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Influencing factors on specific energy consumption of EV in extensive operations

Maximilian Schücking[1,*], Patrick Jochem[1], Wolf Fichtner[1], Olaf Wollersheim[2], Kevin Stella[2]

[1]*(*corresponding author) Chair of Energy Economics, Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT), Building 06.33, Hertzstraße 16, D-76187 Karlsruhe, Germany*
Tel.: +49 721 608 44559, E-Mail: maximilian.schuecking@kit.edu

[2]*Project Competence E, Karlsruhe Institute of Technology (KIT), Building 276, Hermann-von-Helmholtz-Platz 1, D-76344 Eggenstein-Leopoldshafen, Germany*

Abstract

The sensitivities of electric vehicle (EV) energy consumption become significant when operating at long distances. This study analyzes these sensitivities based on empirical data of seven EV over 2.75 years with individual monthly mileages above 3,000 km and a specifically adopted energy consumption model. The results underline the influence of average speed, the distribution of speed and the auxiliaries as well as their opposing effects. It is demonstrated that the point of lowest specific energy consumption is not necessarily identical to the point where EV are most competitive compared to conventional internal combustion engine vehicles.

Keywords: EV (electric vehicle), energy consumption, demonstration, fleet

1 Introduction

The economic break-even for electric vehicles (EV) in comparison to internal combustion engine vehicles (ICEV) can be reached in most countries through a high mileage based on their lower energy costs. Due to the limited charging speeds and battery capacity for most currently available EV this requires operating them at their upper technical boundary. In this context assessing and forecasting their actual energy consumption is key. Empirical studies have shown that empirical energy consumption is usually higher than proclaimed by the manufacturers based on standardized driving cycles for EV [1–6] and for ICEV. This depends on various factors, e.g. driving profiles, driver behavior, battery technology, and the auxiliaries, which leads to specific energy consumption minima between 30 and 40 km/h depending on EV type and other conditions [7–9]. However, the possibility of energy recuperation changes the sensitivities of EV energy consumption in comparison to ICEV.

In this line of research we present the results of a long-term demonstration project, where seven EV were deployed with the goal to reach an economic break-even. The EV were provided to commuting shift workers and for business trips between two sites in France and Germany. The route profiles can therefore be characterized as mostly inter-urban with a significant share of motorways, which does not represent the usual deployment field of EV. However, both applications offer the potential to reach high mileages. In fact the monthly average mileage per EV in this field-test was above 3,000 km and required the regular use of DC fast charging.

2 Method & Data

In order to identify influencing factors and investigate the energy consumption sensitivity three steps were taken. Firstly, the long-term empirically measured energy consumption was evaluated. The changes in state of charge (SOC) values between the start and end of one trip proved unreliable by showing high sensitivities to factors such as temperature and load profiles. Therefore, to calculate the energy consumption for each trip (E_{Trip}, eq. 1) the recorded sum of the average values of battery current (I_{Bat}) and voltage between (U_{Bat}) two data points multiplied by the time difference ($\Delta t_{i,i-1}$) was taken. In the next step the specific energy consumption for each trip ($E_{Trip,spec}$, eq. 2) was calculated by dividing the total energy consumption by the distance covered (D_{Trip}).

$$E_{Trip,total} = \sum_{i=Start+1}^{End} \frac{(I_{Bat,i} - I_{Bat,i-1})}{2} \times \frac{(U_{Bat,i} - U_{Bat,i-1})}{2} \times \Delta t_{i,i-1} \quad (1)$$

$$E_{Trip,spec} = \frac{E_{Trip}}{D_{Trip}} \quad (2)$$

In the following analysis average monthly values were taken. This was done due to the observed high variance of energy consumption for the individual trips on identical routes, most likely depending on factors such as time of day, direction of travel, or current driver, etc., which are not investigated in this study.

Secondly, to analyze the observed effects average driving profiles for both EV types were created based on recorded data (e-Wolf Delta 2 Route 1 and Nissan Leaf Route 7). Identical to the data loggers as the constant equidistant time difference between two data points for the e-Wolf Delta 2 20 s and for the Nissan Leaf 1 s was taken. These artificial diving profiles were put into an individual adjusted theoretical energy consumption model considering the specific efficiency values of the powertrain components (Fig. 2), which were provided by the manufacturers and validated by putting the EV on the dynamometer (Fig. 1) and comparing to values from the literature [10], as well as the individual recuperation algorithms.

