in incentives and fuel prices, more than the actual market shares, which have greater inertia (as the difference of amplitude of the peak around 2013 shows).

The model explains well the sudden increase in sales observed in 2012 and 2013, followed by a relatively flat market evolution. The model would have predicted a further growth of the market if the incentives would have stayed at €7,000.

- The discrepancy observed at the beginning of 2012 can be explained by the fact that the sales data are annual, whereas the calculation of the model includes the subsidy change at mid-year.
- Potential is decreasing from 2014 on, while actual market shares are increasing. This difference can have several explanations. First, the simulation does not integrate in any way the superbonus, obtained when an old Diesel is scrapped at the time of purchase, introduced in 2015.

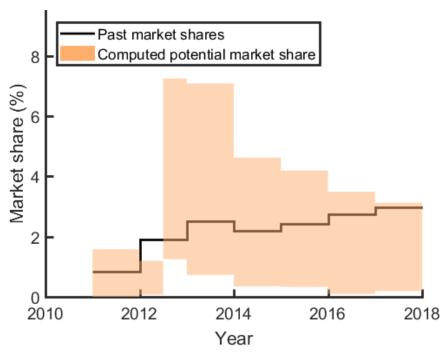


Figure 35 Observed past market shares vs. computed past potential market shares (lower bound only with incentives from public administrations, upper bound with €2,000 additional incentives)

Second, this growth could be due to the diffusion of innovation across the agents (the phenomenon on which innovation diffusion models are based). Third, the technology is assumed to be constant over this period of time when in reality improvements have been made to the vehicle (on the engine or on auxiliary equipment).

The results are satisfactory, although the model is not directly designed to be evaluated year-by-year as it is done here. By assessing the potential of a new generation of vehicles 5 years after its release, and thanks to the calculated balance between subsidies and market shares, our model should not suffer from the high sensitivity observed here in its future estimations.

In order to support behavior changes, and to give a strong signal to all market players, delaying the reduction in incentives after the release of each new generation of vehicle seems to be an interesting strategy for authorities. It keeps high market potentials so that potential customers are considering electric vehicles among their possible next buy. Even if they will not necessary buy one immediately, it will prepare the terrain for a future purchase.

### 6.4 Reference scenario

In this section, we finally use the model for prospective analysis, taking into account rapid technological developments.

#### 6.4.1.1 Reference scenario for small vans

The projection of some input parameters (fuel cost, battery kWh cost, etc.) have already been discussed independently of the model results, others are directly dependent on these results. This is especially the case for national incentives. According to us, they cannot be explored separately as there is a direct two-way interaction between public subsidies and market shares (see 5.4.2.1). We therefore present scenarios as joint time series for predicted market shares and public incentives. Incentives are one, if not the most critical factor. Many studies have shown a strong (but not systematic) correlation between amount of incentives and actual market shares, e.g. (Fearnley et al., 2015; Lutsey, 2015). Public subsidies are eminently political, and hard to predict. Our basic rule of thumb is our best guess.

A second strategic choice, made this time by car manufacturers, is the choice of battery capacity for the next generation of electric vans.

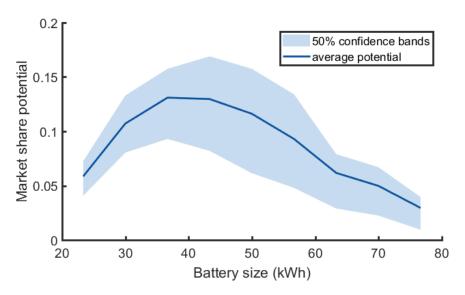


Figure 36 Market share potential (assumptions of 2022) as a function of the battery capacity

#### 6.4.1.2 Battery capacity forecasting

It is indeed essential to imagine what the future vehicle will look like in order to assess its market potential. We assume the supply of a new generation of electric vehicles every 5 years until 2032. In our reference scenarios, we consider that car manufacturers only supply a unique size of battery. It has been outlined that there exists no "one-fits-all" solution, but industrial constraints may encourage car manufacturers to supply only one capacity.

In this setup, we assume that car manufacturers choose the battery that covers the largest share of potential customers (without entering into game theory and competition across car manufacturers). Figure 36 shows this share with the assumptions of 2022, as a function of the battery capacity. We can observe that the optimal battery capacity is around 40 kWh, which we choose as a reference for the third generation of electric LCVs.

The same approach with the assumptions of 2027 leads us to choose a battery capacity of 53 kWh for the fourth generation of vans (2027 to 2032).

#### 6.4.1.3 Reference scenario analysis

Figure 37 shows the reference scenario with all previously stated assumptions. Confidence bands are given only for public incentives, market shares are averaged over all other uncertain parameters. A sensitivity analysis is performed in the next chapter. The figure represents the evolution of market shares for small vans (share of small electric vans in all small vans), in conjunction with the evolution of subsidies (which is endogenous to the model).

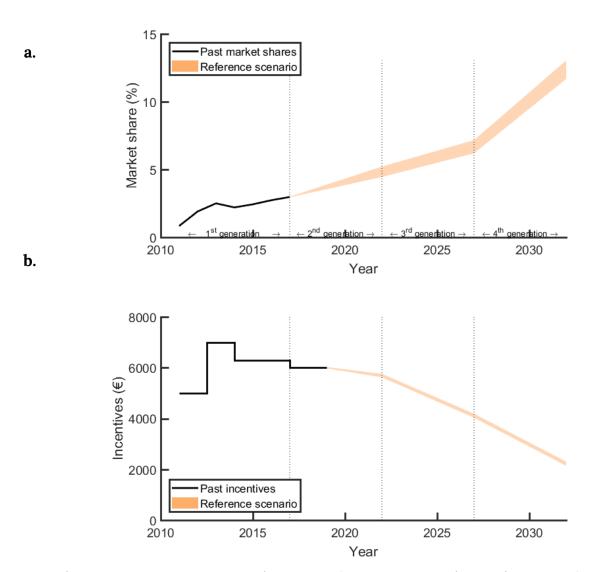


Figure 37 Reference scenario for market shares and incentives. The lower (resp. upper) confidence interval limit is given for a total state budget allocated to electric LCVs of €50M (resp. €60M)

We observe on Figure 37 that:

- **No immediate exponential growth** is foreseen in this reference scenario. When technological change allows for a gain in competitiveness, it is immediately offset in part by the reduction in purchase subsidies. The lower the subsidies, the weaker this effect, and the market growth accelerates (it's noticeable between 2027 and 2032). This is precisely the mechanism described in Figure 31.
- Our reference scenario predicts that the market will double in size in ten years, with a total *small van* market share around 7%. For this to be the case, the financial support to electric vehicles must be continuous over these ten years, with a slight decrease that reduces it to around €3,500 of subsidy per vehicle. Five years later (in 2032), electric vehicles could

represent between 11% and 13% of the whole fleet of small vans, with subsidies of about €2,000.

 We note that the variation in subsidies is small, but nevertheless leads to a significant variation in market potential. This illustrates that the model would have very high sensitivity to subsidies without the subsidy regulation mechanism, which therefore seems indispensable to obtain a stable model.

These results suggest that it will take many years, with continuous public support, for electric vans to reach a mass market.

# 6.5 Investigation by business activity

Based on the declared main use of the vehicle, three categories of business users are investigated: freight transport for own account, freight transport for third account, and a category under the denomination *craftsmen*, which actually includes agents who have reported carrying tools or samples for work, materials, rubble or waste.

The use model has been fitted on each of these categories, each with its own distribution of DVKT, and of share of highway, road and urban environments. The corresponding parameters can be found in the appendix.

Unlike the previous figures, we consider the complete light commercial vehicle market, rather than just the small van market, where we assume that there is no market for larger vans. This becomes more and more inaccurate as time goes by. The subsidy assumptions are those of the reference scenario that balance the overall market. The results are presented in Figure 38. Not knowing the current levels of sales of electric vehicles by sector of activity, the 2017 values are left blank.

According to the SDES database, the proportion of small vans in the total composition of the fleet varies according to the sector of activity: 55% of the vehicles registered for the transport of goods for third account are small vans, against 39% for transport for own account and 47% for craftsmen.

Overall, all three follow the same trend, but third-account freight transport nevertheless offers better opportunities for EVs. The market potential identified by the model is two to three times greater than for own account freight transport and for craftsmen. The observed results have several causes. First, the composition of the fleet favors the transport of goods for third account, with a greater proportion of small vans. Despite a higher average annual

distance, the regularity of the trips allows these activities to stand out from the other two with less regularity. In particular, the variability of the craftsmen's trips puts them at the lowest potential, despite a rather favorable fleet composition.

Looking into the freight for third-account sample, the database distinguishes several activities (not two-by-two exclusive):

- 395 entries are in the category of parcel express transport (aimed for bundling/unbundling supply chains);
- 77 entries are vehicles that make regular delivery rounds for a *unique* client (e.g. for a bank, an insurance company, an administration);
- 77 entries represent couriers, or on-demand freight transportation;
- 33 entries are vehicles that make home deliveries (e-commerce, food etc.).

It is to be noted that these categories are not two-by-two exclusives (as were the main categories), which explains that the sum of entries exceeds the number of entries in the freight for third account sample.

In Chapter 3, we observed that parcel express transport is a sector that is very favorable to the use of electric vehicles. This analysis confirms that these activities are conducive to electric vehicles. The actual market share is

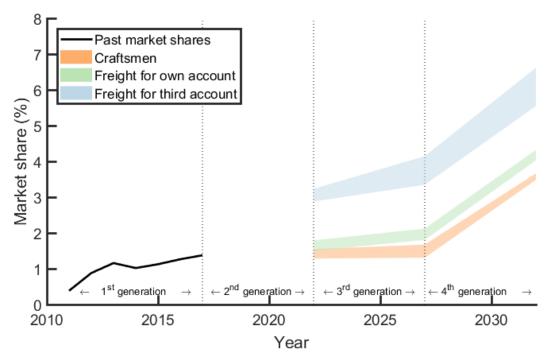


Figure 38 Comparison of market projections for three different business classes (all light commercial vehicles, unlike other figures focusing on small vans).

undoubtedly underestimated by considering an inexistent market for bigger trucks: this is the sector we have identified as the most favorable to their use.

It should also be noted that this illustrates that a certain number of companies will not have the possibility of using an electric vehicle advantageously given their usage patterns.

# 6.6 Customer usage profiles and electric kilometers traveled

#### 6.6.1 Average driven distances

The model estimates not only the possible future market size in terms of the number of vehicles, but also the number of kilometers traveled by these electric vehicles. This information makes it possible to analyze the optimal use profiles.

Figure 39 shows the potential market share calculated by the model based on average daily user distances.

Several observations can be made:

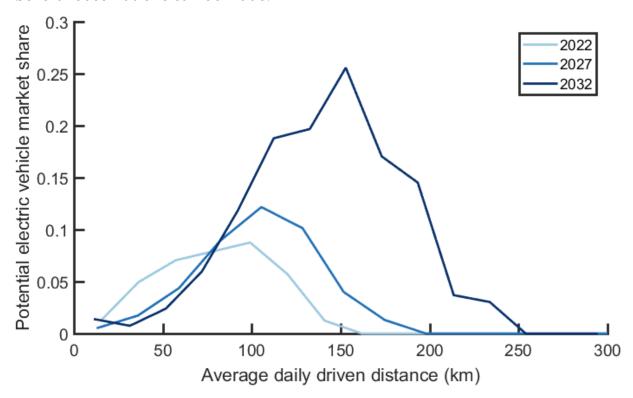


Figure 39 Potential EV market shares as a function of the average daily driven distances for the second (2017-2022), third (2022-2027) and fourth (2027-2032) generations of small vans.

- For very short distances, an electric vehicle is not competitive for economic reasons: the short distances traveled do not compensate for the additional cost of purchasing the vehicle and infrastructure. For greater distances, it is the limited range that poses blocking operational problems. The result is a window of optimal use profiles, for which electric vehicles are economically and operationally favorable.
- With the increase in battery capacity with time, electric vehicles are aimed at profiles that cover increasingly large average distances. This is confirmed in Table 9, where we observe an increase of 46% in the average daily distance traveled (from 85 km to 124 km a day) between the current generation of small electric vans and that projected between 2027 and 2032.
- Each new generation of vehicles increases the maximum use profiles by approximately 50 kilometers. The window of use of electric vehicles is widened with each new generation of vans.
- Low mileage usage patterns (30 to 80 kilometers per day on average), do not benefit from the technological evolution in the baseline scenario (they may be even penalized). This is because in the reference scenario we assume a single battery capacity, with capacity increasing over time. Users who do not use this additional capacity may then have to pay additional kilowatt-hours that they would not use. The fact that there are large players with this usage profile, which correspond in particular to postal activities, could lead to the existence of a battery supply specifically adapted to their needs. The supply of several sizes of batteries by car manufacturers is studied in section 7.3.

#### 6.6.2 Dominant constraints

Figure 40 breaks down the market for small vans according to the constraints that may prevent the use of electric vehicles (with the lower assumption on subsidies from the reference scenario). Limited range is not acceptable (according to our criterion, see section 5.3) for 58% of the agents in 2022. Among the remaining agents, the economic constraint hinders most of the agents to switch to electric vehicles.

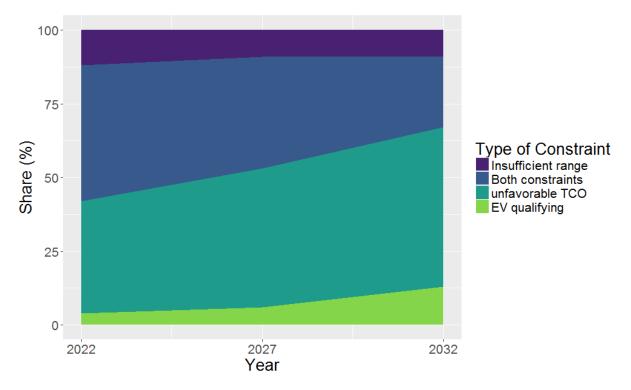


Figure 40 Evolution with time of the range and TCO constraints for electric vans.

We also note that limited battery range is becoming less and less of a problem as battery capacity increases. In 2032, it is considered a constraint for only 33% of the agents. The economic constraint, however, changes little as subsidies decline.

It can therefore be deduced that the dominant constraint will soon be the economic constraint.

