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Strategic electrification and optimization of a commercial vehicle fleet

Michael Haag[1], Carolin Stickel[2]
[1]*Fraunhofer IAO, Stuttgart, michael.haag@iao.fraunhofer.de*
[2]*STAR COOPERATION, Böblingen*

Abstract

The commercial vehicle market is often referred to as an early adopter market for plug-in electric vehicles (PEVs) [1]. This paper seeks to analyse driving profiles of a conventional commercial vehicle fleet. In order to determine the market diffusion of electric vehicles, a simulation model is developed to optimise and electrify vehicle fleets strategically. The analysis aims at determining PEV-potentials for an observation period of six years and to estimate the influence of different factors on the economic and technical potential for PEVs. We conclude that commercial vehicle fleets can economically be electrified in the year 2020. In favourable conditions, battery electric vehicles (BEVs) can substitute every second conventional vehicle. However it becomes apparent, when varying the input parameters of our estimates, that the economic potential is very sensitive to traction battery prices, vehicle prices and energy costs.

Keywords: fleet, EV (electric vehicle), cost, market, deployment, modeling

1 Introduction

In 2013, 4.5 million vehicles (passenger vehicles and light-duty vehicles) were on duty in 1.6 million corporate vehicle fleets in Germany. Vehicle fleets are of special relevance because they represent an important part of the initial market for passenger cars and light-duty vehicles and exhibit twofold annual kilometres travelled [2].

According to Sierra Club (2016) vehicle fleets in the USA own only 7% in the overall vehicle stock, but are responsibe for more than 35% of the transport-based fuel consumption [3]. The Federal Republic of Germany owns the highest share of new registered commercial vehicles among the western industrial nations. In 2016, 65% of all new vehicles were registered as commercially used vehicles [4]. This is by far the highest share of commercially registered vehicles in the international comparison [5]. Therefore, electric vehicles represent an important lever to reduce greenhouse gasemissions in motorised commercial transport.

2 Data and methodology

2.1 Driving profiles

In order to analyse the PEV-potential in vehicle fleets, relevant driving profiles are required. For a large collection of driving profiles in commercial traffic, Motor Traffic in Germany (KiD) is the only available German data source [6]. Though, the observations cover only insufficient information of vehicle fleet affiliation, Fraunhofer IAO collected data in the joint-project 'STAR-Fleet Analysis' with STAR COOPERATION. The database contains 13 different vehicles with about 864 trips, representing the driving behaviour of a section of the company's vehicle fleet with an observation time of three weeks.

Table 1: Characteristics of driving profiles

Criteria	STAR-Fleet
Data collection	GPS-tracking
Avg. observation period	16.3 days
Total number of profiles	13
Avg. VKT per day	59.9 km
Total numer of trips	864

In Table 2 we display the overall vehicles kilometres travelled, the average daily driving distance, the driving-/parking-ratio as well as the calculated annual mileage.

Table 2: Analysis of driving profiles

Vehicle	Total distance [km]	Average daily distance [km]	Share driving/ parking [%]	Calculated annual mileage [km]
1	1,198	48.86	0.05/0.95	17,834
2	717	38.04	0.03/0.97	13,886
3	433	27.46	0.03/0.97	10,024
4	935	46.13	0.04/0.96	16,837
5	1,021	46.19	0.04/0.96	16,859
6	1,625	69.74	0.04/0.96	25,456
7	1,315	76.87	0.06/0.94	28,056
8	149	30.1	0.02/0.98	10,987
9	37	14.55	0.02/0.98	5,309
10	172	11.66	0.01/0.99	4,254
11	626	41.59	0.04/0.96	15,182
12	596	37.07	0.03/0.97	13,529
13	854	53.25	0.04/0.96	19,437

In Figure 1 the cumulative distribution function (CDF) of the vehicle kilometres travelled (VKT) per day is shown, displaying the percentage (abscissa) of trips according to their daily driving distance in the ordinate. We observe that around 86% of all day trips do not exceed 100 km. The average daily distance is 59.95 km, while the median is 41.73 km.

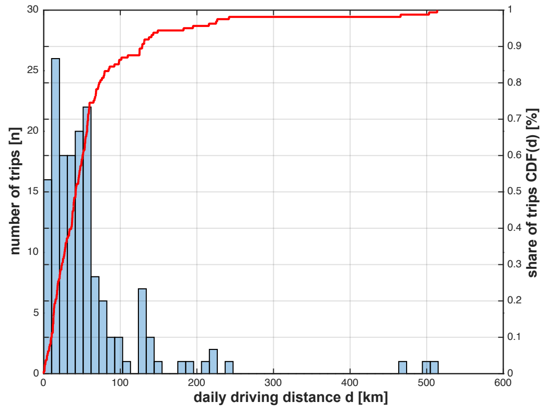


Figure 1: Histogram and cumulative distribution function of daily driving distances.