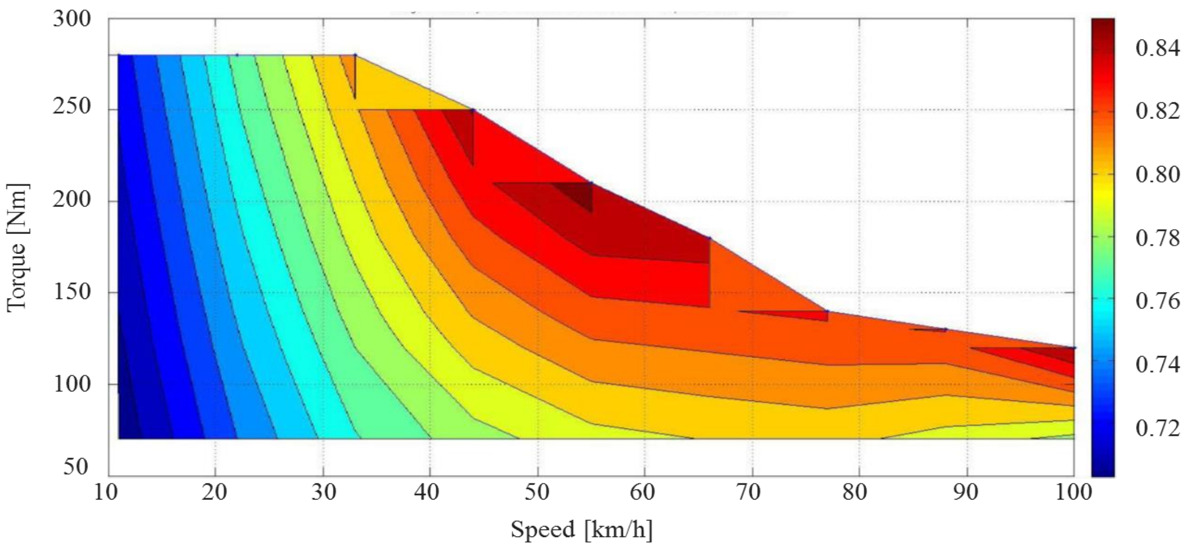

Figure 1: Range of efficiency for Delta 2 powertrain (measured in 11 km/h and 70 Nm intervals)

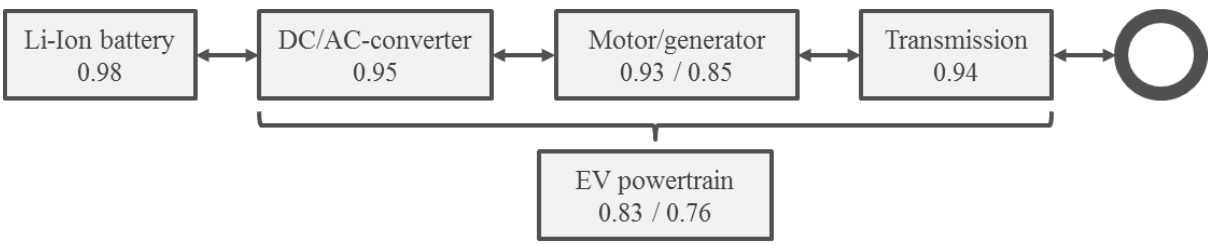

Figure 2: EV powertrain with average measured component efficiency at recorded speed values