# 6.6.3 Total kilometres travelled by electric vehicle

The baseline scenario can also feed into the study of environmental gains from the electric van market. For this we need information on the stock (all small vans) and not only market shares (only new vans). A thorough stock model would be necessary to take into account its evolution over the years. We will content ourselves with a rough estimate.

To this end, we make several simplifying assumptions: we consider a constant age distribution in the fleet over time (obtained from the SDES database), and the service life of electric vehicles (before scrapping) identical to that of conventional vehicles. We also assume that the use of the vehicle is constant throughout its life. The reference scenario then provides us with the market shares and distances travelled by these vehicles.

	2022	2027	2032
Average daily distance traveled	85 km/day	101 km/day	124 km/day
Total annual electrified kilometers traveled (new vehicles)	193.10 <sup>6</sup> km /year	318. 10 <sup>6</sup> km /year	736. 10 <sup>6</sup> km /year
Total annual electrified kilometers traveled (stock, rough estimate)	~1 billion km /year	~1.6 billion km /year	~2.9 billion km /year
Relatively to total distance traveled (stock, rough estimate)	~2%	~3.3%	~6%

Table 9 Distances traveled by small electric vans, and shares in the total vehicle fleet (on the basis of the lower subsidy assumptions in the reference scenario)

Table 9 shows the total number of kilometers traveled by electric vehicles (for small vans), as well as the share of the total kilometers traveled in the total small vans fleet it represents. We arrive at the result that electric vehicles will have contributed to the replacement of around 6% of total kilometers traveled by small vans in 2032, which would otherwise probably be traveled by Euro 6 vehicles.

This provides valuable information for decision-makers, in terms of reasonably expected environmental gains from switching from diesel to electric technology. These percentages should be compared with the stated environmental objectives. Within the framework of the International Climate Conference (COP 21) held in Paris at the end of 2015, France committed itself to reducing GHG emissions in transport by 29% over the period 2015–2028.

Even with a potential 80% reduction in CO<sub>2</sub> emissions with EVs compared with ICEVs, thanks to a mostly carbon-free electricity industry in France, we see that we are far from the goal. EVs certainly do not, on their own, make it possible to achieve short-term reductions of this order of magnitude for light commercial vehicles in freight transport, despite continued support from public authorities. It is only one axis of progress among others. Very proactive and diversified measures are therefore necessary to achieve this ambitious objective.

The same observation can be made for local pollution, even if one assumes that these vehicles mainly run in urban areas: the short-term decrease is far from spectacular.

In our view, it would be a mistake to relate the amount of current subsidies to the associated environmental benefits. This calculation can only give disappointing results. The continued support of public administrations for electric vehicles should be seen as an accompaniment to the transition to more sustainable mobility, rather than as an investment that brings immediate benefits. We recall that significant growth in the electric commercial vehicle market is possible after 2032, once subsidies have reached a low level. In the reference scenario, most of the environmental benefits are to be expected after 2032.

Subsidies can then be justified by several effects that they allow: they encourage learning by doing, so that when competitive electric vehicles are supplied on the market, companies will be able to evaluate them and seize the opportunity immediately. They also stimulate the network effect, whereby a larger mass of users allows new benefits to emerge, triggering a virtuous circle. This is for example the case for publicly accessible infrastructure: the more users there are the more relevant and economically viable it is to offer this service, and vice versa the more infrastructures there are the more users are likely to be interested in EVs. The positive effects of electric vehicles in terms of noise and driving comfort for employees should also not be ignored. Finally, it is a strong signal to car manufacturers about the need to convert their industrial production facilities to this alternative technology.

#### Chapter conclusion

In this chapter, we have implemented the models introduced in Part 2. To do this, assumptions had to be made about the evolution of the supply of electric commercial vehicles and the costs associated with them.

The TCO curves indicate that with a battery rental model, the cost structures are very similar between EVs and ICEVs for small vans. The cost of battery rental, proportional to the distance traveled, and electricity costs are on average of the same order of magnitude, but slightly lower than the cost of diesel for the same distance. Fixed prices are similar but slightly higher (less than  $\[ \in \] 2,000 \]$  euros) for small electric vans, after the current national subsidy of  $\[ \in \] 6,000.$ 

The fixed price difference for the biggest vans, more than €15,000, seems to be far off the mark. The offer is clearly deficient, and the new models are financially very uncompetitive. It is likely that the fact that this is the first generation put on the market by car manufacturers plays an important role in this, for two reasons. First, competition in the segment is weak, and these manufacturers could benefit from the closure of city centers to diesel vehicles, and the willingness to pay more for environmental innovations by innovators. Secondly, the development of the vehicle undoubtedly required investments in research, as well as in industrial equipment, which immediately translate into a high cost.

In any case, it is difficult to project numerical assumptions in such a recent market. We have therefore chosen to deal essentially with small vans, with the assumption that the market for the largest vans will follow the same dynamic a few years later. We have not identified any structural reasons in our research why the price differential between electric and diesel vehicles (excluding batteries) is greater for large vans than for small ones, but perhaps we have missed out. If this price difference were confirmed on a lasting basis, then it is likely that the amount of subsidy would have to be differentiated by vehicle type.

Concerning the small van market, the reference scenario highlights several points. First, subsidies will necessarily have to be reduced, because with such a large amount of subsidies for the purchase of an electric vehicle, any increase in the market involves significant government expenditure. As a result, the evolution in the next ten years will undoubtedly be linear rather than exponential, and if volumes increase, the percentage of the market that electrical technology will be able to convert remains very small (around 6 to 7% estimated in 2027). It is only after the subsidies have been partly absorbed, and reach a level more than twice as low as today, that the evolution of the market starts to show signs of diffusion towards a mass market (provided that the pace of technological evolution is maintained until at least 2030). Continued support from the electric van market is absolutely necessary for many years to come: even in 2032, the last year of our projections, these subsidies are still needed.

Detailed observation of different types of activity shows that the transport of goods for third account is very favorable for EVs, with twice as much potential as for the other activities studied. In particular, own-account transport does not offer the same prospects at all, due to a higher proportion of large vans and less regular uses overall. Craftsmen are the most penalized by the poor regularity of their daily trips.

The most suitable profiles for electric vehicles are those that run long enough to absorb the higher fixed cost of electric vehicles, but low enough not to be penalized by limited range. This window favorable to EVs is widening with technological evolutions, thus touching more and more different potential profiles, whereas today it is mainly aimed at postal distribution activities, and as soon as the bigger vans become competitive, parcel and express transport activities.

In the next chapter, we will discuss the model's assumptions, and highlight different mechanisms that could accelerate the spread of electric vehicles, or on the opposite threaten the current small market.

## 7 SENSITIVITY ANALYSIS

In the three previous chapters, we have constructed and applied an expert model to simulate development scenarios for the electric LCVs. This model is based as much on the knowledge accumulated during interviews with freight transport professionals as on the exploration and modeling of uses.

It has been applied over the past years and has given very relevant results in relation to the actual observed market shares. A reference scenario has been constructed to assess the future 15-year evolution of the electric LCV market. For this, many hypotheses have been made, and the usage model developed in Chapter 4 has been estimated from a database on French commercial vans.

Behind the many assumptions that govern the simulations, not all are certain. Some uncertainties are on the input parameters, due to partial knowledge (how does an error on the use model affect the results?) or to forecasting uncertainties (what happens if the price of diesel is ultimately lower than expected?), or on the model's specifications and mechanisms (what impact does charging on public accessible infrastructure have?). It is these uncertainties that this chapter proposes to study.

It takes a critical look at the model and the results, and proposes from there to explore alternative scenarios. It first lists a number of limitations that have been identified (Section 7.1), sensitivity to main assumptions is explored (Section 7.2) before incorporating into the model ways of evaluating alternative scenarios (Sections 7.3 to 7.5), and concluding that the model results are rather robust, and rather conservative.

#### 7.1 Discussion on model's limitations

#### 7.1.1 Model transfer from taxis to light commercial vehicles

In the absence of longitudinal data on commercial vehicles, some specifications of the use model based on Indian taxis have been transferred to light commercial vehicles without being able to verify the validity of this transfer. This hypothesis would merit further study. An extension for private vehicles would also be possible.

In Chapter 4, we have highlighted several limitations to the usage model. The first is that the model specification was perfectible, and could underestimate up to 10% of the PRA distribution curves, depending on range (sub-section 4.5.5). Some estimation difficulties have been outlined as well when estimating on aggregated data of the SDES database on light commercial vehicles (sub-section 4.5.7).

#### 7.1.2 Diversification of supply

The reference scenario does not incorporate supply diversity as an explicit explanatory variable in the simulation. We can consider that the low supply, and therefore the low competition, present on the segment of the largest vans can partly explain the high prices.

But competition can also be on the size of the battery. As vehicles with different battery capacities do not necessarily address the same customers, the diversity of supplied battery capacities can potentially increase the market size of EVs. This possibility is explored in Section 7.3.

#### 7.1.1 Unchanged uses

We make the assumption, based on the analysis of the interviews we conducted, that companies are not ready to change how they run their business for the transition from conventional vehicles to electric vehicles. In particular, the simulation involves only battery charging during the night, on private infrastructure.

The increasing availability and power of public accessible charging infrastructures could have an impact on usage and make it possible to modulate this strong hypothesis. Section 7.4 shows one way to include this possibility in the simulation.

Another possibility for companies to adapt uses to EVs is to have a mixed fleet. This option has been discussed qualitatively in sub-section 3.2.3.3.

#### 7.1.1 Numerical uncertainties

The market potential calculation is very sensitive to the numerical input parameters, which are numerous. Using a stochastic model allows the integration of uncertain input variables, and the resulting uncertainty about the estimated market potential to be observed.

Nevertheless, the integration of all uncertainties leads to results that are difficult to interpret because they are too variable. The results were therefore averaged with respect to all parameters except subsidies, which have a first-order impact on the result.

A sensitivity analysis is conducted to identify the uncertainties in the input parameters that lead to the greatest variability in the results. Several scenarios are also constructed, which explore a wider range of assumptions than those in the reference scenario (Section 7.5).

#### 7.1.2 Scope of the study

The scope of the study is the French light commercial vehicle market. This market is considered in most cases to be completely independent of the other markets. In some cases this dependence is implicit: for example, the evolution of battery costs is anticipated on the basis of world market demand, all types of vehicles combined. Nevertheless, several hypotheses could be called into question.

For example, we do not observe so far specific financial support for electric commercial vehicles. Until now, the subsidies from public administrations were applied in the same way to passenger cars and commercial vehicles (with some exceptions for local incentives). This can have important repercussions on the competitiveness of electric commercial vehicles: imagine a sharp drop in subsidies due to exponential growth in the market for electric passenger cars. This would have a direct negative impact on the market for electric commercial vehicles. If subsidies were considered separately, then they could support the electric LCV market by taking into account specific taxes, vehicles and uses.

Similarly, the choice of optimal battery capacities is industrially linked to all vehicles marketed by car manufacturers, and exceeds the French LCV market.

#### 7.1.3 From bonus to malus

Commercial vehicles enjoy several tax advantages and have so far been rather sheltered from the financial penalties that apply to polluting vehicles.

Commercial vehicles are exempt from the company car tax (*taxe sur les véhicules des sociétés*, TVS), and therefore electric vehicles do not benefit from its exemption. Commercial vehicles also do not suffer the ecological penalty (*malus écologique*), which can amount up to  $\leq$  10,500, which is imposed on the most polluting private vehicles. Finally, the VAT (*taxe sur la valeur ajoutée*) is 100% deductible from fuel for a commercial vehicle, whereas it is only 80% deductible for a company car and not at all for an individual car.

Thus, in the same way as in Norway, but to a lesser extent, the tax advantages offered to commercial vehicles make it more difficult for electric vehicles to compete.

One could imagine, in the future, that rather than supporting the electric vehicle market with subsidies, conventional LCVs would be subject to a penalty. From a simulation point of view, an equivalent scenario would add the amount of penalties to the diesel vehicle purchase price. This is done in the different fixed cost scenarios in sub-section 7.5.3.

From an economic point of view, however, incentives for electric vehicles or penalties for conventional vehicles would not be equivalent, as in one case, it is the public administrations who bear the costs, while in the other, it is the companies (which would inevitably impact the economy).

#### 7.1.4 No technological breakthrough

Finally, the technological developments considered concern only incremental technological improvement, based on current lithium-ion technology. This assumption was made given the short term predictions, for which a technological breakthrough is unlikely in our view, given the significant time that is required between proof of concept and actual industrial production of a new technology.

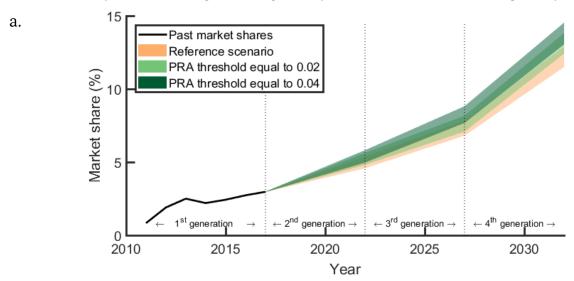
Beyond the 15 years simulated, however, it is not impossible that a new, much more efficient technology will replace lithium-ion technology, rendering the simulations made with this model obsolete.

## 7.2 Sensitivity to model assumptions

#### 7.2.1 Probability of requiring adaptation threshold of acceptability

In our model, the range constraint is measured by the frequency at which the range is exceeded, which we have called the probability of requiring adaptation (PRA). If this PRA exceeds a certain threshold, then the limited range is considered blocking for this specific use.

This threshold has been set quite demandingly at 0.4%, which corresponds to about 1 day of exceeding the range per year for a vehicle traveling every



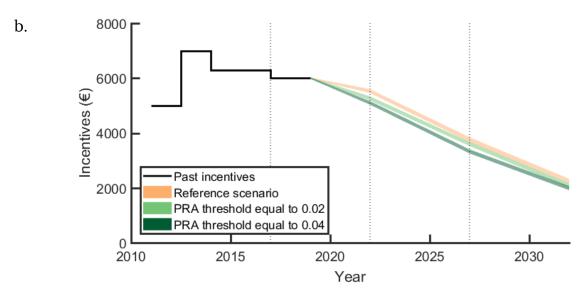


Figure 41 Scenario with a loosened range constraint, with a PRA threshold 5 times and 10 times greater than in the reference scenario respectively.

working day. In this subsection we wish to test the sensitivity of the results to the choice of this threshold.