In Figure 2 the daily driven distances of each vehicle are displayed as a boxplot. The boxplot combines different position parameters like the lower and upper quartile, the median as well as outliers within a chart and gives a quick overview of the distribution of the values [7]. Furthermore, in the form of a blue dot, the arithmetical mean value of the daily driving distance for each vehicle is shown. It can be seen that the daily driving distance of individual vehicles varies. Given the daily driving distance, the vehicles can be divided into two clusters. Cluster one consists of the vehicles 4, 7, 11, 12 and 13, which have the highest driving distances with a simultaneously large scattering. Cluster two consists of more than half of the vehicles which have low daily driving distances of less than 50 km.

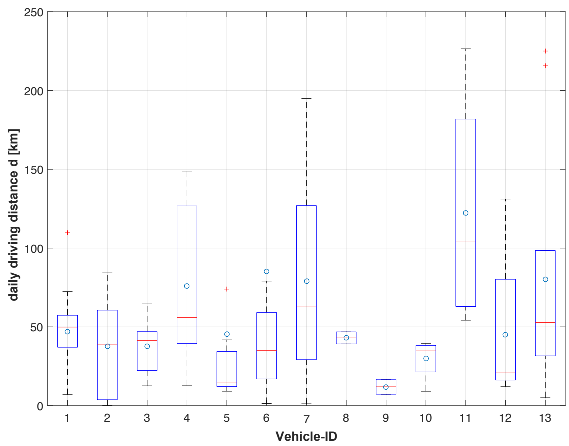


Figure 2: Boxplot of daily driving distances of 13 vehicles in fleet.

2.2 Methodology

Given the above mentioned data, we use agent based modelling to analyse driving profiles by simulating the battery profile and to receive the technical PEV-potential. Hence, real driving behaviour along with individual characteristics, such as the annual mileage as well as various technical specifications, are taken into account for each driving profile [8]. The technical PEV-potential delineates whether a battery electric vehicle (BEV) would be feasible to operate the whole driving profile with a fixed battery size, or in the case of hybrid vehicles such as plug-in hybrid vehicles (PHEV) or electric range-extended vehicles (EREV), what electric driving share could be achieved. In a second step, considering the specific PEV-potential of a driving profile, the economic potential is determined. Applying a microeconomic approach, we determine the Total Cost of Ownership-Analysis (TCO) for every driving profile individually. Analysed propulsion technologies are gasoline (ICE-SI), diesel (ICE-CI), liquefied petroleum gas (LPG), plug-in hybrid, extended-range electric vehicles, battery electric vehicles and fuel cell electric vehicles (FCEV). Thus the aim is to find the profiles vehicle option with the lowest TCO in a given year [9].

An observation period of six years is being analysed, starting in the year 2015 up to the year 2020. Given the technical and economic potential, a dynamic programming approach is carried out to determine the most suitable propulsion technology for every driving profile in each year of the observation period. Starting with the optimal propulsion technology in each year for a vehicle (micro-level), this inductive approach allows to derive an economically optimal fleet policy (macro-level), which leads to a minimisation of the TCO of a vehicle fleet.

With the driving profiles described above we calculate the battery state of charge (SOC):

$$SOC_{p,s,a,y}(t+1) = \begin{cases} SOC_{p,s,a,y}(t) - w_{\Delta t_p} \cdot c_{e_{s,a,y}} \\ min(SOC_{p,s,a,y}(t) + \Delta t_p \cdot CP_{loc_t}, \kappa_{s,a,y})^1 \end{cases}$$

for the given electric propulsion technologies PHEV, EREV, BEV and FCEV [9],[10]. Therefore, the vehicle segment s, the propulsion technology a and its corresponding battery capacity κ in year y for every driving profile p are taken into consideration. The annual TCO is given by:

$$TCO^{j}_{p,s,a,y} = j^{p,s,a,y}_{capex} + j^{p,s,a,y}_{opex}$$

To determine the j_{capex} the equivalent annuity method is used

$$AF = \frac{(1+z)^L * z}{(1+z)^L - 1}$$

in which AF is the annuity, z denotes the interest rate and L is the holding period. We choose z = 5% and L = 1 year throughout this paper.

$$j^{p,s,a,y}_{capex} = ((NCP_{s,a,y}) \cdot AF - RW_{p,s,a,y}) \cdot (1 + VAT)$$

NCP denotes the net price of a vehicle with propulsion technology a of vehicle segment s in year y. *RW* denotes the residual value, which is modeled using a hedonistic price index according to [11] and [12].

$$j^{p,s,a,y}_{opex} = \Big((s_{e_{p,s,a,y}} \cdot c_{e_{s,a,y}} \cdot d_{e_y} + s_{k_{p,s,a,y}} \cdot c_{k_{s,a,y}} \cdot d_{k_y} + d_{m_{s,a,y}}) \cdot AM_p \cdot (1 + VAT) \Big) + l_{s,a,y}.$$

The annual operating expenses j_{opex} are given for a propulsion technology by their specific electric or conventional consumption (c_e or c_k), multiplied with the respective costs for electricity (d_e) and fuel (d_k) plus the costs for service and maintenance (d_m). Because all these parameters are standardised values per kilometre, they must be multiplied accordingly by the travelled annual mileage (*AM*). Beyond that, the vehicle tax (l) must be added to determine the annual operating expenses for a vehicle. However, hybrid vehicles (e.g. EREV/PHEV) are an exemption. Because hybrid vehicles unite conventional as well as electric propulsion technologies, the travelled annual mileage consists of an electric (s_e) and a conventional driving portion (s_k). Therefore, the shares in electric and conventional driving portions are multiplied by the specific consumption and the energy costs.