The developed energy consumption simulation model distinguishes two driving states at different points of time during the trip (index k): taking electric energy from the battery for propelling the EV forward ($P_{k,el.sup}$, eq. 4) and recuperating electric energy back into the battery ($P_{k,el.rec}$, eq. 5.1 – 5.3). For both driving states an individual powertrain efficiency ($\eta_{pt,sup}$, $\eta_{pt,rec}$) is considered dependent on speed (v), torque (τ), and Temperature (T). The required power at the wheels ($P_{k,wheels}$, eq. 3) is the sum of the power for acceleration ($P_{k,acc.}$), the power necessary to climb an ascending slope ($P_{k,climb}$) as well as the power to overcome the rolling resistance ($P_{k,roll.res}$) and drag ($P_{k,drag}$). It is calculated based on the current speed (v), the change in speed ($\dot{v}$), the additional load (m), and the road gradient (α). The energy required for acceleration as well as to climb an ascending slope can potentially be recuperated, while the one used to overcome rolling resistance and drag is lost. The equations for the recuperation below exemplary show the calculation for the e-Wolf Delta 2 based the specific design of the algorithm: only recuperating energy above the speed of 20 km/h (eq. 5.1) and only up to a maximum of 22 kW battery charging power (eq. 5.3). The power demand or supply for each point in time of the driving cycle was added to the power demand of the auxiliaries ($P_{k,aux}$), which was then multiplied by the equidistant time difference ($\Delta t_{k,k-1}$), added up, and divided by the temperature dependent battery efficiency (η_{bat}) to calculate the total energy consumption for a single trip (E_{Trip}, eq. 6). To get the specific energy consumption ($E_{Trip,spec}$, eq. 7) the total energy consumption was again divided by the covered distance (D_{Trip}). To validate the model the results of the total energy consumption as well as the progression for different individual trips were subsequently compared to the energy consumption empirically measured confirming the accuracy of the developed model for the analyzed EV types.

$$P_{k,wheels} = P_{k,acc.}(v, \dot{v}, m) + P_{k,climb}(v, \alpha) + P_{k,roll.res}(m, v, \alpha) + P_{k,drag}(v) \tag{3}$$

$$P_{k,el.sup} = P_{k,wheels} \times \frac{1}{\eta_{pt,sup}(v,\tau,T)} \tag{4}$$

$$P_{k,el.rec} = 0 \quad if \ \frac{\sum_{i=k-1}^{k+1} v_k}{3} < 20\ km/h \tag{5.1}$$

$$P_{k,el.rec} = P_{k,wheels} \times \eta_{pt,rec}(v,\tau,T) \quad if\ P_{k,wheels} \times \eta_{pt,rec}(v,\tau,T)\ \leq 22\ kW \tag{5.2}$$

$$P_{k,el.rec} = 22\ kW \quad if\ P_{k,wheels} \times \eta_{pt,rec}(v,\tau,T)\ > 22\ kW \tag{5.3}$$

$$E_{Trip} = \frac{1}{\eta_{bat}(T)} \left[\sum_{k=Start+1}^{End} (\Delta t_{k,k-1} \times (P_{k,el.sup} + P_{k,aux})) + \sum_{k=Start+1}^{End} (\Delta t_{k,k-1} \times (P_{k,rec} + P_{aux})) \right] \tag{6}$$

$$E_{Trip,spec} = \frac{E_{Trip}}{D_{Trip}} \tag{7}$$

In this study the developed simulation model was mainly used to investigate the effects of auxiliaries and drag in relation to travelling speed. Since the EV were deployed on constant routes and the individual driver was unknown, influence factors such as driving style, or drivers experience were excluded in this study. Also the vehicle load influencing the power to overcome the rolling resistance as well as the power required for acceleration was only estimated with the average number of passengers. It was the only way, because for privacy reasons for the individual trips there was no data available at which points on the route the workers where embarking or disembarking the EV or how many workers were using the EV for a business trip. To specifically examine the sensitivities to drag and the use of the auxiliaries of the energy consumption in relation to the average driving speed for both EV types the speed values of the created average driving profiles were put into the model and varied proportionally.

Thirdly, to not only study the relation to average speed, but also to investigate the effects of a greater distribution of speed values the recorded data of the Nissan Leaf was analyzed, by comparing the standard deviation of the speed values to the specific energy consumption and the average speed. The Nissan Leaf was taken since the data logger had a higher measurement resolution and therefore allowing a more precise calculation of the statistical distribution. The empirical and simulated values for the total and specific energy consumption are based on a tank-to-wheel (TTW) system boundary.