For this, we run simulations with parameters identical to the reference scenario, in which we vary this threshold to 2% and 4%, which correspond to 5 and 10 days of exceeding the range per year for a vehicle traveling every working day (respectively). The limiting range constraint is thus loosened.

Figure 41 presents the resulting differences compared with the reference scenario. Incentives are slightly lowered and market shares increases by 13% (approximately +1.5 point) with a PRA threshold equal to 0.02 and by 20% (approximately +2.5 points) with a PRA threshold equal to 0.04.

These variations are relatively small when one recalls the strong impact that the PRA threshold can have on the range constraint (see for instance Figure 24 for private vehicles). First, let us note that in 2032, the economic constraint weighs more than the range constraint, thanks to the battery capacity increase (see section 6.6.2). In addition, the gains obtained on the range constraint are partly offset by the decrease in subsidies.

The observed difference is not of nature to change the interpretation of results, and this therefore confirms that **the market shares scenario is robust to possible error on the use model**. The subsidy regulatory mechanism is the key element of this stability. As soon as this mechanism disappears (for example if EVs no longer need support), we believe that the model no longer has the necessary precision to be relevant and another approach is desirable.

It also confirms the validity of our assumption of constant uses of LCVs over the next 15 years. Even if this is an approximation, a slight (exogenous) evolution of the uses should not affect the results. However, evolution of the uses with the intention of using EVs (as for instance mixed fleets solutions, which does currently not raise much enthusiasm) could be an effective leverage.

#### 7.2.2 Alternative incentive assumptions

The regulation mechanism is one of possible behaviors of the public administrations. This sub-section explores other possibilities.

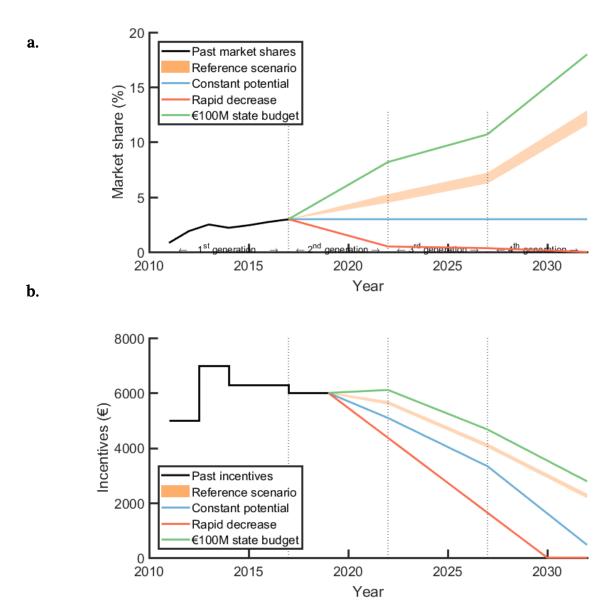


Figure 42 Alternative strategies from public authorities, either reducing public expenses progressively (Constant potential, keeping the market shares constant) or systematically (Rapid decrease, decreasing the subsidies by  $\leqslant 500$  per year) or wanting to double public support to electric LCVs ( $\leqslant 100 \text{M}$  budget of public administrations)

We first observe in Figure 42 what happens if the total budget is doubled compared with our reference scenario, i.e. a total budget of € 100M allocated to subsidizing electric light vans. Obviously, this has a noticeable positive impact on market shares, as because the market can grow as long as the budgetary constraint is not met (between 2017 and 2022), or put differently, during this timeframe, a more favorable equilibrium position between potential market shares and incentives is reached (as presented in Figure 31). It should be noted, however, that once this market is reached, the market growth resumes at a pace similar to that of the reference scenario (after 2022). Thus, while the increase in subsidies has a significant impact on volumes, it does not allow a different

dynamic to be given to the market than in the reference scenario, and will not anticipate exponential growth.

A second scenario (Constant potential scenario) examines the amount of subsidies needed to maintain the current market. This gives information on the amount of subsidies that can be offset by technological change, while maintaining a constant competitiveness. This amount is of around  $\in$  3,000, in 10 years, that is half of the current subsidies, and reaches almost zero only in 2032. Another likely scenario is that the public administration decides in advance on a roadmap, for example with a  $\in$  500 reduction in incentives each year (Rapid decrease scenario). We observe on Figure 42 that if incentives decrease more rapidly than the technological improvements allow, then the market is practically non-existent.

All scenarios confirm that making the EV market independent of public subsidies could take many years.

## 7.3 Effect of the broadening of supply

Another limitation of the model is that it has so far considered only one electric vehicle battery capacity. However, different capacities, and therefore different ranges, address different potential customers. Thus, the diversity of the supply expands the potential market.

To illustrate this, we consider in this scenario the supply of two different battery capacities, from 2022 onwards. Each customer chooses the battery capacity that suits him best. The market share of EVs is then the sum of the market shares of these two options.

For the choice of the two battery capacities, we use the parameters of the reference scenario and vary the capacities of the two batteries. Changes in market shares under these conditions are shown in Figure 43. The battery capacities which optimize the market potential in 2022 are approximately 32 kWh for the smaller one and 48 kWh for the bigger one. In 2027, despite a slightly noisier figure, we can identify approximately the two optimal battery capacities at 42 kWh and 68 kWh. Figure 44 shows that this broader supply leads to an improvement for the market shares and a decrease in public subsidies. They could be further improved by multiplying the number of battery capacities supplied by car manufacturers, the paroxysm being tailor-made battery capacities.

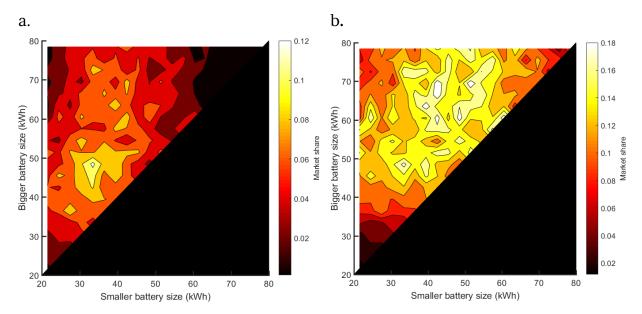


Figure 43 EV market potential resulting in 2027 (a.) and 2032 (b.) as a function of two battery capacities (instead of one) supplied by car manufacturers

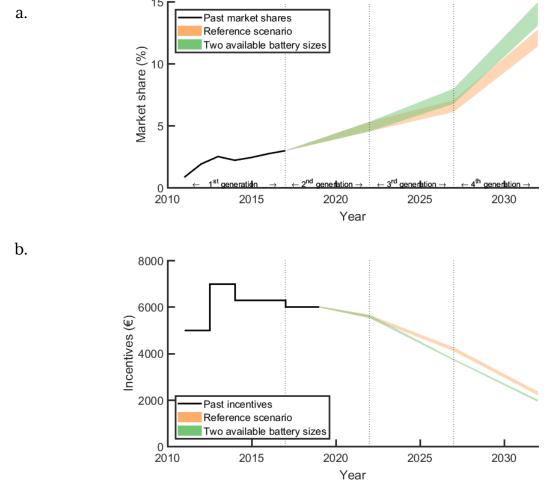


Figure 44 Impact of the supply of two different battery capacities (35 kWh and 50 kWh from 2022 to 2027, 42 kWh and 68 kWh from 2027 to 2032) by car manufacturers

This diversification of supply has an industrial cost for car manufacturers, and may be unlikely to occur if the expected gains are small. However, if these gains are achievable in other markets (passenger cars, other countries, other car model etc.), the LCV market may benefit from technology transfer. The benefit of diversification of the supply increases with technological improvements, and this is therefore most certainly what we are heading towards as soon as car manufacturers consider that they find it in their interest. Competition between car manufacturers could allow this diversity of batteries, because supplying a battery of different capacity would make it possible to address a different customer base.

## 7.4 Publicly accessible infrastructure

In the reference scenario, the decision model is strictly defined, with the assumption that the vehicle is only charged on private charging infrastructure and at night. However, availability of publicly available charging infrastructure (in short, by simplification: public infrastructure) could change the situation. Indeed, if it is acceptable to the business user, rare long trips could be covered by using fast charging during the trip.

We are therefore exploring a scenario in which a public charging infrastructure network is available. We remove the range constraint and replace it by the possibility to drive with an increased cost per kilowatt-hour. This cost accounts for the price of the service, and even more importantly, for the time it takes to charge the battery during the trip.

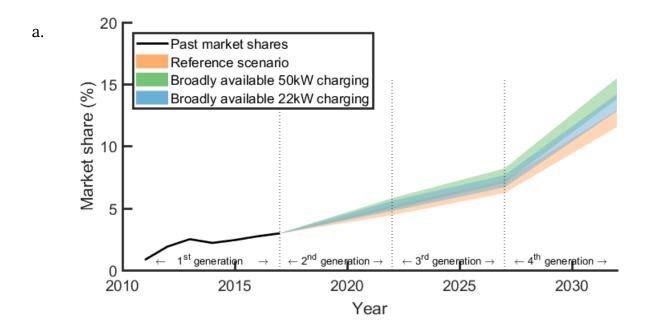
Two scenarios are considered. In the first scenario we assume full coverage of the territory by fast charging 50 kW public charging stations. We also assume that electric vans are able to support this charging power (which is mostly not the case today). Possible detour and waiting time are (arbitrarily) fixed to 10 minutes. The second one assumes accelerated 22 kW public charging stations instead, with 15 minutes detour and waiting time.

For both scenarios, the charging fare is 0.20 €/kWh, and the cost of time 27.6 €/hour (tutelary cost of time for bus drivers, according to Quinet (2014)).

We observe in Figure 45 a strong positive impact of the fast charging availability, and a moderate impact of the accelerated charging infrastructure. The 50 kW public charging network leads to an increase in market share of around 3 points. The gains obtained by such a public infrastructure network actually exceed the gains presented here because they have an important

reinsurance role. In addition, the reference assumption considers as acceptable if the range is insufficient one day per year. The total lack of public infrastructure could further reduce this acceptability threshold.

Finally, it is considered here that the driver's time is lost during charging. The efficiency of the public infrastructure network is all the more effective when recharging takes place in masked time.



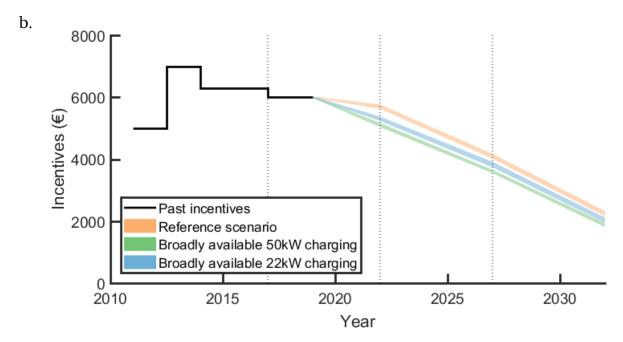


Figure 45 Simulating a wide coverage of the territory with publicly available charging stations of 50 kW or 22 kW.

## 7.5 Sensitivity on model inputs

#### 7.5.1 Most influential inputs

Until now, all variability of input parameters was averaged to keep only variability on subsidies to electric vehicles. To study the impact of the other input parameters, we now set the subsidies at a fixed value (equal to the lower value in the reference scenario), and observe the sensitivity of the result to these other parameters. To do this, we use Sobol sensitivity indexes (see section 5.5).

First, let us note that the computed potential market share in 2022 is distributed with the lower quartile equal to 2.64% and the upper quartile equal to 6.68%, showing the wide variability of results even with fixed subsidies. Depending on the combination of unfavorable or favorable uncertain parameters, the result varies by several points. Figure 46 shows Sobol's total sensitivity indices for the uncertain input parameters of the second generation of electric vans (in 2022, after 5 years of diffusion).

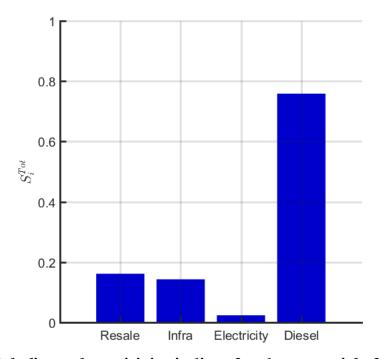


Figure 46 Sobol's total sensitivity indices for the potential of the second generation of small electric vans (2022): on the resale value of electric vehicles (Resale), the purchase and installation price of charging infrastructure (Infra), the price of electricity (Electricity) and the price of Diesel at the pump (Diesel).

The factor responsible for the great variability is undoubtedly the price of diesel at the pump. This is not a surprise, first because we considered a high uncertainty on this parameter (due to its volatile nature), and second because fuel costs represent a significant share of total costs of ownership for conventional vans.

In contrast, uncertain electricity prices have only a tiny impact, as it is the exact opposite. Electricity prices have been much more predictable in the past, and in addition the share of electricity is second order in the TCO of electric vehicles.

Two other uncertain factors are the resale value of electric vehicles and the costs of installing the charging infrastructure. The moderate impact of the latter is the result of an infrastructure that lasts longer than the four-year study period. Thus, reasonable uncertainty about installation costs is diluted over this longer lifetime.

One absent from this list is the price of the battery. This is a limitation to our input data, in which we assume that current rental rates remain constant for 5 years (therefore without uncertainty), while they may be updated regularly along with battery improvements.

Figure 47 shows the same sensitivity indices for the simulation done on the third generation vans in 2027.

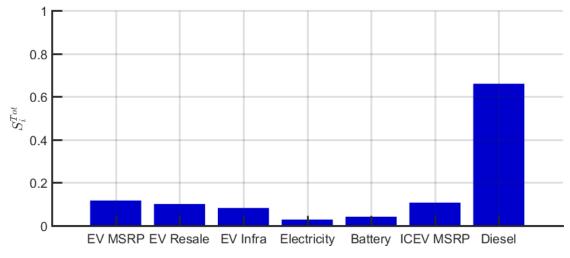
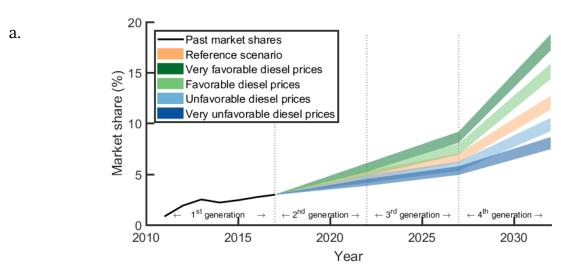


Figure 47 Sobol's total sensitivity indices for the potential of third generation of small electric vans (2027): on the purchase price of EVs (EV MSRP), their resale value (EV Resale), and the purchase and installation costs of charging infrastructure (EV Infra), the price of electricity (Electricity), the price per kWh of battery (Battery), the purchase price of ICEVs (ICEV MSRP) and the price of Diesel (Diesel).