2.3 Techno-economical parameters

The parameters are anticipated values for Germany in the year 2020. The vehicle specific values for a exemplary middle class car are given in Table 3. We assume fuel prices at 1.26 Euro/l for gasoline and 1.10 Euro/l for diesel plus 0.15 Euro/kWh for electricity. Value-added tax (VAT) of 19 % is added to fuel and electricity prices.

The charging power depends on the utilised charging infrastructure. Since there are different driving and parking strategies for the corporate fleet vehicles, multiple charging scenarios apply. Depending on the location, the vehicles can be charged at the enterprise location, at public charging stations or at the drivers home location. Given the location of the charging event, the power rates of the charging event varies, ranging from 3.7 kW (private), 11 kW (enterprise location and public) to 50 kW (public).

[1] The battery will be discharged if driven mileage w in time interval Δt_p is bigger than zero or charged otherwise.

Table 3: Techno-economical parameters for medium sized vehicle in 2020.

Parameter	ICE-SI	ICE-CI	LPG	PHEV	EREV	BEV	FCEV
Investment [Euro]	25.869	26.893	29.590	31.976	34.656	32.944	57.257
Battery capacity [kWh]	-	-	-	12	28	45	2
Electricity consumption [kWh/km]	-	-	-	0,184	0,196	0,196	-
H_2-consumption [l/km]	-	-	-	-	-	-	0,95
Fuel consumption [l/km]	0,065	0,053	0,072	0,063	0,072	-	-
Maintenance [Euro/km]	0,0723	0,0723	0,0723	0,0673	0,0531	0,0587	0,0637
Tax [Euro/anno]	161	227	94	33	24	0	0

3 Results

3.1 Simulation of driving profiles

In Figure 3 the initial logbooks of all 13 vehicles are displayed in a three-day extract (10^{th} to the 12^{th} October 2016) from the observation period. Each line represents a vehicle. The travel times of a vehicle are applied in blue colour horizontally over the time. In addition, the colour depth of a bar illustrates the length of a trip. The legend of Figure 3 shows that the darker the colour the longer the driven distance. Examining the displayed observation period the course of a day can recognised. Further, the number of journeys per vehicle varies considerably. Two of the vehicles show no journey in this exemplary elective period of observation. The average trip length during this extract of the observation period is 8.52 km.