Both EV types in the project were chosen based on the technical and user specific requirements of the two applications. The main technological selection criteria were the possibility of DC fast charging, sufficient battery capacity to ensure a one-way trip even under restrictive conditions, and cycle stability under the intensive and frequent use of DC fast charging. In addition to the technological requirements the EV needed to fit the demands of the travelers concerning size and comfort. According to these criteria only two EV models were available at that time: the e-Wolf Delta 2 (and the updated EVO-version) for the commuters and the Nissan Leaf for the business trips. The technical specifications can be found in Table 1.

Table 1: Technical specification of the deployed EV (Source: Technical datasheet provided by manufacturers)

	e-Wolf Delta 2	e-Wolf Delta 2 (EVO)	Nissan Leaf
Number of EVs deployed	3	3	1
Specific energy consumption (NEDC) [Wh/km]	187	200	173
Max. motor power output [kW]	90	90	80
Cabin heating	Biodiesel	Biodiesel	Battery
Nominal battery capacity [kWh]	24.20	32.00	24.00
Real battery capacity [kWh]	22.26	29.44	20.85
Battery chemistry	Li-ion NMC	Li-ion NMC	Li-ion G/LMO-NCA
Drag coefficient	0.31	0.31	0.285
Frontal area [m^2]	3.32	3.32	2.6
Vehicle mass [kg]	1,660	1,650	1,525

All EV were equipped with data loggers connected to the CAN bus recording powertrain and GPS data. For the e-Wolf Delta 2 EV amongst others the following powertrain and GPS data was recorded: date and time, parameters of the high-voltage-battery, such as voltage, battery current, medium cell temperature, and SOC, speed and odometer based on axis turning, GPS height, GPS odometer, GPS speed, GPS position latitude and longitude. For the Nissan Leaf a data logger directly connected via Bluetooth to the on-board diagnostic system (OBD) was installed. This allowed detailed access to a wide range of powertrain data, e.g. battery currents, voltages, temperatures, SOC, charging status as well as GPS data. Over the duration of 2.75 years for the seven EV over 450,000 km were logged. Additionally the EV were set on a dynamometer to assess their energy consumption and power train efficiency under controlled conditions.

3 Results

In order to investigate the effect of the influence factors on the specific energy consumption the results presented in the following are the recorded energy consumption values, the simulated effects of drag and auxiliaries in relation to average speed, and the consequence of a higher speed variance in the driving profile.

3.1 Long-term specific energy consumption

As first step of identifying influence factors the values for the long-term energy consumption are analyzed. Even though all EV were deployed on constant routes, for the two applied EV types significant differences in the energy consumption over the time of use can be observed (Fig. 3). For the specific energy consumption of the e-Wolf Delta 2 vehicles differences between the routes and time of year can be detected. As one reason for the variations between the routes the different shares of inter-urban and motorway route parts can be stated. Route 4 is mostly motorway and shows the highest average speed of all commuter routes with 60 km/h also leading to the highest specific energy consumption. Concerning the fluctuations a clear identification of causing factors is more difficult. Sometimes one worker being on holiday changes the route of the commuting group and therefore the specific energy consumption varies. Some fluctuations however can be explained by the changes in outside temperature. Especially between November 2014 and March 2015 an increase in specific energy consumption for almost all e-Wolf Delta 2 of around 20 Wh/km can be observed. Since the heating for the e-Wolf Delta 2 is done with Biodiesel the increase cannot be directly explained with an increase in auxiliary demand. Further analysis indicated that in the cold months the increase can be explained by a combination of battery chemistry and battery management design: Lower outside temperatures also cool down the battery temperature leading to a higher battery's inner resistance which decreases battery efficiency. Additionally the battery management system reduces the recuperation power depending on the current cell temperature to avoid potentially harming effects on the cell chemistry by charging with higher currents. The energy instead is lost through mechanical breaking, leading to a higher specific energy consumption. Other potential factors can be a more frequent use of specific auxiliaries such as headlights, wipers, and cabin fan. Secluding it should be noticed that on average the specific energy consumption lies around 235 Wh/km, which is significantly higher than the NEDC value stated by the manufacturer (Table 1).