The variability of the result is logically greater than for the second generation, with the first quartile at 3.5% and the third quartile at 9.6% market share for the electric model. The sensitivity analysis for the third generation of small vans does however not raise a different predominant factor: the uncertainty on the price of diesel crushes all other uncertain parameters. Surprisingly enough, the price of the battery is one of the least influential parameters. Perhaps the uncertainty of battery price has been somewhat underestimated in inputs. However, battery prices are uncertain but less volatile than diesel prices.

#### 7.5.2 Variable costs sensitivity



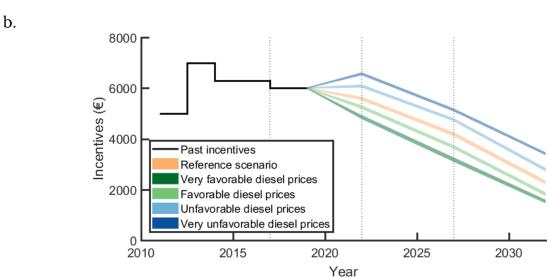


Figure 48 Different scenarios with variable Diesel prices (from -20% to +20% compared with the reference scenario).

Exploring in more detail the impact of these input parameters on EV-market shares can almost be summarized by two different scenario types: variable costs and fixed costs scenarios. Costs are almost linear (depending on the number of kilometers traveled; apart from a few details like the minimal monthly rent for the battery), and with these two categories a very wide range of scenarios are actually covered.

Furthermore, it is the TCO difference that counts, so that the scenarios include uncertainties on both technologies: a penalty on ICEVs will produce the same effects (in the model) as a subsidy of the same amount for EVs.

As highlighted in the previous sub-section, uncertainties about variable costs are in fact dominated by diesel costs, so we use this parameter as a reference to construct the scenarios. Favorable scenarios (for EVs) consider +10% and +20% increases in the diesel price, while unfavorable scenarios consider -10% and -20% decreases respectively. A variation of 10% of diesel prices sums up to approximately €0.80 for 100 kilometers.

This price variation could, instead of being due solely to the price of diesel, be a combination of the following factors: ageing of EVs and battery wear per kilometer traveled, maintenance differences between EVs and ICEVs, electricity prices, etc. A table of correspondence of these variables is given in Table 10.

Figure 48 a. and b. show the impact of different scenarios on the market shares and incentives. We observe that the most unfavorable scenario imposes very high subsidies (with constant public budget, even first an increase in incentives) for the market to maintain with the second generation of vans. The third and fourth generations offer at last meager growth prospects, while still being heavily subsidized.

<u> </u>	
	+ 0.80€/100km for conventional vehicles
Price of diesel	+0.12€/L (+10%)
Price of electricity	-0.04€/kWh (-23%)
Maintenance costs savings (EVs)	-0.80€/100km
Battery rent	-0.80€/100km (-28%)
Discount rate	-0.07 (-100%)

Table 10 Table of correspondence for variable cost scenarios (with 2032 assumptions)

The most favorable scenario offers on the opposite very interesting prospects, and allows a rapid reduction of incentive, with good growth prospects. Subsidies cross the  $\in$  2,000 threshold in 2032, and market shares reach almost 20%. However (and has been already noticed several times by now), the regulation mechanism by the constant public budget still prevents from having an accelerating growth before 2017.

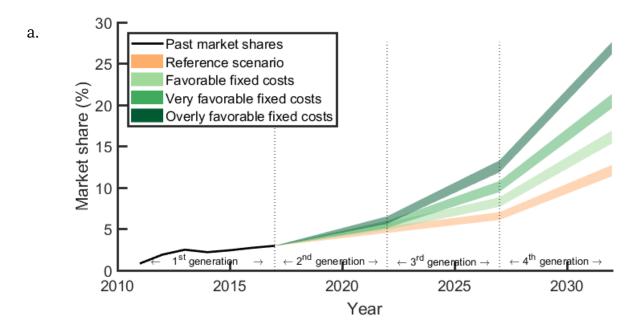
The price of diesel, along with the amount of incentives, is the second influential factor that presents a strong risk of preventing the growth of EV markets. This raises the question of the power of the oligopolistic oil market to stop the growth of the EV-market if it flourishes worldwide, as stakeholders have interests in keeping a majority of vehicles running on petroleum products derivatives.

#### 7.5.3 Fixed costs sensitivity

At last, the fixed costs sensitivity is analyzed. Only scenarios in favor of EVs are analyzed, as ICEVs are under a growing pressure, and reference scenario assumptions are cautious. Again, the fixed costs differences can be additional savings on EVs, but also additional costs on ICEVs or any combination of it.

To correctly interpret these results, we remind that the reference scenario forecasts a  $\leqslant$  500 decrease in the price of EVs (excluding battery) and a  $\leqslant$  500 increase in ICEVs every 5 years. The amounts in these scenarios are in addition to those in the reference scenario.

The scenarios tested are € 1,000, € 2,000 and € 3,000 difference in the fixed costs in favor of EVs (half in 2022, and all from 2027). Factors included in these fixed costs are mostly vehicle purchase prices (MSRPs), infrastructure costs, resale values or battery calendar ageing. Reasons that could lead to be in one of these most favorable scenarios are multiple: learning and optimization from car manufacturers, economies of scale on EVs (not only LCVs, but also private cars), growing competition between car manufacturers and thus reduced margins, regulatory pressure on ICEVs imposing costly pollution control devices. The most optimistic scenario is less likely, and would probably require a penalty on ICEVs. This would be, for example, a fixed toll of € 885/year/vehicle with an exemption for EVs.



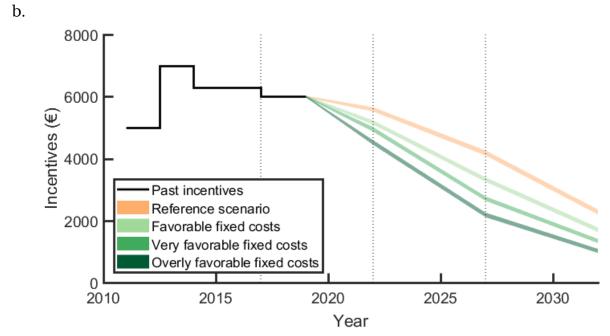


Figure 49 Different scenarios with variable fixed costs (cost reductions from €1,000 to €3,000 in 2022 for EV fixed costs)

No surprise in Figure 49, such important price differences are boosting the market share. The most optimistic scenario seems to initiate for the first time in all the sensitivity analysis an exponential growth as soon as 2022, as a good half of the incentives has been instantly absorbed by these fixed cost reduction and technological improvements.

## 7.6 Chapter conclusion

This chapter has exposed a number of limitations to the model, and explored different scenarios to qualify the results of the reference scenario.

These scenarios illustrate how the model would be highly sensitive to input parameters (notably the price of diesel) without the endogenous computation of the amount of subsidies. The uncertainty is no longer carried by market shares, but rather by the amount of subsidies for the purchase of an electric van. This has several consequences. First, as long as electric vehicles are dependent on these subsidies, market growth is systematically hampered by the associated decline in incentives. Conversely, the market would be virtually non-existent without sufficient public support. The question that this raises is how long it will take for technological and industrial improvements in electric vehicles, and the pressure placed on conventional vehicles, to absorb much of the current subsidy. The scenario with constant market shares gives an answer to that: subsidies reach almost 0 around 2032. From that point on, any additional improvements will directly fuel market growth. The diffusion of EVs is therefore a long-term process.

One very optimistic scenario (on fixed costs) shows that in a favorable setup, incentives can be significantly lowered in less than ten years, but most of the scenarios are more pessimistic.

Two risks are identified by these scenarios. First the risk of insufficient subsidies, condemning the electric vehicle market to wait for technology to become mature. There is of course the risk that this will not happen, if the meager market does not encourage investment. This is very much in line with the analysis of (Fearnley et al., 2015): "The main conclusion [...] is that successful and large market uptake of electric vehicles require massive, stable, expensive and combined policies."

The second identified risk lies in durable low Diesel prices. If experts all bet on a growing price of the barrel of oil, oil price forecasts are complicated and these same experts have already made erroneous upward forecasts in the past.

It should also be noted that apart from the risks mentioned above, all other scenarios are actually favoring EVs comparing to the reference scenario: a combination of all these scenarios may lead to a positive surprise. However, these scenarios (numerous and rapid public charging infrastructures, diversification of battery capacity, favorable fixed or variable costs for electric vehicles) are anything but obvious in the short term: they require additional

private or public investment, industrial decisions from car manufacturers or are speculative. However, they all seem relevant and without major obstacles in a long-term perspective, supporting exponential growth when it breaks out.

## **CONCLUSION**

In a context of growing environmental awareness, public authorities are setting ambitious targets for reducing global and local pollution. Achieving these goals requires coordinated efforts across all sectors, including transportation. The electrification of light commercial vehicles seems to be a key element in reducing long-term greenhouse gas and local pollutants emissions, particularly in cities.

The battery electric technology has lately experienced a real boom with production electric vehicles in the range of major car manufacturers. However, the market is emerging and its future remains uncertain. In France, 1.2% of the electric vehicle market and 1.4% of the light commercial vehicle market were electric in 2017 but the example of the passenger car market in Norway (with 20% of electric passenger cars sold in 2017) shows that with strong incentives the mass market is within reach (EAFO, 2017). The market for electric commercial vehicles is surprisingly low in Norway, at less than 2% in 2017. If the trend towards electrification is underway, the technical, economic, social and political uncertainties are still very high and several scenarios are possible to date.

It is these scenarios that our work has explored in this doctoral work for the electric light commercial vehicle market, with a focus on urban freight. We combined a qualitative and a quantitative approach. The qualitative approach consisted of interviews with carriers, whereas the quantitative approach jointly modeled the economic and the operational constraints for the use of electric light commercial vehicles by business users, with future projections.

## Current low market shares are well explained

The current low market shares of electric commercial vehicles can be explained very well today.

Technology is beginning to be relevant to some commercial activities, but is generally not competitive enough for many others. There is today a clearly identified target market: the postal distribution market. This activity represents a case study in the use of electric vehicles as it benefits from an optimal use framework. It is optimal in the size of the vehicles used, which are often small vans, as mail and small parcels volume does not require larger vehicles. This vehicle segment is the most covered by the current supply. It is optimal for range, because the trips are regular, predictable, and the trip lengths correspond well to current ranges. It is economically optimal, as electric vehicles run as far as possible given their limited range, taking maximum advantage of their reduced operating cost. Finally, it is optimal for charging, because historic postal operators often have many premises, even in city centers, in which vehicles are parked overnight. It is theoretically an ideal place to install private charging infrastructures. If we add to this the investment and experimentation capacity of these large companies, it is not surprising that the two largest European customers of electric commercial vehicles today are La Poste in France and Deutsche Post/DHL in Germany.

The parcel transport business benefits from most of these advantages, and seems to be the ideal case of use of electric vehicles with a greater capacity (from 3.5 tons gross vehicle weight) that are beginning to multiply in the supply of manufacturers.

When one or more of these elements are not met, the equation becomes more complicated. We have shown that the change from conventional to electric vehicles is complex for transportation companies, in the sense of innovation diffusion theory, that is, it is perceived as an innovation that is difficult to evaluate and use.

It is complex to *evaluate*, because it entails many uncertain parameters that need to be taken into account: the real range, the ageing of the battery, the technological evolution (which affects the residual value of the used vehicle), the reliability of public accessible infrastructures, etc.

It is complex to use because it requires many process changes. It can call into question the organization of tours and, by extension, tour management software, the coordination of drivers or independent carriers, the management

of vehicle parking, and requires careful planning of vehicle charging. It may require the abandonment of certain clients or missions, impossible to achieve with an electric vehicle, and this loss of opportunity is today perceived as unacceptable.

The relative advantage of innovation is not enough to offset problems; in particular, electric vehicles are rarely financially advantageous. The benefits are environmental, marketing based (the company benefits from the positive image of electric vehicles) and social (electric vehicles provide more pleasant working conditions for drivers).

The case of Norway is enlightening. The market shares of electric passenger cars are at an all-time high (20% of new battery electric vehicles in 2017, and it keeps growing), but electric light commercial vehicles are struggling to find their way to a mass market (around 2% of the sales in the same period). It is the difference in the taxation of private and commercial vehicles that fully explains this huge difference: electric vehicles are less financially advantageous for light commercial vehicles, as tax exemptions for electric vehicles have less impact on them.

According to our study, the fact that electric commercial vehicles are a niche market is therefore explainable.

# What hopes should be placed in technological change?

Technological evolution is impressive. Between 2011 and 2017, the battery capacity has increased by 80%, with roughly constant volume, weight and cost. A prolonged continuation of technological improvements is expected, with a rate of 8% per year of decrease in the price per kilowatt-hour of battery. This changes perspectives on the two major constraints of range and cost and could provide some good prospects to electric vehicles.

The current additional costs of the technologies are mostly offset by a significant subsidy. However, this subsidy is unlikely to be maintained if the market increases (since the total cost for public administrations is directly proportional to the size of the market). The gains due to technological advances must therefore be greater than the reduction in individual subsidies to ensure market growth. We have chosen to consider a total budget that public administrations are willing to put every year into the support of electric light

commercial vehicles. From this, the amount of subsidies per vehicle is calculated as an endogenous variable to the model.

As a result if the budget of public administrations remains constant, then any increase in market potential is immediately partly offset by a decrease in individual subsidies. As long as vehicles require subsidies, we should not expect a spectacular exponential growth, but rather a slow and steady growth. A larger total budget to support electric vehicles mechanically leads to a larger market, but we have shown that it may not lead to a faster market growth.

We have showed that electric vans would need financial support for many more years, at least until 2032 (as shown in the constant potential scenario, sub-section 7.2.2). However, this continuous support will enable market shares to reach 10% from 2030 onwards in the reference scenario.

Our sensitivity studies have identified the cost of diesel as one of the dominant variables. Unfavorable low diesel prices would lead to a lastingly low market for electric vans, reducing by comparison the benefit of low operating costs for electric vehicles.