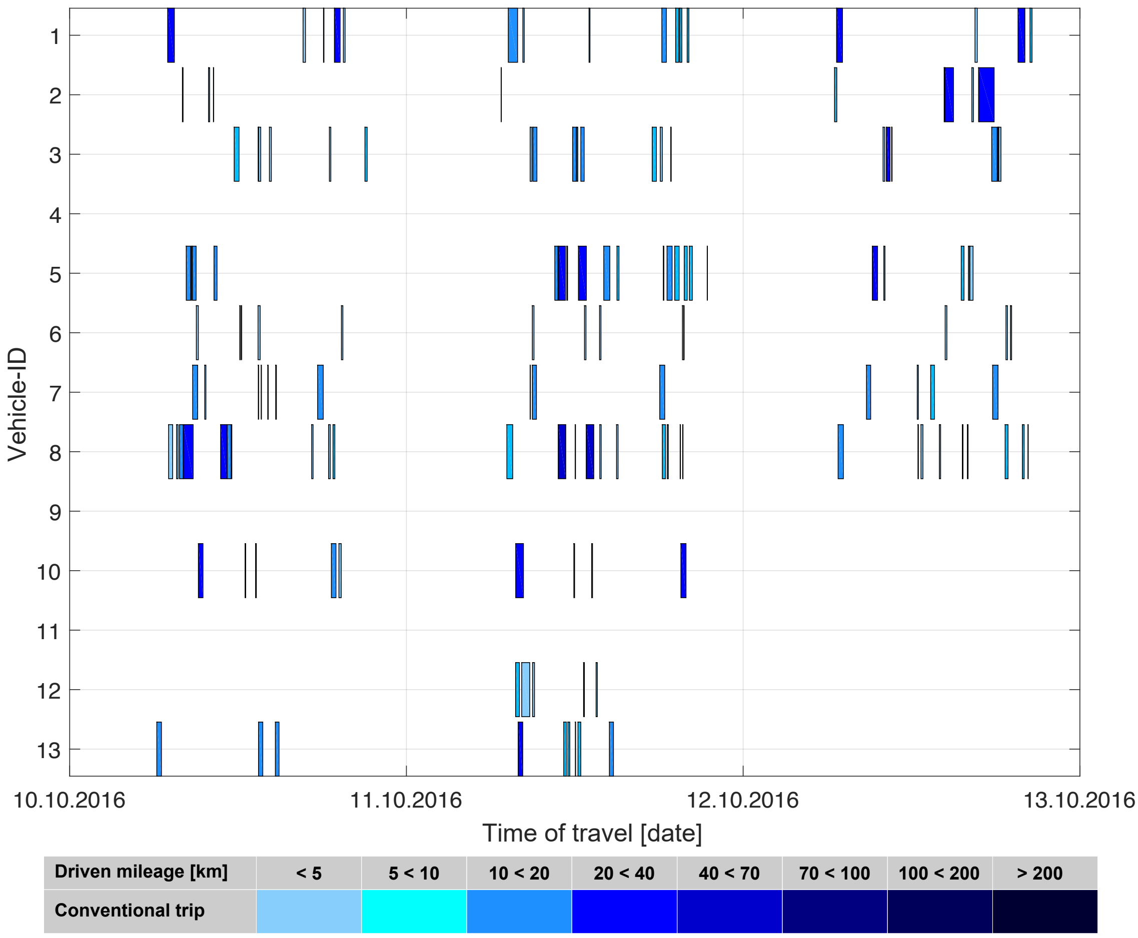


Figure 3: Logbook of the analysed thirteen vehicles for a three-day extract. The legend illustrates the length of single trips.

In Figure 4 the simulation of an exemplary driving profile of a BEV and an observation period of seventeen days is given. In the top panel the simulated vehicle status is displayed (driving, parking elsewhere or at the company, charging at the company/public or private). While in the middle panel the travelled distance is displayed, the bottom panel shows the corresponding battery state of charge. In the analysed observation period a distance of 1315.1 kilometres in total was travelled with an average mileage of 69.7 km per day. It can be recognised that during the course of a day a vehicle can be charged at the enterprise location and at drivers residence over night. Charging events at public charging infrastructure are not to be registered. The longest travelled single trips amounts to 76 km, this leads with the preceding journeys in sum to a battery discharge of 29.13 kWh.

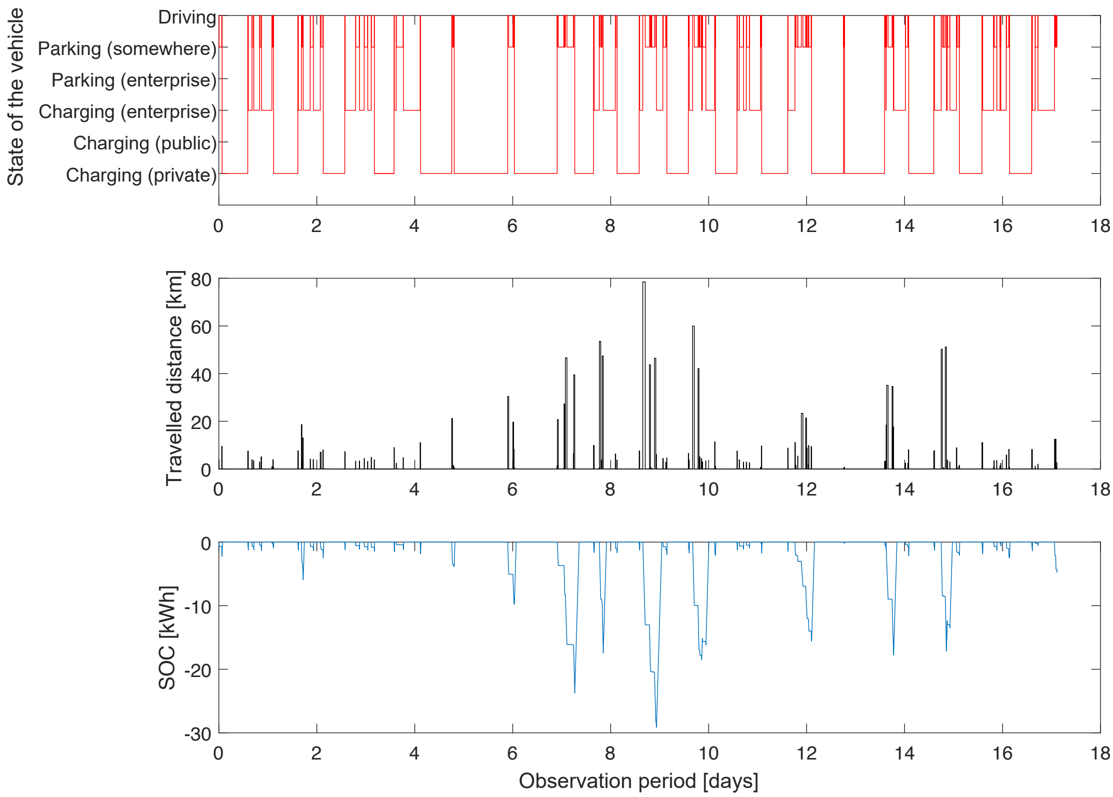


Figure 4: BEV-simulation of a driving profile for the observation period of seventeen days. The top panel shows the states of the simulated electric vehicle. The middle panel displays the travelled distance, while the bottom panel shows the corresponding SOC.