The Nissan Leaf, due to the lower weight and better aerodynamics in comparison shows lower specific energy consumption, with the lowest point at 150 Wh/km (Fig. 3), which even lies below the NEDC value stated by the manufacturer (Table 1). On the other hand it shows a much higher variance between winter and summer. Even though different reasons for this increase in months of lower average temperatures can be adduced, the data shows that the cabin heating, that takes energy from the battery instead of an additional heating device, has the biggest influence. A maximum value of close to 4 kW was recorded for cabin heating power taken from the battery. This indicates the significant influence of the cabin heating on the specific energy consumption even at the relatively high average speed: At the measured average speed of around 70 km/h for the business trips the full heating power of 4 kW leads to an additional specific energy consumption of 57 Wh/km, which is an increase of 33% to the NEDC. Under these circumstances short term test measurements on urban routes showed specific energy consumption values up to 280 Wh/km.

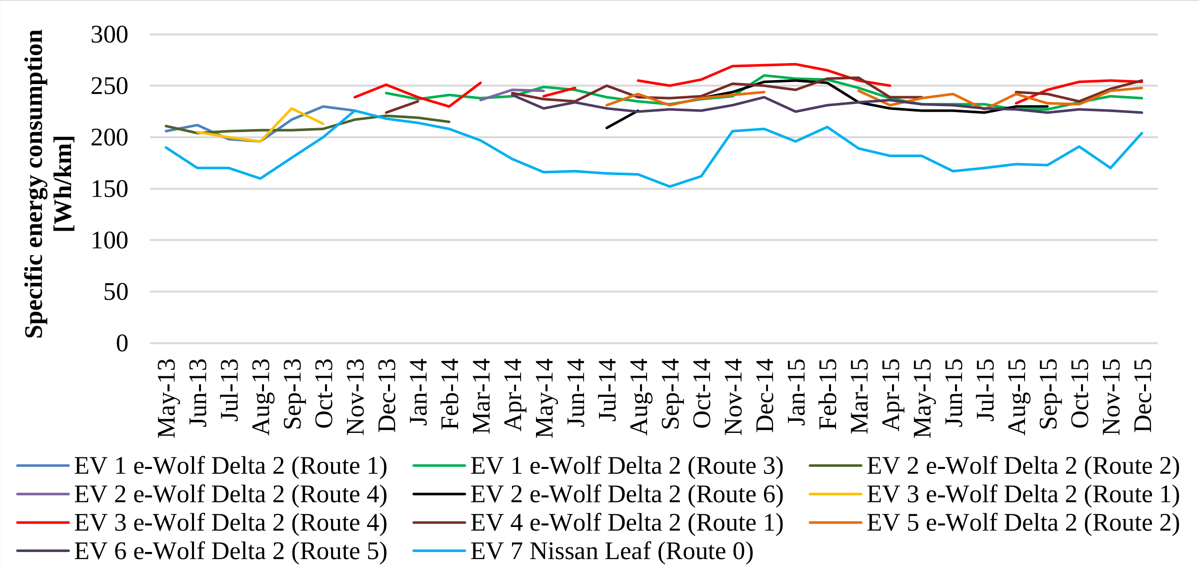

Figure 3: Measured monthly average specific energy consumption of the RheinMobil EV

3.2 Effect of drag and auxiliaries on specific energy consumption

The results of the specifically for both EV types developed energy consumption simulation model for the averaged recorded empirical driving profiles with proportionally varied speed values clearly underline the reverse effects of the auxiliaries and drag in relation to average speed on the specific energy consumption. Figure 4 shows the total specific energy consumption taken from the battery depending on the average speed for both EV types and two levels of auxiliary demand. The auxiliaries' power demand levels of 1.1 kW as average and 4 kW as maximum were chosen according to the recorded values. At the same level of auxiliaries' power demand the energy consumption at low average speeds for both EV types is very similar. With an increase in average speed the difference between the two curves increases. At higher average speeds the discrepancy between the different auxiliary demand levels diminishes. The progression of the curves illustrates the relatively changing influence of auxiliaries and drag at different speed levels. At a constant use of 1.1 kW auxiliaries under these driving conditions the minimum specific energy consumption lies at 22 for the Delta 2 and 28 km/h for the Leaf. The maximum auxiliaries' power demand of 4 kW leads to a minimum of specific energy consumption at 38 or 42 km/h respectively.