In the most favorable scenarios (i.e. assuming that we would have underestimated future diesel prices by 20%, or overestimated the price of the electric van by  $\leq$ 2,000 in the reference scenario) market shares could start growing rapidly already around 2027, reaching some 20% in 2032, or even more if there is a combination of favorable factors.

Beyond these errors in projections, we have also highlighted certain mechanisms, all in favor of electric vehicles, which could contribute to the transition from a niche market to a mass market. If the expectation of gain is less significant than those mentioned in the previous paragraph, their contribution is more likely if the market grows. These mechanisms are the use of charging infrastructures accessible to the public, the diversification of the supply on a specific vehicle segment, or a better acceptability of long trips exceeding the limited range of the vehicle.

## Is the reference scenario conservative?

We have selected the most appropriate assumptions from our perspective, sometimes more demanding on electric vehicles than what might be found in the literature. Among these choices, we have chosen to consider that electric vehicles are acceptable only if their use does not exceed the limited range more than once a year (equivalent to a probability of requiring adaptation of 0.4%). Our

choice for infrastructure prices is also rather in the high range compared with other total cost of ownership calculations. We have also chosen a residual value equal in euros between conventional and electric vehicles, despite the higher purchase price of the latter.

The reference scenario may therefore appear conservative in some respects. However, the sensitivity study shows that these assumptions are not likely to change the conclusions. The market share model appears to be very stable with slight changes in input data.

We considered alternative scenarios to show how complementary mechanisms could be favourable to electric vehicles. We investigated the effect of the supply of several battery capacities (instead of one in the reference scenario), the possible use of public infrastructures, or explored the impact of an increasing acceptability of the limited range. All scenarios favour electric vehicles, modestly in the short term, but they could be significant contributors in the medium term to accelerating the growth of the electric van market.

One risk, however, has been identified additionally to insufficient subsidies: that of permanently low diesel prices, which would make the growth of the electric vehicle market much more complicated.

## Supporting the uptake of the electric vehicle market

Our research shows that the support of public administrations is essential to the emergence of a market for electric vehicles. Direct financial support is not the only means of action. We have also shown that the environmental gains from electric vehicles are to be expected in the long term, and that they should not be relied upon to achieve ambitious targets by 2030.

Policies can influence demand: transport companies must find an interest in buying electric vehicles. This interest is assessed in terms of relative advantage relatively to conventional vehicles, so it can pass through the support of electric vehicles but also through increasingly strict regulations towards conventional vehicles. This raises problems of political acceptability. Political acceptability is all the more complicated because not all uses are conducive to the use of electric vehicles. Not all companies are therefore affected in the same way by such regulations.

Policies can also have a significant impact on vehicle supply. Strong regulations have brought car manufacturers to develop electric vehicles in China, as China's clean vehicle policy requires car manufacturers to obtain credits for the production of EVs (which requires alternative energy vehicles to represent about 4% of all vehicles sold). China is thus attracting a huge share of investments for the development of electric vehicles. This encourages the diversification of vehicle models and battery capacities, the installation of a charging infrastructure network by car manufacturers. Thanks to competition, excessively high prices are avoided.

In our opinion, the success of supporting policies will depend on their ability to involve all stakeholders, i.e. electric vehicle customers (for instance freight companies), but also car manufacturers, researchers, freight consumers (such as retailers) and even final consumers.

## Methodological contributions and recommendations for further research

To process data on electric commercial vehicles, a statistical model was proposed to model the uses. This original model has made it possible to integrate the heterogeneity of uses, with encouraging results. We believe that this model has great potential for decision support, even if no longitudinal data are available. It can be estimated on different types of data, and once the model estimated, it can shed light on concrete operational questions. It also can easily be extended to the assessment of different technologies, including hybrids. We hope that work in this direction will continue. One area for improvement would be to refine the area of relevance of the model, in terms of type of use (passenger cars, taxis, freight, etc.), sample size, and the nature of the data on which the model is estimated. We have identified some estimation difficulties depending on the nature of the data, which would be interesting to explore and overcome.

The originality of the market share model, in addition to being based on the uses model mentioned above, is that it incorporates two endogenous variables: the capacities of the batteries of future vehicles, and the individual subsidy for the purchase of a vehicle. This significantly reduces the sensitivity of the model results to changes in input parameters, and results can thus be more robustly interpreted.

We evaluated the model based on past market shares, but the prospective analysis is uncertain in many respects. Hindsight will make it possible to judge any errors made and potentially to correct them. These errors can directly concern the model or the input parameters, but also mechanisms that were not anticipated.

This model could in the future be applied effectively to other markets (e. g. passenger cars), other technologies (plug-in hybrid) or other countries. A relevant validation field would be Norway, the country in Europe (or even worldwide) with the most experience on battery and plug-in electric vehicles.

## **LIST OF ACRONYMS**

CDF Cumulative distribution function

DVKT Daily vehicle kilometers traveled

ECDF Empirical cumulative distribution function

EV Electric vehicle

ICEV Internal combustion engine vehicle

PRA Probability of requiring adaptation

SOC State of charge

TCO Total cost of ownership

UF Urban freight

# APPENDIX 1: ASSUMPTIONS FOR MARKET SHARE PREDICTIONS, SMALL VANS' SEGMENT

Table 11 Use and model parameters fitted on the French LCV database (SDES)

Study Period	4				
Acceptable PR	1/250				
Discount rate (%)	7				
Number of working days	254 business days				
All small vans (<2,700kg gross weight)					
Use model parameter $P_1$ Log-normal $(\mu = 1.63, \sigma = 1.63)$					
Use model parameter P <sub>2</sub>	Gamma( $\lambda = 3.03$ , $\theta = 32.8$ )				
Use model copula	Clorton(0-0.740)				
parameter	$Clayton(\theta = 0.748)$				
Share of distance on	Poto(0.245.1.452)				
highway	Beta(0.345,1.452)				
Share of remaining	Beta(0.529,0.411)				
distance in urban context	, ,				
	s, freight transport for own account				
Use model parameter $P_1$	Log-normal( $\mu = 0.891, \sigma = 1.396$ )				
Use model parameter $P_2$	Weibull( $\lambda = 95.97, k = 1.774$ )				
Use model copula	$\theta = 1.504$				
parameter	0 - 1.501				
Share of distance on	Beta(0.513,2.915)				
highway	Betta(0.010,2.010)				
Share of remaining	Beta(0.692,0.581)				
distance in urban context	, , ,				
	s, freight transport for third account				
Use model parameter P <sub>1</sub>	Log-normal( $\mu = 0.867, \sigma = 1.704$ )				
Use model parameter P <sub>2</sub>	Weibull( $\lambda = 82.44, k = 1.414$ )				
Use model copula	$\theta = 2.179$				
parameter	5 =:=>;				
Share of distance on	Beta(0.294,3.513)				
highway	, , ,				
Share of remaining	Beta(0.301,0.246)				
distance in urban context					
Small van, craftsmen					
Use model parameter P <sub>1</sub>	Log-normal( $\mu = 1.262, \sigma = 1.080$ )				
Use model parameter P <sub>2</sub>	Weibull( $\lambda = 116.9, k = 2.025$ )				
Use model copula	$\theta = 0.3455$				
parameter Share of distance on					
highway	Beta(0.519,2.110)				
Share of remaining					
distance in urban context	Beta(0.740,0.745)				
distance in urban context	· · · · · · · · · · · · · · · · · · ·				

Table 12 Reference energy prices scenario

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Electricity €\100 <i>kWh</i> (VAT free)	7.21	7.59	8.18	8.44	8.64	9.42	10.17	10.38	10.84
Diesel €\ <i>L</i> (VAT free)	1.116	1.167	1.129	1.070	0.957	0.922	1.027	1.124	1.141
Year	2020	2021	2022	2023	2024	2025	2026	2027	2028
Electricity €\100 <i>kWh</i> (VAT free)	11.30	11.77	12.23	12.70	13.16	13.62	14.09	14.55	15.01
Diesel €\ <i>L</i> (VAT free)	1.147	1.152	1.158	1.163	1.169	1.175	1.181	1.187	1.193
Year	2029	2030	2031	2032	2033	2034	2035	2036	2037
Electricity €\100 <i>kWh</i> (VAT free)	15.47	15.94	16.41	16.87	17.33	17.80	18.26	18.73	19.19
Diesel €\ <i>L</i> (VAT free)	1.199	1.205	1.211	1.217	1.223	1.229	1.235	1.241	1.247

**Table 13 Public incentives** 

Public budget to support EVs (lower assumption)	€ <b>50</b> <i>M</i>
Public budget to support EVs (upper assumption)	€60 <i>M</i>

## **SMALL VAN: FIRST GENERATION**

Parameter:	Small van, ICEV		Small van, EV 1 <sup>st</sup> generation		
Introduction year		20	011		
Purchase price	€16,050	Kangoo Express dCi 75 VAT free <sup>38</sup>	€21,300	Kangoo Z.E. 2013, VAT free <sup>39</sup>	
Battery capacity	n.	a.	22 l	kWh	
Battery Rental (€/year)	n.a.		$864 + (d - 10^4) \cdot 0.0274$		
Infrastructure (€)	n.a.		Uniform(1,500; 2,500) + €200/year for maintenance Lifetime: 8 years		
Charging efficiency	n.a.		0.85		
Mean consumptions (L/100km, kWh/100km)	Urban: 7.10 Road : 5.75 Highway: 7.10		Urban:15.6 Road: 22.3 Highway: 31.4		
Mean consumptions (L/100km, kWh/100km)	Not used		Urban : 22.2 Road: 29.44 Highway: 40.4		
Residual Value (%)	$dep_0 = 0.526$ $dep_t = 0.0045$ $dep_k = 0.0656$		$dep_0 = 0.396 (\pm 0.02)$ $dep_t = 0.0045$ $dep_k = 0.0656$		

d is for the annual driven distance, n. a. is for "not applicable".

<sup>&</sup>lt;sup>38</sup> Price from 2013 : http://www.vehiculesutilitairesmag.com/news-65-renault-kangoo-express-restyle-les-dents-longues.html

http://www.largus.fr/actualite-automobile/le-renault-kangoo-ze-change-en-2013-2557369.html

# **SMALL VAN: SECOND GENERATION**

Parameter:	Small van, ICEV	Small van, EV 2 <sup>nd</sup> generation
Introduction year	2017	
Purchase price	€17,450	€21,850
Battery capacity	n. a.	33 kWh
Battery Rental		
(€/year)	n. $a$ .	$696 + (d - 7.5 \cdot 10^3) \cdot 0.04$
Infrastructure (€)	n.a.	Uniform(1,500; 2,500) + €200/year for maintenance Lifetime: 8 years
Charging efficiency	n.a.	0.85
Mean consumptions (L/100km, kWh/100km)	Urban: 7.10 Road : 5.75 Highway: 7.10	Urban:13.6 Road: 19.4 Highway: 27.3
Worst consumptions (L/100km, kWh/100km)	Not used	Urban : 19.3 Road: 25.6 Highway: 35.1
Residual Value (%)	$dep_0 = 0.526$ $dep_t = 0.0045$ $dep_k = 0.0656$	$dep_0 = 0.420 (\pm 0.02)$ $dep_t = 0.0045$ $dep_k = 0.0656$

d is for the annual driven distance, n. a. is for "not applicable".

# **SMALL VAN: THIRD GENERATION**

Parameter:	Small van, ICEV	Small van, EV 3 <sup>rd</sup> generation
Introduction year	2022	
Purchase price	€17,950(±€250)	€21,350(±€250)
Battery capacity	n. a.	40 kWh
Battery Rental		
(€/year)	n. $a$ .	$556 + (d - 7.5 \cdot 10^3) \cdot 0.0320$
Infrastructure (€)	n.a.	Uniform(1,500; 2,500) + €200/year for maintenance Lifetime: 8 years
Charging efficiency	n.a.	0.85
Mean consumptions (L/100km, kWh/100km)	Urban: 7.10 Road : 5.75 Highway: 7.10	Urban:13.6 Road: 19.4 Highway: 27.3
Mean consumptions (L/100km, kWh/100km)	Not used	Urban : 19.3 Road: 25.6 Highway: 35.1
Residual Value (%)	$dep_0 = 0.511 \ dep_t = 0.0045 \ dep_k = 0.0656$	$dep_0 = 0.430 (\pm 0.02)$ $dep_t = 0.0045$ $dep_k = 0.0656$

# **SMALL VAN: FOURTH GENERATION**

Parameter:	Small van, ICEV	Small van, EV 4 <sup>th</sup> generation
Introduction year	2027	
Purchase price	€18,450(±€250)	€20,850(±€250)
Battery capacity	n. a.	53 kWh
Battery Rental (€/year)	n.a.	$486 + (d - 7.5 \cdot 10^3) \cdot 0.028$
Infrastructure (€)	n.a.	Uniform(1,500; 2,500) + €200/year for maintenance Lifetime: 8 years
Charging efficiency	n.a.	0.85
Mean consumptions (L/100km, kWh/100km)	Urban: 7.10 Road : 5.75 Highway: 7.10	Urban:13.6 Road: 19.4 Highway: 27.3
Mean consumptions (L/100km, kWh/100km)	Not used	Urban : 19.3 Road: 25.6 Highway: 35.1
Residual Value (%)	$dep_0 = 0.497$ $dep_t = 0.0045$ $dep_k = 0.0656$	$dep_0 = 0.440 (\pm 0.02)$ $dep_t = 0.0045$ $dep_k = 0.0656$

# BIGGER VAN (3.5T GROSS WEIGHT): FIRST GENERATION

Parameter:	Big van, ICEV	Big van, EV 1 <sup>st</sup> generation
Introduction year	2018	
Purchase price	€28,600	€48,200
Battery capacity	n. a.	33 kWh
Battery Rental		
(€/year)	n. $a$ .	$912 + (d - 7.5 \cdot 10^{-3}) \cdot 0.069$
Infrastructure (€)	n.a.	Uniform(1,500; 2,500) + €200/year for maintenance Lifetime: 8 years
Charging efficiency	n.a.	0.85
Mean consumptions (L/100km, kWh/100km)	Urban: 12.20 Road : 9.70 Highway: 12.20	Urban: 23.4 Road: 32.7 Highway: 45.5
Mean consumptions (L/100km, kWh/100km)	Not used	Urban : 31.8 Road: 42.2 Highway: 57.9
Residual Value (%)	$dep_0 = 0.526$ $dep_t = 0.0045$ $dep_k = 0.0656$	$dep_0 = 0.312 (\pm 0.02)$ $dep_t = 0.0045$ $dep_k = 0.0656$

d is for the annual driven distance, n. a. is for "not applicable".