3.2 Technical potential

Determination of technical potential for BEV

In this subsection the technical potentials for battery electric vehicles are described. In Table 4 the relative technical BEV-potentials - depending on the vehicle segment - are displayed for the years 2016, 2018 and 2020. On this occasion the relative technical potential depicts the share of the vehicles whose driving profile can be realised by a BEV (in a specific vehicle segment).

It can be observed that in the small vehicle segment two thirds of the vehicles can be operated as a BEV. Concerning the medium sized vehicles an increased technical BEV-potential of about 78% arises. The greater annual mileage travelled in this segment are offset by the bigger battery capacity and the accordingly increased range of BEVs.

Table 4: Relative technical potential for battery electric vehicles and small- and medium sized vehicles in the years 2016, 2018 and 2020.

	2016	2018	2020
Small vehicles:	66,6 %	66,6 %	66,6 %
Medium vehicles:	77,8 %	77,8 %	77,8 %

Determination of electric driving share

In Figure 5 the simulated electric driving shares for PHEV and EREV and the years 2016 and 2020 are plotted over the annual mileage travelled. It can be recognised, that EREVs obtain higher electric driving shares than PHEVs. Comparing the simulated years 2016 and 2020, it can be seen that with rising battery capacity also the electric driving share increases. This is illustrated by the first-order polynomial fits, which are plotted for the two propulsion technologies and the years analysed. It can be concluded that - independent of the observed year - with increasing annual mileage the electric driving share of both propulsion technologies decreases.

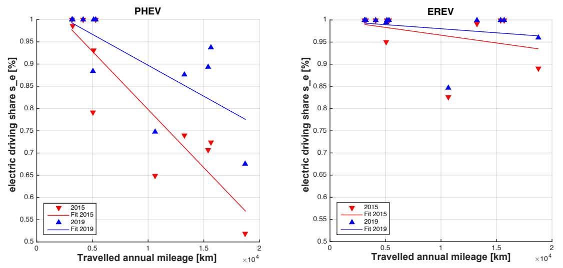


Figure 5: Simulated electric driving shares for PHEVs and EREVs in medium sized vehicle segment.

Charging curve for electric vehicles

In this subsection, load curves are derived which reflect the charging behaviour of all driving profiles with technical BEV potential over the three-week observation period. Figure 6 shows the simulated charging behaviour for charging at the company location, at publicly available charging infrastructure and private charge poles with the resulting charging curves. In the case of private charging, charging is understood over night at the home location of the vehicle driver. It can be observed that the electric vehicles are mainly charged at the company location. There is no charging at public charging columns over the entire observation period. Concerning the private charging, equally distributed charging events are clearly visible. Looking at the cumulative peak charging performance, it becomes evident that the level at the company and in the private sector are approximately equal and add up to about 29 kW. Regarding the charged amount of energy, it can be said that the charged energy at the private sites with 1076.42 kWh predominates over the company site with 810.82 kWh.