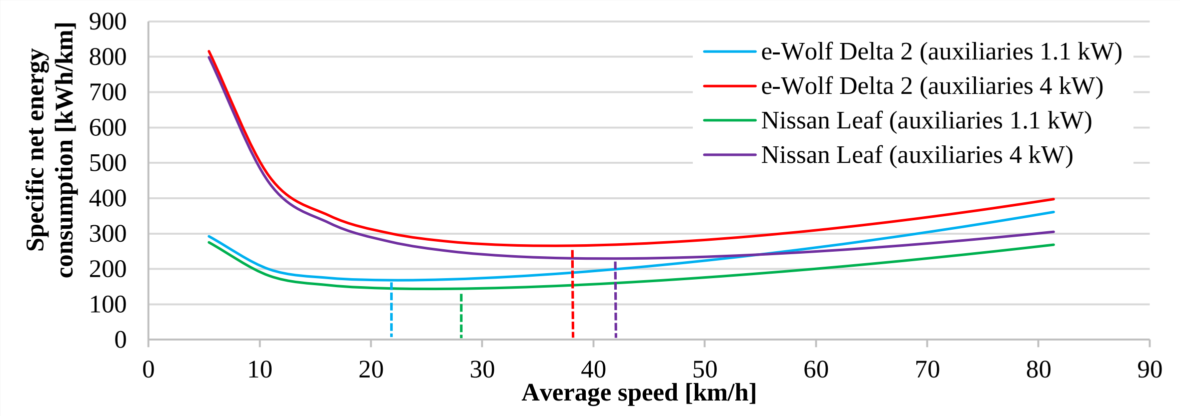

Figure 4: Energy consumption model e-Wolf Delta 2 and Nissan Leaf based on average empiric driving profiles

3.3 Effect of speed variance on energy consumption

Furthermore the empirical results suggest that even at high average speed values the distribution has an effect on the specific energy consumption that should not be neglected. Figure 5 shows the relation of specific energy consumption and recuperation to the standard deviation of the speed values for one trip as well as its relation to average speed. Even for the limited range of average speed values from 56 to 73 km/h, due to the constant mostly inter-urban and motorway driving profile the, clear correlations can be detected. The specific energy consumption as well as the specific recuperation increases with a higher standard deviation of speed values. The increase in recuperation does not fully compensate the increase, which is understandable due to efficiency rates, imperfect driving, and the quadratic with speed increasing losses due to drag. Therefore the specific net energy consumption increases with a higher speed variance. The data also shows that with a higher average speed the standard deviation of speed values for one trip decreases. This has to be interpreted carefully since the EV was deployed on a fixed route and therefore cannot be accounted to changes in the route profile, but might be the effect of traffic density or driving style.

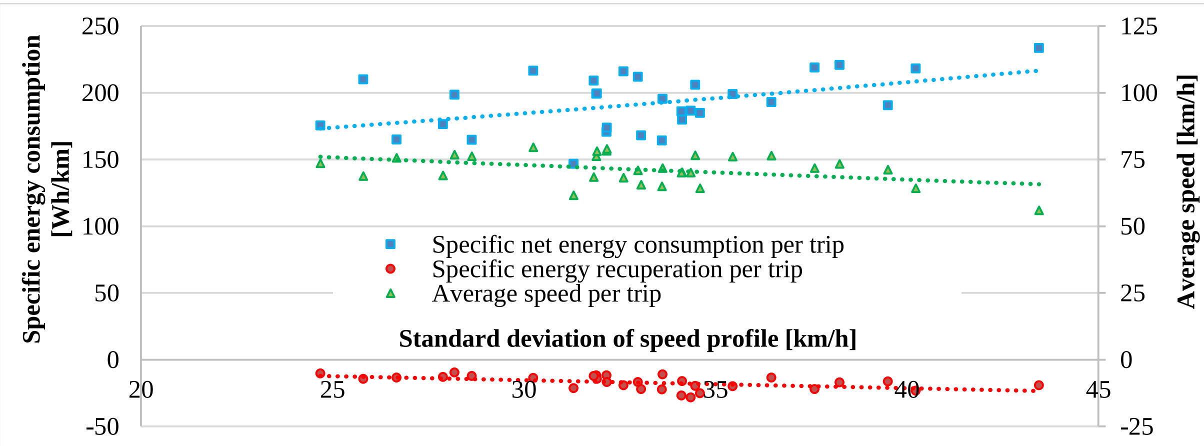

Figure 5: Measured effects of speed volatility on specific energy consumption and recuperation Nissan Leaf