# APPENDIX 2: ALTERNATIVE ESTIMATION PROCEDURE WITH LONGITUDINAL DATA

If longitudinal data are available, then the model can be fit by a very natural approach, following the steps of the model construction (4.2):

- First, the DVKT distribution (in our case, the Weibull distribution) is fit on each agent's observations (agent-by-agent fit). For agent a, we obtain the maximum likelihood estimates of the parameters  $\lambda^{(a)}$  and  $k^{(a)}$ .
- Then, for each  $a \in [1, m]$ , intermediate variables are computed:

$$\left(p_1^{(a)}, p_2^{(a)}\right) = \Phi^{-1} \left(\lambda^{(a)}, k^{(a)}\right)$$

• We choose the marginal distributions of (p1, p2) that have the maximum likelihood, then we estimate the distribution based on a Clayton copula. This raises estimates of the parameters  $\epsilon$ .

A similar procedure has been opted for instance by Tamor et al. (2015). This stepwise procedure does however not give the maximum likelihood.

Using equation 4.3 as a starting point:

$$-LL\left(\left(x_{k}^{(a)}\right)_{k,a}; m\right)$$

$$= -\sum_{a} log\left(\iint_{\mathbb{R}^{2}_{+}} f_{X|P}\left(\left(x_{k}^{(a)}\right)_{k} \middle| p^{(a)}\right) dF_{P}(p^{(a)} \middle| \epsilon\right)\right)$$

$$= -\sum_{a} log\left(\iint_{\mathbb{R}^{2}_{+}} \prod_{k} f_{X|P}\left(x_{k}^{(a)} \middle| p^{(a)}\right) dF_{P}(p^{(a)} \middle| \epsilon\right)\right)$$

The last line uses the assumption of independent DVKT. Again, a Monte-Carlo method is used to compute this integral.

Particular attention must be paid to the digital processing of the product, which results in extremely small quantities. We have retained the powers of 10 in a separate variable for this calculation as well as for the sum of the Monte Carlo method. The application of the logarithm makes it possible to switch to directly easy to handle numerical values.

#### **BIBLIOGRAPHY**

- À quand la voiture électrique? (1968, April 26). *Panorama*. Retrieved from http://www.ina.fr/video/CAF86014983
- ACEA. (2017). ACEA Pocket Guide 2017 2018. European Automobile Manufacturers Association.
- ACEA. (2018). *Making the Transition to Zero-emission Mobility*. European Automobile Manufacturers

  Association. Retrieved from https://www.acea.be/publications/article/study-making-the-transition-to-zero-emission-mobility
- ACOSS. (2018). Les micro-entrepreneurs en 2016: toujours plus nombreux, avec un chiffre d'affaire en hausse (Acoss stats No. 270). Agence centrale des organismes de sécurité sociale.
- AFGNV. (2015). *Le Gaz Naturel Véhicule (GNV) en France*. Association Française du Gaz Naturel Véhicule.
- Air Resources Board. (2015, September 18). Admission of Defeat Device and California Air Ressources

  Board's Requests. Retrieved from

  https://www.arb.ca.gov/newsrel/in\_use\_compliance\_letter.pdf
- Airparif. (2017, October). 2016 Airparif en bref. Qualité de l'air et bilan des activités. Retrieved January 9, 2018, from https://www.airparif.asso.fr/ pdf/publications/2016-enbref.pdf
- Al-Alawi, B. M., & Bradley, T. H. (2013). Review of hybrid, plug-in hybrid, and electric vehicle market modeling Studies. *Renewable and Sustainable Energy Reviews*, *21*, 190–203. https://doi.org/10.1016/j.rser.2012.12.048
- Albergel, A., Segalou, E., Routhier, J.-L., & De Rham, C. (2006). Méthodologie pour un bilan environnemental physique du transport de marchandises en ville. Retrieved from https://hal.archives-ouvertes.fr/halshs-00113850/
- Alex Stewart. (2012). Ultra low emissions van study. Element energy.
- Alizon, F., Shooter, S. B., & Simpson, T. W. (2009). Henry Ford and the Model T: lessons for product platforming and mass customization. *Design Studies*, *30*(5), 588–605.

- Augereau, V., & Dablanc, L. (2008). An evaluation of recent pick-up point experiments in European cities: the rise of two competing models. *Innovations in City Logistics. Nova Science, New York*, 301–320.
- Axsen, J., & Kurani, K. S. (2008). The early US market for PHEVs: Anticipating consumer awareness, recharge potential, design priorities and energy impacts.
- Barfod, M. B., Kaplan, S., Frenzel, I., & Klauenberg, J. (2016). COPE-SMARTER A decision support system for analysing the challenges, opportunities and policy initiatives: A case study of electric commercial vehicles market diffusion in Denmark. *Research in Transportation Economics*, 55, 3–11. https://doi.org/10.1016/j.retrec.2016.04.005
- Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, *15*(5), 215–227.
- Bass, F. M. (2004). Comments on "a new product growth for model consumer durables the bass model." *Management Science*, *50*(12\_supplement), 1833–1840.
- Bauer, R. A. (1960). Consumer behavior as risk taking. In *Proceedings of the 43rd National Conference*of the American Marketing Assocation, June 15, 16, 17, Chicago, Illinois, 1960. American

  Marketing Association. Retrieved from http://ci.nii.ac.jp/naid/10021015676/
- Becker, T. A., Sidhu, I., & Tenderich, B. (2009). Electric vehicles in the United States: A new model with forecasts to 2030. *Center for Entrepreneurship & Technology (CET) Technical Brief*, (2009.1). Retrieved from http://www.odpowiedzialnybiznes.pl/public/files/CET\_Technical%20Brief\_EconomicModel20 30.pdf
- Beziat, A. (2017). Approche des liens entre transport de marchandises en ville, formes urbaines et congestion: Le cas de l'Ile-de-France (PhD Thesis). Université Paris-Est.
- Beziat, A., Launay, P., & Toilier, F. (2015). A Comprehensive View of Goods Transport Systems -Typology and Analysis of Delivery Tours in the Paris Region. Presented at the 6th Metrans
  International Urban Freight Conference, Long Beach, CA, USA.

- Bielaczyc, P., Woodburn, J., & Szczotka, A. (2014). An assessment of regulated emissions and CO<sub>2</sub> emissions from a European light-duty CNG-fueled vehicle in the context of Euro 6 emissions regulations. *Applied Energy*, *117*, 134–141. https://doi.org/10.1016/j.apenergy.2013.12.003
- Boutueil, V. (2015). *Towards a sustainable mobility system : Leveraging corporate car fleets to foster innovations*. Université Paris-Est.
- Browne, M., Allen, J., Nemoto, T., & Visser, J. (2010). Light goods vehicles in urban areas. *Procedia-Social and Behavioral Sciences*, 2(3), 5911–5919.
- Browne, M., Allen, J., Woodburn, A., & Piotrowska, M. (2007). Literature review WM9: part II-light goods vehicles in urban areas. *Work Module*, 1.
- Brunel, P., & Perillo, T. (1992). La voiture propre. Economie et Statistique, 258(1), 89–94.
- Byrd, R. H., Gilbert, J. C., & Nocedal, J. (2000). A trust region method based on interior point techniques for nonlinear programming. *Mathematical Programming*, 89(1), 149–185.
- Camilleri, P. (2014). La problématique des véhicules utilitaires âgés en circulation pour le transport de marchandises en ville: Comparaison du transport de fruits et légumes en compte propre destinataire et de la sous-traitance dans le secteur du transport de messagerie (Mémoire de recherche). IFSTTAR / Renault.
- CGDD. (2014, June). Les véhicules utilitaires légers : une bonne complémentarité avec les poids lourds. Retrieved August 20, 2015, from http://www.statistiques.developpement-durable.gouv.fr/fileadmin/documents/Produits\_editoriaux/Publications/Le\_Point\_Sur/2014/lps190-vul.pdf
- CGDD. (2017a). Analyse coûts bénéfices des véhicules électriques. Les voitures (Théma). Commissariat général au développement durable.
- CGDD. (2017b). Évolution du transport léger dans les secteurs du transport routier de fret et de la messagerie entre 1995 et 2013 (Data Lab Essentiel). Commissariat Général au Développement Durable.

- CGDD. (2017c). Les comptes des transports en 2016 (Rapport de la Commission des comptes des transports de la Nation No. 54). Commissariat Général au Développement Durable.
- Chiche, A., Attard, P., Thoni, O., Nicolas, P., Novel-Cattin, F., & Scremin, L. (2017). Les véhicules électriques au service du système électrique en 2050 ? (Livrable du projet MIC (Modélisation, Interopérabilité, Coopération)). SystemX. Retrieved from https://www.artelys.com/downloads/pdf/rapports-etudes/Etude\_VehiculeElectrique\_MIC2.pdf
- Cluster Paca Logistique. (2013). L'emploi en logistique urbaine: spécificités et potentiel (Les cahiers thématiques No. 8).
- Code général des impôts Article 298, 298 Code général des impôts §.
- Conway, A. J., Thuillier, O., Dornhelm, E., & Lownes, N. E. (2013). *Commercial vehicle-bicycle conflicts:*a growing urban challenge.
- Conway, A., Wang, X., Chen, Q., & Schmid, J. (2016). Freight Costs at the Curbside.
- Cottignies, M. (2012). Transport et développement durable. Ed. Techniques Ingénieur.
- Crénin, F. (2015). Truncated Weibull Distribution Functions and Moments.
- Crist, P. (2012). *Electric Vehicles Revisited* (International Transport Forum Discussion Papers No. 2012/03). Retrieved from http://www.oecd-ilibrary.org/transport/electric-vehicles-revisited 5k8zvv7h9lq7-en
- Cruz, C. (2010). How is own account transport well adapted to urban environments? In *12th World*Conference on Transport Research (p. 19p). Retrieved from https://hal.archivesouvertes.fr/hal-00615151/document
- Cui, X., Liu, C., Kim, H. K., Kao, S.-C., Tuttle, M. A., & Bhaduri, B. L. (2010). A multi agent-based framework for simulating household PHEV distribution and electric distribution network impact. *TRB Comittee on Transportation Energy (ADC70)*, *1250*, 21.
- Dablanc, L. (2010). Le territoire urbain des konbini et des takkyubin au Japon. Flux, (4), 68–70.

- Dablanc, L. (2013). Une grande oubliée, la logistique. In Seura, Les rendez-vous de la mégapole, AIGP2 saison 2. Atelier international du Grand Paris. *Une Grande Oubliée, La Logistique. In Seura, Les Rendez-Vous de La Mégapole, AIGP2 Saison 2. Atelier International Du Grand Paris,* pp–13.
- Dablanc, L., & Andriankaja, D. (2011). Desserrement logistique en Île-de-France: la fuite silencieuse en banlieue des terminaux de fret. *Flux*, (3), 72–88.
- Dablanc, L., & Montenon, A. (2015). Impacts of Environmental Access Restrictions on Freight Delivery

  Activities: Example of Low Emissions Zones in Europe. *Transportation Research Record:*Journal of the Transportation Research Board, (2478), 12–18.
- Dablanc, L., Morganti, E., Arvidsson, N., Woxenius, J., Browne, M., & Saidi, N. (2017). The rise of ondemand 'Instant Deliveries' in European cities. In *Supply Chain Forum: An International Journal* (Vol. 18, pp. 203–217). Taylor & Francis.
- Dablanc, L., & Rodrigue, J.-P. (2012). City logistics. The Sage Handbook of Transport Studies.
- Dablanc, L., & Routhier, J.-L. (2009). La partie urbaine de la chaîne de transport, premiers enseignements tirés de l'enquête ECHO. In: enquête" ECHO"-Les apports des enquêtes chargeurs pour la connaissance des chaînes de transport de marchandises et de leurs déterminants logistiques. La Partie Urbaine de La Chaîne de Transport, Premiers Enseignements Tirés de l'enquête ECHO. In: Enquête" ECHO"-Les Apports Des Enquêtes Chargeurs Pour La Connaissance Des Chaînes de Transport de Marchandises et de Leurs Déterminants Logistiques, pp–167.
- Dablanc, L., Savy, M., Veltz, P., Culoz, A., & Vincent, M. (2017). *Des marchandises dans la ville: un enjeu social, environnemental et économique majeur* (p. 110). terra nova.
- Dargay, J., Gately, D., & Sommer, M. (2007). Vehicle ownership and income growth, worldwide: 1960-2030. *The Energy Journal*, 143–170.

- Davis, B. A., & Figliozzi, M. A. (2013). A methodology to evaluate the competitiveness of electric delivery trucks. *Transportation Research Part E: Logistics and Transportation Review, 49*(1), 8–23.
- DENA. (2015). Nachhaltige Mobilität mit Erdgas und Biomethan: Marktentwicklung 2014/2015.

  Retrieved from http://www.dena.de/fileadmin/user\_upload/Publikationen/Verkehr/Dokumente/9132\_3.\_Z wischenbericht\_der\_Initiative\_Erdgasmobilitaet.pdf
- Diamond, D. (2009). The impact of government incentives for hybrid-electric vehicles: Evidence from US states. *Energy Policy*, *37*(3), 972–983.
- Do, C. B. (2008). More on multivariate gaussians. *URL Http://Cs229. Stanford. Edu/Section/More\_on\_gaussians. Pdf.[Online.*
- Dong, J., & Lin, Z. (2014). Stochastic modeling of battery electric vehicle driver behavior: impact of charging infrastructure deployment on the feasibility of battery electric vehicles.

  \*Transportation Research Record: Journal of the Transportation Research Board, (2454), 61–67.
- Ducret, R., & Delaître, L. (2013). Parcel delivery and urban logistics-changes in urban courier, express and parcel services: the French case. In *13th World Conference on Transport Research, July 15-18, 2013-Rio de Janeiro, Brazil*. Retrieved from https://halshs.archives-ouvertes.fr/halshs-00853932/document
- Dudenhöffer, F., Bussmann, L., & Dudenhöffer, K. (2012). Elektromobilität braucht intelligente Förderung. *Wirtschaftsdienst*, *92*(4), 274–279.
- EAFO. (2017). European Alternative Fuels Observatory. Retrieved March 24, 2017, from http://www.eafo.eu/
- Edwards, R., Mahieu, V., Griesemann, J.-C., Larivé, J.-F., & Rickeard, D. J. (2014). Well-to-wheels analysis of future automotive fuels and powertrains in the European context v4.a. SAE Technical Paper.