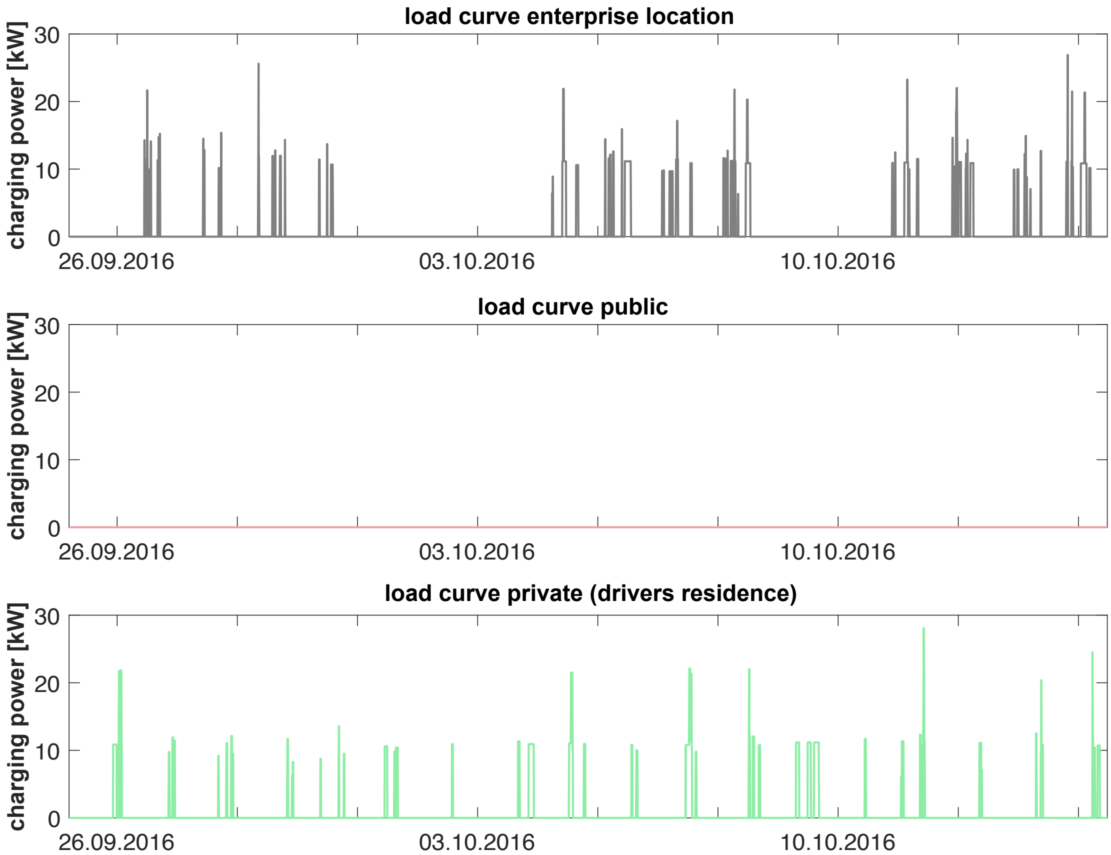


Figure 6: Resulting load curves for charging electric vehicles at enterprise location, at public charging stations and drivers residences (over night).

3.3 Economic potential

Figure 7 shows the TCO-optimal propulsion technologies for each driving profile in the years 2015 to 2020. (with a holding period of one year). The costs for the charging infrastructure are not included in this analysis. It can be seen that by 2017, combustion vehicles (ICE-CI and ICE-SI) dominate the analysed vehicle fleet economically. From 2018 onwards, an increasing diffusion of PHEVs in the investigated vehicle fleet appears. By the end of the observation period in 2020, 50% of the driving profiles can be technically and economically operated as BEV while ICE-CIs lose their economic relevance. For the propulsion technologies LPG, EREV and FCEV, no economic potential can be seen over the entire observation period.

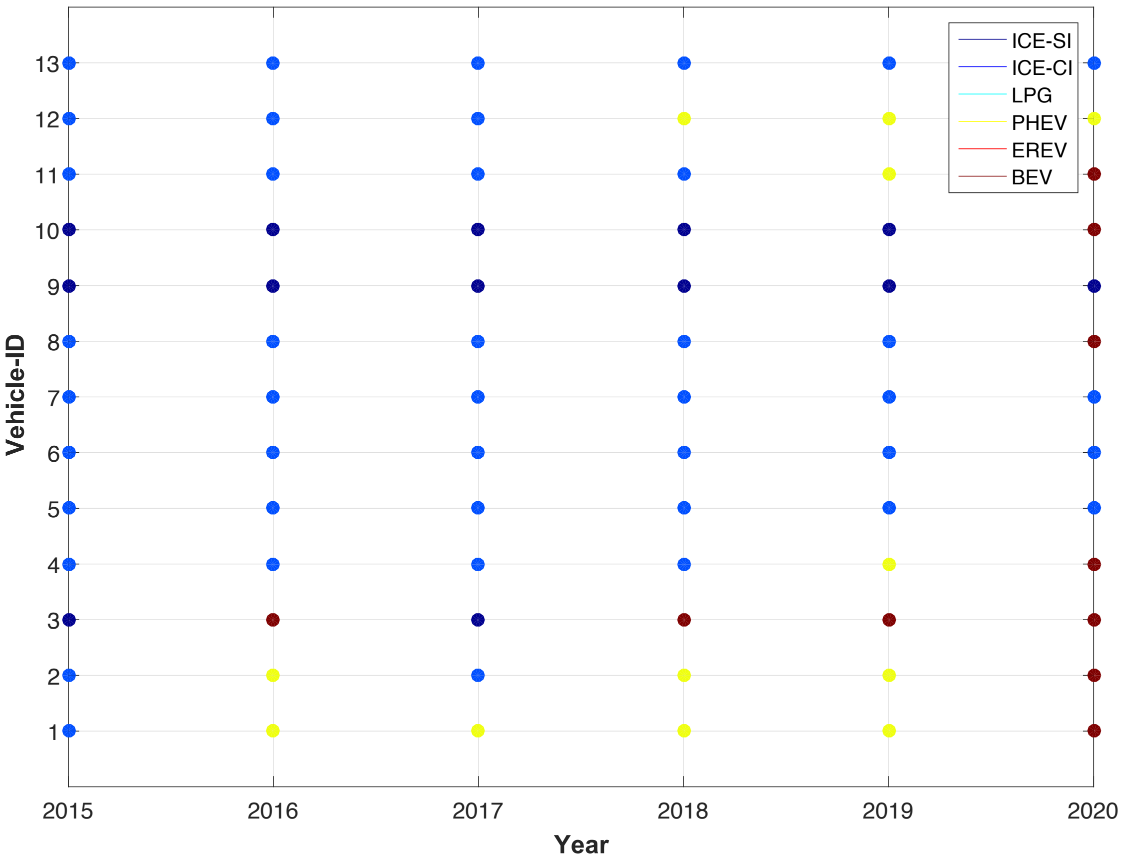


Figure 7: TCO-optimal propulsion technologies for each driving profile in the years 2015 to 2020.