4 Discussion & Outlook

The empirical results and the adapted theoretical model underline the importance of a careful EV energy consumption assessment and forecast. They specifically demonstrate the opposing effects of auxiliaries and drag at different average speed levels on the specific energy consumption. Furthermore, they substantiate that not only the average speed, but also the volatility of speed and therefore the amount and amplitude of acceleration and deceleration processes has a significant impact. The ramifications of these influencing factors become particularly relevant when operating EV on fixed routes at their upper technical boundary, with the goal of reaching an economic break-even.

Considering the presented influence factors in the context of economic deployment from a technological point of view the maximum specific energy consumption even under the most challenging circumstances must be low enough to allow a full one way tour on a single battery charge. As the empirical results (cf. Fig. 3) and the simulation results (cf. Fig. 4) show a changing use of auxiliaries plays a significant role when it comes to variations in energy consumption on constant routes – even more so at lower average speeds. They can lead to a high variance between specific energy consumption in winter (represented by a high auxiliary energy demand) and milder temperatures. Therefore, the worst case assumption, the constant maximum energy demand of the auxiliaries, has to be taken as restriction limiting the maximum distance. In this context the TTW energy consumption is relevant variable, since the EV battery capacity sets the limit.

The empirical and simulation results further suggest that the presented influencing factors have a direct effect on the point where EV deployment is most economical in comparison to ICEV. An intuitive approach would be to identify the point of the comparable highest relative energy efficiency. The values in Table 2 show energy consumption values measured by ADAC for identical vehicles with different means of propulsion. They indicate that the point of most comparable energy efficiency between EV and ICEV is not necessarily identical to the EV specific consumption minimum. It rather lies at low speeds on inner-city routes characterized by frequent starts and stops. The values in Table 2 however do not consider a variation in auxiliary energy demand. As the results of this field-test show, to provide a more comprehensive analysis, the variance in energy consumption based on the auxiliary demand must be taken into consideration. This is especially true for the effects of an additional energy demand for passenger cabin heating. For ICEV the required energy can be taken from the excess heat of the combustion process and is not increasing the total energy consumption. Therefore, from an economic point of view the realistic long-term average energy consumption including all relevant influencing factors has to be taken for EV ICEV comparison. Regarding the system boundary in this context the ICEV fuel consumption needs to be compared to the EV grid-to-wheel (GTW) energy consumption, since this way also losses occurring in the charging process, which are hence payed for when charging the EV, are included.

Table 2: Empiric TTW consumption EV & ICEV (Source: ADAC EcoTest Data base, last accessed 01.03.2016)

	NEDC	**ADAC EcoTest**				
	Average	**Average**	**Inner-city**	**Inter-urban**	**Motorway**	
Smart fortwo electric drive (55 kW)	15,1	19,0	13,2	17,1	26,8	[kWh/100km]
Smart fortwo (gas, 52 kW)	4,1	5,1	5,5	4,5	6,3	[l/100km]
Energy saving EV vs. ICEV[1]	57%	56%	72%	55%	50%	
VW e-up! (60 kW)	11,7	13,7	10,4	11,6	18,6	[kWh/100km]
VW up! (gas, 55 kW)	4,7	5,5	5,9	4,1	6,4	[l/100km]
Energy saving EV vs. ICEV[1]	71%	71%	79%	67%	66%	
VW e-Golf (85 kW)	12,7	18,2	12,7	16,3	25,1	[kWh/100km]
VW Golf (diesel, 77 kW)	3,8	4,5	5,1	3,9	5,3	[l/100km]
Energy saving EV vs. ICEV[1]	66%	59%	75%	57%	52%	
Nissan e-NV200 (80 kW)	16,5	21,8	11,5	21,8	32,4	[kWh/100km]
Nissan NV200 (diesel, 81 kW)	5,5	6,2	6,3	5,0	8,0	[l/100km]
Energy saving EV vs. ICEV[1]	69%	64%	81%	56%	59%	