- Eppstein, M. J., Grover, D. K., Marshall, J. S., & Rizzo, D. M. (2011). An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy*, *39*(6), 3789–3802. https://doi.org/10.1016/j.enpol.2011.04.007
- EU. (2006). Directive 2006/66/EC of the European Parliament and of the Council of 6 September 2006 on batteries and accumulators and waste batteries and accumulators and repealing Directive 91/157/EEC. *OJ L*, 266(26.9), 2006.
- EU. Directive 2007/46/EC of the European Parliament and of the Council of 5 September 2007 establishing a framework for the approval of motor vehicles and their trailers, and of systems, components and separate technical units intended for such vehicles (Framework Directive) (Text with EEA relevance), Pub. L. No. 32007L0046, OJ L 263 (2007). Retrieved from http://data.europa.eu/eli/dir/2007/46/oj/eng
- EU. Council Directive 2009/132/EC of 19 October 2009 determining the scope of Article 143(b) and (c) of Directive 2006/112/EC as regards exemption from value added tax on the final importation of certain goods, Pub. L. No. 32009L0132, OJ L 292 (2009). Retrieved from http://data.europa.eu/eli/dir/2009/132/oj/eng
- EU. DIRECTIVE (EU) 2015/ 719 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL (2015).

  Retrieved from http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32015L0719&from=EN
- European Commission. (2011a). A Roadmap for moving to a competitive low carbon economy in 2050.
- European Commission. (2011b). Roadmap to a Single European Transport Area: Towards a

  Competitive and Resource Efficient Transport System: White Paper. Publications Office of the

  European Union.
- European Commission. (2016). Communication from the Commission to the European Parliament, the

  Council, the European Economic and Social Committee and the committee of the regions: A

- European Strategy for Low-Emission Mobility. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52016DC0501
- Fearnley, N., Pfaffenbichler, P., Figenbaum, E., & Jellinek, R. (2015). E-vehicle policies and incentives:

  assessment and recommendations. *Compett Deliverable D, 5*. Retrieved from http://www.compett.org/documents/E\_-\_vehicle\_policies\_and\_incentives\_\_assessment\_and\_recommendations.pdf
- Fernández-Antolín, A., de Lapparent, M., & Bierlaire, M. (2018). Modeling purchases of new cars: an analysis of the 2014 French market. *Theory and Decision*, *84*(2), 277–303.
- FEVAD. (2018). *E-commerce in France: key figures*. French e-commerce federation. Retrieved from https://www.fevad.com/chiffres-cles-cartographie-e-commerce-2017/
- Frees, E. W., & Valdez, E. A. (1998). Understanding relationships using copulas. *North American Actuarial Journal*, *2*(1), 1–25.
- Frenzel, I. (2016). Who Are the Early Adopters of Electric Vehicles in Commercial Transport—A

  Description of Their Trip Patterns. In U. Clausen, H. Friedrich, C. Thaller, & C. Geiger (Eds.),

  Commercial Transport (pp. 115–128). Springer International Publishing.

  https://doi.org/10.1007/978-3-319-21266-1\_7
- Frenzel, I., Jarass, J., Stefan Trommer, & Barbara Lenz. (2015). Erstnutzer von Elektrofahrzeugen in Deutschland. Retrieved from https://core.ac.uk/download/pdf/31017693.pdf
- Fréry, F. (2000). Un cas d'amnésie stratégique: l'éternelle émergence de la voiture électrique. In IXème Conférence Internationale de Management Stratégique. Montpellier.
- Gaines, L. (2014). The future of automotive lithium-ion battery recycling: Charting a sustainable course. *Sustainable Materials and Technologies*, 1, 2–7.
- Garçon, A.-F. (2003). La voiture électrique dans La Nature (1890\_1900). Approche micro-historique d'un échec technique. In *Cahiers François Viète* (pp. 17–43). Retrieved from https://halshs.archives-ouvertes.fr/halshs-00003858/

- Gasmi, N., & Grolleau, G. (2003). Spécificités des innovations environnementales. *Innovations*, *18*(2), 73–89. https://doi.org/10.3917/inno.018.0073
- Giuliano, G. (2013). Synthesis of freight research in urban transportation planning (Vol. 23).

  Transportation Research Board. Retrieved from http://books.google.fr/books?hl=fr&lr=&id=qh5BJ\_BVhrkC&oi=fnd&pg=PP1&dq=synthesis+o f+freight+research+in+urban+transportation+planning&ots=LZiqfCDDKX&sig=zZ5hoEpnHD8C ON5ASV830ZLiNTA
- Glerum, A., Stankovikj, L., Thémans, M., & Bierlaire, M. (2013). Forecasting the demand for electric vehicles: accounting for attitudes and perceptions. *Transportation Science*, *48*(4), 483–499.
- Global E.V. (2017). Outlook 2017, Two million and counting. International Energy Agency.
- Graille, F., Omont, L., & Saugnac, C. (2015). *375 000 emplois salariés dans la logistique en Île-de-*France (Insee Analyses Île-de-France No. 13). INSEE.
- Grebel, A. (1919, February 1). L'emploi du gaz dans les automobiles. *Le Génie Civil*. Retrieved from http://www.afgnv.info/attachment/524224/
- Greene, D. L. (1985). Estimating daily vehicle usage distributions and the implications for limited-range vehicles. *Transportation Research Part B: Methodological*, 19(4), 347–358. https://doi.org/10.1016/0191-2615(85)90041-4
- Guilbault, M., & Soppé, M. (2009). Apports des enquêtes chargeurs. Connaissance Des Chaînes de Transport de Marchandises et de Leurs Déterminants Logistiques. Les Collections INRETS, (121), 220.
- Hacker, F., Harthan, R., Matthes, F., & Zimmer, W. (2009). Environmental impacts and impact on the electricity market of a large scale introduction of electric cars in Europe-Critical Review of Literature. *ETC/ACC Technical Paper*, *4*, 56–90.
- Hanke, C., Hüelsmann, M., & Fornahl, D. (2014). Socio-Economic Aspects of Electric Vehicles: A Literature Review. In *Evolutionary Paths Towards the Mobility Patterns of the Future* (pp. 13–36). Springer. Retrieved from http://link.springer.com/10.1007/978-3-642-37558-3\_2

- Harnay, P., Cruz, C., & Dablanc, L. (2014). La sous-traitance de la messagerie urbaine: logiques économiques et rapports de dépendance. *Socioéconomie Du Travail (Série AB d'Economies et Sociétés)*, 48(36).
- Hawkins, T. R., Gausen, O. M., & Strømman, A. H. (2012). Environmental impacts of hybrid and electric vehicles—a review. *The International Journal of Life Cycle Assessment*, *17*(8), 997–1014. https://doi.org/10.1007/s11367-012-0440-9
- Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative environmental life cycle assessment of conventional and electric vehicles. *Journal of Industrial Ecology*, 17(1), 53–64.
- Heitz, A., & Dablanc, L. (2015). Logistics spatial patterns in Paris: rise of Paris Basin as Logistics

  Megaregion. *Transportation Research Record: Journal of the Transportation Research Board*,

  (2477), 76–84.
- Helms, H., Pehnt, M., Lambrecht, U., & Liebich, A. (2010). Electric vehicle and plug-in hybrid energy efficiency and life cycle emissions. In *18th International Symposium Transport and Air Pollution, Session* (Vol. 3, p. 113). Retrieved from http://www.ifeu.org/verkehrundumwelt/pdf/Helms%20et%20al.%20(2010)%20Electric%20v ehicles%20(TAP%20conference%20paper).pdf
- Holguín-Veras, J. (2006). The truth, the myths, and the possible in freight road pricing in congested urban areas. In *National Urban Freight Conference, Long Beach*. Retrieved from http://web.mit.edu/11.951/oldstuff/albacete/Other\_Documents/Europe%20Transport%20C onference/freight\_and\_logistics/the\_truth\_the\_myth1740.pdf
- Holguín-Veras, J., & Aros-Vera, F. (2014). Geographically Focused Incentives to Foster Off-Hour Deliveries. *Transportation Research Record: Journal of the Transportation Research Board*, 2411, 27–33. https://doi.org/10.3141/2411-04

- Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2016). Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors. *American Economic Review*, 106(12), 3700–3729. https://doi.org/10.1257/aer.20150897
- Hu, L., Dong, J., Lin, Z., & Yang, J. (2018). Analyzing battery electric vehicle feasibility from taxi travel patterns: The case study of New York City, USA. *Transportation Research Part C: Emerging Technologies*, 87, 91–104. https://doi.org/10.1016/j.trc.2017.12.017
- ICCT. (2018a). China's new energy vehicle mandate policy (final rule).
- ICCT. (2018b). European vehicle market statistics: Pocketbook 2017/18. International Council on Clean Transportation Berlin, Germany.
- Infini-drive. (2014). *Pour un futur [simple] du véhicule électrique*. Retrieved from http://www.energie2007.fr/images/upload/projet-infini-drive-ebook.pdf
- IPCC. (2014). IPCC Climate Change 2014 Synthesis.
- Jain, P. K. (1999). Theory and problems in financial management. Tata McGraw-Hill Education.
- Julsrud, T., Figenbaum, E., Nordbakke, S., Denstadli, J. M., Tilset, H., & Schiefloe, P. M. (2016).

  Pathways to Sustainable Transport among Norwegian Crafts and Service Workers.
- Justel, A., Peña, D., & Zamar, R. (1997). A multivariate Kolmogorov-Smirnov test of goodness of fit.

  Statistics & Probability Letters, 35(3), 251–259.
- Klauenberg, J., Gruber, J. ( V. ), & Rudolph, C. ( V. ). (2015). Suitable electromobility for commercial transport: SELECT: Schlussbericht zum Projekt. https://doi.org/10.2314/GBV:865929564
- Klauenberg, J., Rudolph, C., & Zajicek, J. (2016). Potential users of electric mobility in commercial transport–identification and recommendations. *Transportation Research Procedia*, *16*, 202–216.
- Koning, M., Coulombel, N., Dablanc, L., Gardrat, M., & Descartes, I. C. (2017). A new look at the environmental assessment of logistics sprawl Part 1 The Environmental Impact of Urban Road Freight: A Modeling Exercise for the Paris Region.

- LAET. (2014). Enquête transport de marchandises en ville. Méthodologie et premiers résultats. Région Île-de-France.
- Lee, D.-Y., Thomas, V. M., & Brown, M. A. (2013). Electric urban delivery trucks: Energy use, greenhouse gas emissions, and cost-effectiveness. *Environmental Science & Technology*, 47(14), 8022–8030.
- Leurent, F., & Windisch, E. (2011). Triggering the development of electric mobility: a review of public policies. *European Transport Research Review*, *3*(4), 221–235. https://doi.org/10.1007/s12544-011-0064-3
- Lin, Z., Dong, J., Liu, C., & Greene, D. (2012). Estimation of Energy Use by Plug-In Hybrid Electric Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2287, 37–43. https://doi.org/10.3141/2287-05
- Lin, Z., & Greene, D. (2011). Promoting the Market for Plug-In Hybrid and Battery Electric Vehicles.

  \*Transportation Research Record: Journal of the Transportation Research Board, 2252, 49–56.

  https://doi.org/10.3141/2252-07
- Luciani, G. (2015, April 15). Pétrole: le grand bluff. *Le Un N°52*. Retrieved from https://le1hebdo.fr/journal/numero/52
- Lutsey, N. (2015). Supporting the electric vehicle market in U.S. cities | International Council on Clean Transportation. ICCT. Retrieved from http://theicct.org/supporting-electric-vehicles-US-city-total-cost
- Macharis, C., Lebeau, P., Van Mierlo, J., & Lebeau, K. (2013). Electric versus conventional vehicles for logistics:

  A total cost of ownership. Retrieved from http://ieeexplore.ieee.org/xpls/abs\_all.jsp?arnumber=6914980
- Malins, C., Searle, S., & Baral, A. (2014). A guide for the perplexed to the indirect effects of biofuels production. *International Council on Clean Transportation, Washington, DC*.
- McMorrin, F., Anderson, R., Featherstone, I., & Watson, C. (2012). Plugged-in fleets: A guide to deploying electric vehicles in fleets. *The Climate Group, Cenex, and Energy Saving Trust. URL*

- Http://Www. Theclimategroup. Org/\_assets/Files/EV\_report\_final\_hi-Res. Pdf. Last Accessed, 27(5), 2014.
- Messagie, M., Boureima, F.-S., Coosemans, T., Macharis, C., & Mierlo, J. V. (2014). A range-based vehicle life cycle assessment incorporating variability in the environmental assessment of different vehicle technologies and fuels. *Energies*, 7(3), 1467–1482.
- Mock, P. (2017). Real-driving emissions test procedure for Exhaust gas pollutant emissions of cars and light commercial vehicles in europe (Policy update). ICCT. Retrieved from https://www.theicct.org/sites/default/files/publications/EU-RDE\_policy-update\_18012017\_vF.pdf
- Mock, P. (2018). THE ROLE OF STANDARDS IN REDUCING CO 2 EMISSIONS OF PASSENGER CARS IN

  THE EU (Briefing). ICCT. Retrieved from

  https://www.theicct.org/sites/default/files/publications/Role\_of\_EU
  CO2\_Standard\_20180212.pdf
- Morganti, E., & Browne, M. (2018). Technical and operational obstacles to the adoption of electric vans in France and the UK: An operator perspective. *Transport Policy*, *63*, 90–97.
- Morganti, E., Dablanc, L., & Fortin, F. (2014). Final deliveries for online shopping: The deployment of pickup point networks in urban and suburban areas. *Research in Transportation Business* & *Management*, *11*, 23–31.
- Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., & Lenz, B. (2014). The impact of e-commerce on final deliveries: alternative parcel delivery services in France and Germany. *Transportation Research Procedia*, *4*, 178–190.
- Moultak, M., Lutsey, N., & Hall, D. (2017). Transitioning to Zero-Emission Heavy-Duty Freight Vehicles.
- Nesbitt, K., & Sperling, D. (2001). Fleet purchase behavior: decision processes and implications for new vehicle technologies and fuels. *Transportation Research Part C: Emerging Technologies*, 9(5), 297–318.