3.4 Uncertainty analysis

In order to test the robustness of the analysis, a Monte Carlo simulation is performed in this section. A stochastic alternation of the input parameters is analysed taking into account random drawing in 10,000 simulation runs.

Figure 8 displays the results of the Monte Carlo simulation for an exemplary medium-class vehicle and the propulsion technologies BEV, PHEV, ICE-CI and ICE-SI with their total operating costs per kilometre in the years 2016 and 2020. In each simulation run, a single random number is drawn for each input parameter, according to its given distribution function [13]. It can be seen that the TCOs of all propulsion technologies are influenced by the variation of the parameters. The maximum variance takes place in 2016 for BEVs and amounts to 0.171 Euro per kilometer travelled. Furthermore, the cost of kilometres for PHEV, ICE-CI and ICE-SI will increase between 2016 and 2020, whereas the cost per kilometre travelled will decrease for BEV. On one hand, this can be explained by the lower costs for the traction battery between the years, which leads to a significant reduction in the total operating costs for battery-electric vehicles. On the other hand this phenomenon is due to the increased fuel costs for combustion and hybrid vehicles.

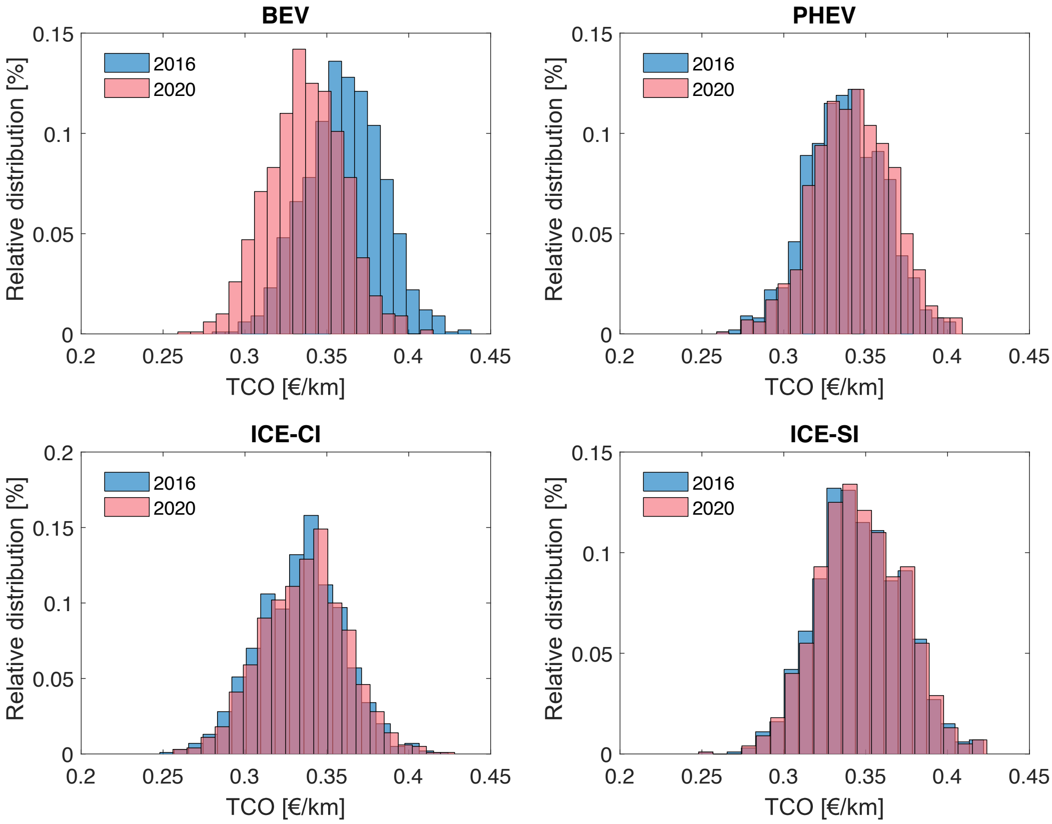


Figure 8: Monte Carlo Simulation for variation of input parameters. Depicted are the TCO for different propulsion technologies in the years 2016 (blue) and 2020 (red).

4 Conclusions and discussion

The aim of this paper is to provide a techno-economical potential analysis for strategic optimisation and electrification of vehicle fleets. The application of the model showed that there exits a diversity of technically and economically relevant propulsion technologies for commercial vehicle fleets in the observation period between 2015 and 2020. It also becomes evident that electric propulsion systems have a roughly constant technological potential over the observation period. Further, it can be stated that at the beginning of the observation period, vehicles with conventional internal combustion engines are favourable in economic terms. Battery electric vehicles in particular can only be economically viable when operated at a later date.