[1] neglecting the losses occurring during EV charging, which should be considered for an economic comparison

When considering the worst-case energy consumption as technological limitation for the one way distance and the realistic long-term average energy consumption as basis for economic valuation it can be deduced that the point of the highest comparable energy efficiency just based on the energy required for propulsion might not be the best for EV deployment when aiming for the fastest economic break-even. On the contrary the results indicate that deploying EV on constant routes profiles with higher average speeds accrues advantages that can redeem the lower comparable energy efficiency. The lower maximum specific energy consumption at full use of auxiliaries means that the EV can be deployed constantly on routes with longer one way distances. This increases the possible maximum annual mileage and hence the multiplier for reaching the economic break-even. As the values in Table 2 show the loss in relative efficiency between inner-city and inter-urban or even motorway route profiles is not high and the relative efficiency still lies above 50%. Therefore, increasing the annual mileage through longer one-way distances has the potential to more than compensate the losses in relative efficiency. When operating on a system with flexible EV deployment under predictable conditions the maximum energy consumption has only be considered under the current conditions and therefore the utilization of the economic potential could be increased further.

Considering the research method, setting, and focus of this field-test, transferring the findings and conclusions into a broader context must be done cautiously. Several limitations can be identified that could be addressed in future research. The empirical results are limited to the two analyzed EV types and are restricted for deployment on constant routes with average speed ranges between 55 and 75 km/h. This especially limits the validity for the influence of speed variance, which should be investigated in detail for urban profiles. Also under these conditions with more frequent starts and stops and a potentially higher share of energy recuperation the driving style can also play a more significant role. Furthermore, the volatility of auxiliary use is based on the changes in German climate conditions throughout the year. In other climate zones these effects might be stronger or less relevant. Lastly, the results of this case study can only indicate a potentially different way of thinking about economic EV deployment when considering the current state of technology. No direct empirical comparison of ICEV and EV deployment under identical conditions over a longer time frame is presented. To verify the presented suggestions this should be done while varying the route profiles between inner-city and motorway and carefully considering the right energy measurement system boundaries.

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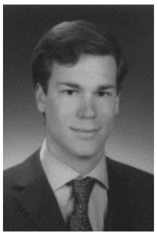
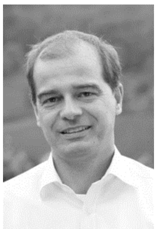


Maximilian Schücking is a scientist at project Competence E (PCE) at the Karlsruhe Institute of Technology (KIT). He is responsible for the data analysis in the research project RheinMobil. He is also a Ph.D.-student at the chair of energy economics. He holds a Master's degree in Industrial Engineering from the KIT.

Patrick Jochem is research group leader at the KIT-IIP, -DFIU, -KSRI, and chair of energy economics. In 2009 he received his Ph.D. in transport economics from KIT. He studied economics at the universities in Bayreuth, Mannheim and Heidelberg, Germany. His research interests are in the fields of electric mobility and ecological economics.



Wolf Fichtner is director of the KIT-IIP, -DFIU, and -KSRI. He is full professor and holder of the Chair of Energy Economics at KIT. His main areas of research are energy system modelling and the techno-economic analysis of energy technologies.

Olaf Wollersheim is head of PCE, which bundles all work in the field of electric energy storage for mobile and stationary applications at the KIT. He studied physics in Bonn, where he received his Ph.D. His research focuses on the development of lithium-ion-based batteries for stationary and mobile applications.

Kevin Stella is project manager and scientist for the application of storage technologies at PCE (KIT). Since 2013 he is the leader of the research project RheinMobil. 2012 he completed his MBA studies at the Collège des Ingénieurs (Paris, Munich, Turin). In 2011 he received his Ph.D. in physical chemistry from the University of Duisburg-Essen.