- Nesterova, N., Quak, H., Balm, S., Roche-Cerasi, I., & Tretvik, T. (2015). Project FREVUE deliverable

  D1. 3: State of the art of the electric freight vehicles implementation in city logistics Update

  2015. TNO and SINTEF. European Commission Seventh Framework Programme.
- Nicco, L., Serveau, L., Chang, J.-P., Vincent, J., Allemand, N., BOUTANG, J., ... VILMAIN, J.-B. (2014).

  Inventaire des émissions de polluants atmosphériques en France—Séries sectorielles et analyses étendues (format SECTEN). CITEPA.
- Nicolle, J.-M. (2009). Les perspectives du GNV dans le monde, en Europe et en France. *Annales des Mines Réalités industrielles, Août 2009*(3), 19–24.
- Nordelöf, A., Messagie, M., Tillman, A.-M., Söderman, M. L., & Mierlo, J. V. (2014). Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment? *The International Journal of Life Cycle Assessment*, *19*(11), 1866–1890. https://doi.org/10.1007/s11367-014-0788-0
- Norman, D., Lu, L., Gordon, J., Wulf-Holger, A., Marius, B., Florian, B., ... Frithjof, W. (2016).

  Elektrifizierungspotenzial kommerzieller Kraftfahrzeug-Flotten im Wirtschaftsverkehr als dezentrale Energie-Ressource in städtischen Verteilnetzen komDRIVE. Universitätsverlag der TU Berlin.
- Norton, J. A., & Bass, F. M. (1987). A diffusion theory model of adoption and substitution for successive generations of high-technology products. *Management Science*, *33*(9), 1069–1086.
- Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, 5(4), 329–332. https://doi.org/10.1038/nclimate2564
- OPTL. (2017). *Rapport 2017*. Observatoire Prospectif des métiers et des qualifications dans les Transports et la Logistique.
- OVE. (2015). TCO Scope 2015 | OVE www.observatoire-vehicule-entreprise.info. Retrieved July 15, 2015, from http://www.observatoire-vehicule-entreprise.com/tco-scope-2015
- Paine, C., & Kirsch, D. A. (2006). Who killed the electric car?

- Paine, C., & Morgan, P. G. (2011). Revenge of the Electric Car. New Video.
- Patier, D. (2004). La place du transport de marchandises en compte propre. Rapport final-Volet 3.
- Pearre, N. S., Kempton, W., Guensler, R. L., & Elango, V. V. (2011). Electric vehicles: How much range is required for a day's driving? *Transportation Research Part C: Emerging Technologies*, *19*(6), 1171–1184. https://doi.org/10.1016/j.trc.2010.12.010
- Pelletier, S., Jabali, O., & Laporte, G. (2014). Battery Electric Vehicles for Goods Distribution: A Survey of Vehicle Technology, Market Penetration, Incentives and Practices. Retrieved from https://www.cirrelt.ca/DocumentsTravail/CIRRELT-2014-43.pdf
- Plötz, P., Gnann, T., & Wietschel, M. (2012). Total ownership cost projection for the German electric vehicle market with implications for its future power and electricity demand. In *7th conference on energy economics and technology infrastructure for the energy transformation* (Vol. 27, p. 12). Retrieved from https://www.researchgate.net/profile/Patrick\_Ploetz/publication/267825503\_Total\_Owners hip\_Cost\_Projection\_for\_the\_German\_Electric\_Vehicle\_Market\_with\_Implications\_for\_its\_F uture\_Power\_and\_Electricity\_Demand/links/5460b38a0cf2c1a63bff312b.pdf
- Plötz, P., Gnann, T., & Wietschel, M. (2014). Modelling market diffusion of electric vehicles with real world driving data—Part I: Model structure and validation. *Ecological Economics*, *107*, 411–421.
- Plötz, P., Jakobsson, N., & Sprei, F. (2017). On the distribution of individual daily driving distances.

  \*\*Transportation Research Part B: Methodological, 101, 213–227.\*\*

  https://doi.org/10.1016/j.trb.2017.04.008
- Quak, H., Koffrie, R., Rooijen, T., & Nesterova, N. (2017). *Economics of Electric Vehicles for City Logistics FREVUE Deliverable 3.2*. https://doi.org/10.13140/RG.2.2.29145.62566
- Quinet, E. (2014). L'évaluation socioéconomique des investissements publics. HAL. Retrieved from https://ideas.repec.org/p/hal/psewpa/halshs-01059484.html

- Ramjerdi, F., & Fearnley, N. (2014). Risk and irreversibility of transport interventions. *Transportation*\*Research Part A: Policy and Practice, 60, 31–39.
- Riemersma, I., & Mock, P. (2017). *Too low to be true? How to measure fuel consumption and CO*<sub>2</sub>

  emissions of plug-in hybrid vehicles, today and in the future (Briefing). Retrieved from https://www.theicct.org/sites/default/files/publications/EU-PHEV\_ICCT-Briefing-Paper\_280717\_vF.pdf
- Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster. Retrieved from https://books.google.com/books?hl=fr&lr=&id=v1ii4QsB7jIC&oi=fnd&pg=PR15&dq=Diffusion +of+Innovations&ots=DKZrsLVn7P&sig=UDgSAuCrpJgiCOvcAh5bgXW21Zc
- Routhier, J. L., & Aubert, P. L. (1999). FRETURB, un modèle de simulation des transports de marchandises en ville. 8th WCTR Antwerp Proceedings, 1, 531–544.
- Routhier, J.-L., DUFOUR, J.-G., & PATIER, D. (2002). *Du transport de marchandises en ville à la logistique urbaine*. Ed. Techniques Ingénieur. Retrieved from http://books.google.fr/books?hl=fr&lr=&id=fjYKKyLO2YAC&oi=fnd&pg=PA1&dq=Du+transport+de+marchandises+%C3%A0+la+logistique+urbaine&ots=XfVr7br\_Y-&sig=CM-BxtxuVN6NaxS3xlazmGNmsOk
- Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index.

  \*\*Computer Physics Communications, 181(2), 259–270.\*\*

  https://doi.org/10.1016/j.cpc.2009.09.018
- Savy, M. (2011). *Le transport de marchandises*. Editions Eyrolles. Retrieved from http://books.google.fr/books?hl=fr&lr=&id=GZDFZ0\_gXnMC&oi=fnd&pg=PR7&dq=Le+transp ort+de+marchandises&ots=3628vSrpgP&sig=vh2TqrgxlrBLTWl1mCtGBAyE6rI
- Schroeder, A., & Traber, T. (2012). The economics of fast charging infrastructure for electric vehicles.

  \*Energy Policy, 43, 136–144. https://doi.org/10.1016/j.enpol.2011.12.041

- SDES. (2016, November). Chiffres clés du climat France et Monde Édition 2017 [Publications, Datalab, 2016]: Observation et statistiques. Retrieved January 5, 2018, from http://www.statistiques.developpement-durable.gouv.fr/publications/p/2587/1072/chiffres-cles-climat-france-monde-edition-2017.html
- Shacket, S. R. (1980). The complete book of electric vehicles.
- Shi, X., Pan, J., Wang, H., & Cai, H. (2017). Considering Individual Battery Range Needs in Environmental Assessments of Electric Vehicles. Presented at the Transportation Research Board 96th Annual MeetingTransportation Research Board. Retrieved from https://trid.trb.org/view.aspx?id=1439385
- Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043
- Smithson, M., & Verkuilen, J. (2006). A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. *Psychological Methods*, *11*(1), 54.
- Sperling, D. (2018). Electric vehicles: Approaching the tipping point. *Bulletin of the Atomic Scientists*, 74(1), 11–18.
- Sullivan, J. L., Salmeen, I. T., & Simon, C. P. (2009). PHEV marketplace penetration: An agent based simulation.
- Syrota, J. (2008). *Perspectives énergétiques de la France à l'horizon 2020-2050*. Documentation Française. Retrieved from http://www.prebat.net/IMG/pdf/2007\_sirota\_resume.pdf
- Taefi, T. T., Kreutzfeldt, J., Held, T., Konings, R., Kotter, R., Lilley, S., ... Jacobsson, S. (2016).

  Comparative Analysis of European Examples of Freight Electric Vehicles Schemes—A

  Systematic Case Study Approach with Examples from Denmark, Germany, the Netherlands,

  Sweden and the UK. In *Dynamics in Logistics* (pp. 495–504). Springer.
- Taefi, T. T., Kreutzfeldt, J., Held, T., Konings, R., Kotter, R., Lilley, S., ... others. (2015). pré. In *Proceedings of Dynamics in Logistics: Fourth International Conference*. Retrieved from

- http://www.researchgate.net/profile/Richard\_Kotter/publication/276274106\_Comparative\_
  Analysis\_of\_European\_examples\_of\_Freight\_Electric\_Vehicles\_Schemes.\_A\_systematic\_case
  \_study\_approach\_with\_examples\_from\_Denmark\_Germany\_The\_Netherlands\_Sweden\_and
  \_the\_UK/links/55548fa508ae6fd2d81fc0e5.pdf
- Tamor, M. A., Gearhart, C., & Soto, C. (2013). A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. *Transportation Research Part C: Emerging Technologies*, 26, 125–134.
- Tamor, M. A., Moraal, P. E., Reprogle, B., & Milačić, M. (2015). Rapid estimation of electric vehicle acceptance using a general description of driving patterns. *Transportation Research Part C:*Emerging Technologies, 51, 136–148.
- The Electric Revolution. (2011). Retrieved from https://www.youtube.com/watch?v=44mFzZI1\_r0&feature=youtube\_gdata\_player
- Tietge, U., Zacharof, N., Mock, P., Franco, V., German, J., Bandivadekar, A., ... Lambrecht, U. (2015).

  From laboratory to road. A 2015 update of official and "real-world" fuel consumption and

  CO2 values for passenger cars in Europe (White paper). ICCT. Retrieved from

  http://www.theicct.org/sites/default/files/publications/ICCT\_LaboratoryToRoad\_2015\_Repo

  rt\_English.pdf
- Tilman, D., Socolow, R., Foley, J. A., Hill, J., Larson, E., Lynd, L., ... Somerville, C. (2009). Beneficial biofuels—the food, energy, and environment trilemma. *Science*, *325*(5938), 270–271.
- Traut, E., Hendrickson, C., Klampfl, E., Liu, Y., & Michalek, J. J. (2012). Optimal design and allocation of electrified vehicles and dedicated charging infrastructure for minimum life cycle greenhouse gas emissions and cost. *Energy Policy*, *51*, 524–534.
- Trummer, W., & Hafner, N. (2016). Potentials of e-Mobility for Companies in Urban Areas. In U. Clausen, H. Friedrich, C. Thaller, & C. Geiger (Eds.), *Commercial Transport* (pp. 129–139). Cham: Springer International Publishing. Retrieved from http://link.springer.com/10.1007/978-3-319-21266-1\_8

- United Nations, Department of Economic and Social Affairs, Population Division. (2014). World urbanization prospects: the 2014 revision, highlights. *Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, New York*.
- Van Amburg, B., & Pitkanen, W. (2012). Best fleet uses, key challenges and the early business case for e-trucks: findings and recommendations of the e-truck task force. Calstart. Retrieved from http://www.calstart.org/Libraries/E-
  - Truck\_Task\_Force\_Documents/Best\_Fleet\_Uses\_Key\_Challenges\_and\_the\_Early\_Business\_C ase\_for\_E-Trucks\_Findings\_and\_Recommendations\_of\_the\_E-Truck\_Task\_Force.sflb.ashx
- Van den Bergh, J. C., Truffer, B., & Kallis, G. (2011). Environmental innovation and societal transitions:

  Introduction and overview. *Environmental Innovation and Societal Transitions*, 1(1), 1–23.
- Van Noorden, R. (2014). A better battery. *Nature*, 507(7490), 26.
- van Noort, A. M., Kooyman, P. P., & Dittrich, M. G. (2003). Measurement methods for peak noise during loading and unloading. *TNO Report*.
- Verlinde, S., Macharis, C., Debauche, W., Heemeryck, A., Van Hoeck, E., & Witlox, F. (2010). Night-time delivery as a potential option in Belgian urban distribution: a stakeholder approach. In 12th World Conference on Transport Research (WCTR), Lisbon, Portugal. http://intranet.imet.gr/Portals/0/UsefulDocuments/documents/02535.pdf.
- Visser, J., Nemoto, T., & Browne, M. (2014). Home delivery and the impacts on urban freight transport: A review. *Procedia-Social and Behavioral Sciences*, *125*, 15–27.
- Vogt-Schilb, A., Sassi, O., Cassen, C., & Hourcade, J. C. (2009). Electric vehicles: What economic viability and climate benefits in contrasting futures? Report of Centre International de Recherche Sur l'Environnement et Le Développement, CIRED October. Retrieved from http://actions
  - incitatives.ifsttar.fr/fileadmin/uploads/recherches/geri/PFI\_VE/pdf/CIRED\_electricvehicule.pdf
- WHO. (2016). WHO Global Urban Ambient Air Pollution Database (Update 2016).

- Wikström, M., Hansson, L., & Alvfors, P. (2015). An End has a Start Investigating the Usage of Electric Vehicles in Commercial Fleets. *Energy Procedia*, *75*, 1932–1937. https://doi.org/10.1016/j.egypro.2015.07.223
- Windisch, E. (2014). *Driving electric? A financial assessment of electric vehicle policies in France*. Ecole des Ponts ParisTech. Retrieved from https://tel.archives-ouvertes.fr/docs/00/95/77/49/PDF/2013\_EW\_Thesis\_Final.pdf
- Wolfram, P., & Lutsey, N. (2016). Electric vehicles: Literature review of technology costs and carbon emissions (WORKING PAPER 2016-14). ICCT. Retrieved from http://www.theicct.org/sites/default/files/publications/ICCT\_LitRvw\_EV-tech-costs\_201607.pdf
- World Bank. (2017, October 26). World Bank Commodities Price Forecast. Retrieved from http://pubdocs.worldbank.org/en/678421508960789762/CMO-October-2017-Forecasts.pdf
- World Health Organization Regional Office for Europe. (2015). Economic cost of the health impact of air pollution in Europe: Clean air, health and wealth. Retrieved May 4, 2015, from http://www.euro.who.int/en/health-topics/environment-and-health/air
  - quality/publications/2015/economic-cost-of-the-health-impact-of-air-pollution-in-europe