The model results, calculated on the basis of the case study, illustrate that up to 50% of the investigated vehicles in a fleet will be able to be operated economically as electric vehicles in 2020. The results further show that plug-in hybrid and battery-electric vehicles make the bulk of the electrified drivetrain architectures. Under economic aspects fuel cell vehicles can play no role in vehicle fleets by the year 2020. The results of the case study in relation to CO_2 emissions reveal that a substantial reduction in emissions is possible through electrification of the drivetrain. By means of the electrification and optimisation of the investigated vehicle fleet a relative CO_2 reduction to 31,7% is possible.

The sensitivity analysis further shows that in addition to fuel costs, particularly the price of traction batteries, affects the diffusion of electric vehicles in a vehicle fleet significantly.

References

[1] NPE. “Nationale Plattform Elektromobilität (NPE): Fortschrittsbericht der Nationalen Plattform Elektromobilität (Dritter Bericht)”. In: *Gemeinsame Geschäftsstelle Elektromobilität der Bundesregierung (GGEMO)* (2012).

[2] Thomas Renner. *Shared E-Fleet - Fahrzeugflotten wirtschaftlich betreiben und gemeinsam nutzen*. Tech. rep. Fraunhofer IAO, Apr. 2016.

[3] Sierra Club. *Future Fleet - How Companies Can Clean Up Their Acts*. 2016. URL: http://content.sierraclub.org/beyondoil/content/future-fleet-how-companies-can-clean-their-acts.

[4] Kraftfahrt-Bundesamt. *Jahresbilanz der Neuzulassungen 2016*. Tech. rep. Kraftfahrt-Bundesamt (KBA), 2017. URL: https://www.kba.de/DE/Statistik/Fahrzeuge/Neuzulassungen/n_jahresbilanz.html?nn=644522.

[5] Jan-Philipp Hasenberg. *Fleet business in BRIC and emering markets*. Tech. rep. Roland Berger Strategy Consultants, März 2014.

[6] IVS et al. *Kraftfahrzeugverkehr in Deutschland 2002 (KiD2002) - Schlussbericht Band 1*. Tech. rep. Institut für Verkehr und Stadtbauwesen, TU Braunschweig, Institut für angewandte Verkehrs- und Tourismusforschung e. V., Heilbronn, Prof. Dr. Wermuth Verkehrsforschung und Infrastrukturplanung GmbH, Braunschweig, Kraftfahrt-Bundesamt, Flensburg, Projektforschung Unternehmensberatung Transport und Verkehr, Gappenach, 2002. URL: http://daten.clearingstelle-verkehr.de/194/04/kid2002_-_schlussbericht_band1.pdf.

[7] Thomas Cleff. *Deskriptive Statistik und moderne Datenanalyse*. Gabler Verlag, 2011.

[8] Michael Haag and Clemens Fischer. "Potential analysis of electric vehicle road sweepers in Germany". In: *Electric Vehicle Symposium EVS29, Montréal, Québec, Canada*. June 2016.

[9] Michael Haag et al. *Elektromobilisiert.de - Erfahrungsbericht zur Elektrifizierung von (kommunalen) Fahrzeugflotten*. Tech. rep. Stuttgart: Fraunhofer IAO, 2015.

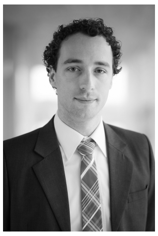
[10] Till Gnann, Patrick Plötz, and Fabian Kley. "Vehicle charging infrastructure demand for the introduction of plug-in electric vehicles in Germany and the US". In: *Electric Vehicle Symposium 26 (EVS26)*. Los Angeles, May 2012.

[11] Verena Dexheimer. "Hedonic methods of price measurement for used cars". In: *Statistisches Bundesamt (Destatis)* (2003).

[12] Patrick Plötz et al. *Markthochlaufszenarien für Elektrofahrzeuge - Langfassung*. Tech. rep. Karlsruhe: Fraunhofer ISI, Sept. 2013, p. 211. URL: http://www.isi.fraunhofer.de/isi-de/e/projekte/npetco_316741_plp.php.

[13] Geng Wu, Alessandro Inderbitzin, and Catharina Bening. "Total cost of ownership of electric vehicles compared to conventional vehicles: A probabilistic analysis and projection across market segments". In: *Energy Policy* 80.0 (2015), pp. 196–214. ISSN: 0301-4215. DOI: http://dx.doi.org/10.1016/j.enpol.2015.02.004. URL: http://www.sciencedirect.com/science/article/pii/S0301421515000671.

Authors



Michael Haag studied Business Engineering at the Karlsruhe Institute of Technology (KIT). He works as a scientist in the Competence Center Mobility Innovation at the Fraunhofer Institute for Industrial Engineering IAO. His current research focuses on electric vehicles and connected driving.

Carolin Stickel is responsible for the business segment New Mobility at the Böblingen-based STAR COOPERATION. For ten years, she has been developing concepts in after sales marketing and supporting OEM's evolution from mere manufacturers to providers of mobility services.