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Real-world data analysis of battery electric trucks operating in Germany

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Executive Summary

Under the influence of the European Union policies, sales of battery electric trucks (BET) are gradually increasing in Europe [1]. However, the market is still at an early stage, and the deployment of BETs is subject to a multitude of uncertainties and challenges. In order to shed light on the first practical experiences with BET, this study analyses real-world data from nineteen BETs of case study partners, operating in regional delivery transport in Germany in 2023 and 2024. The main focus of this work lies in the analysis of vehicle energy consumption and activity patterns.

The results show that exterior temperature, vehicle weight, and driving uphill or downhill clearly influence the total energy consumption of BETs. The average consumption is 0.96 kWh/km. Activity patterns indicate different usage between one-shift and two-shift operations, including intermediate daytime charging and extended night-time charging.

Keywords: Heavy duty electric Vehicles & busses; Modelling & Simulation

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1 Introduction

Under the influence of the European Union policies, sales of battery electric trucks (BET) are increasing gradually in Europe [2]. From the point of view of users, several aspects come into play when considering purchasing a battery electric truck (BET). One of the decisive criteria is the vehicle range in kilometre (km), which is a key factor in determining whether their delivery tours will be feasible. BETs sold in Europe in 2023 and early 2024 have a range of 300 km to 400 km and are therefore suitable for regional and last mile delivery [2]. However, the vehicle range of an electric or, in other words, the vehicle total energy consumption is influenced by various parameters, as already observed in a multitude of studies [[3], [4]].

The first objective of this study is to quantify the influence of several parameters on the total energy consumption of BETs based on real-world data. Key questions in this context are: What are the orders of magnitude of the variations? Which parameter has the greatest influence on total energy consumption? Is there a gap between real-world consumption and consumption figures provided by the manufacturers? A better understanding of these matters through several studies is of particular relevance, as better predicting energy consumption plays a key role in ensuring that range requirements can be met and journey planning software predicts accurate ranges for instance.

Another important aspect for BETs first users is the predictability of their journey and charging times. First users who took part in this study indicated that they currently consider recharging at the BETs home depot to be a practical and less expensive option than public charging. In this context, the following questions are the key to determining the feasibility of depot charging: How long are the vehicles usually parked at the depot? At what time of day and/or night can they recharge? Does this vary considerably over the months? This information is useful not only for users, but also for journey planning software developers, public authorities or other stakeholders planning public charging infrastructure for instance.

Several studies analyse real-world data for electric light-duty vehicles and buses [[3], [5]]. Yet, as BETs have only recently come onto the market, few studies based on real-world BETs data are available. Two published studies are of particular interest: The ICCT analysed real-world data of more than 10,000 heavy-duty vehicles operating in China in 2021, focusing on the effect of temperature on the consumption and charging patterns [6] and Cenex analysed real-world data of 20 BETs operating in the UK in 2022 and 2023 focusing on factors affecting energy consumption such as the drive cycle, ancillaries, weight, and temperature [1].

Our study analyses real-world data collected from some of the first series battery-electric heavy-duty vehicles operating in Germany, in 2023 and 2024. It is important to note that the basis of this study is a data set from only 19 vehicles, of the same model, which is not a representative sample. Consequently, it is not appropriate to generalise the observations made. Nevertheless, the results obtained can supplement and consolidate previous findings of the two aforementioned studies.

2 Data Availability, Data Treatment and Limitations

2.1 Data Availability

As part of the ELV-LIVE project, real-world data from several BETs operating in Germany has been collected and analysed. This project was funded by the German Federal Ministry for Economic Affairs and Climate Action (BMWK) and was carried out in cooperation with the Daimler Truck Group AG, which enabled the data collection of several Daimler BETs through their telematic system, the Fleetboard software.

The battery electric vehicle models analysed are Daimler’s eActros 300 or eActros 400 BET, which fall into the N3 category (maximum mass exceeding 12 tonnes). These rigid lorries are used for regional delivery transport and belong to the five case study partners of the ELV-LIVE research project, operating in diverse applications. To maintain the confidentiality of case study partners information and protect the privacy of drivers, the data collected has been anonymised. During the study, contact was kept with the partners and site visits were organised to gain a better understanding of the framework conditions in which the vehicles were put into operation. Thus, it has been established that most partners are operating in flat or slightly hilly areas, with a single partner operating in a mountainous region. Plus, while some of them use the lorries to transport their own goods, most of the partners provide hire or reward transport services and carry goods on behalf of third parties. Finally, the partners have vehicles with different axle combinations: 4x2, 6x2, and lorries carrying a trailer.

The data was collected between September 2023 and January 2025, at the frequency of approximately one week real-data downloaded per month. Data was collected from a total of nineteen vehicles, operating in different regions of Germany. At the start date of the study data from only six vehicles was available. Over the year, new BETs were put into operation by the case study partners and joined the pool of studied vehicles. The amount of nineteen vehicles was reached in August 2024. Although the number and type of vehicles (19, only eActros lorries) is not large enough to produce representative results, findings can provide initial indications, and give an estimate of the order of magnitude of fluctuations in energy consumption values for the case of the first BETs operating in regional delivery in Europe.

The Daimler’s telematic software “Fleetboard” displays the data in the form of a succession of events corresponding to three types of activities: vehicle driving, standing, and charging. For each event, a comprehensive summary is available, including the following parameters: the type of activity (driving, stationary, or charging), the gross combination vehicle weight (in tonnes), which encompasses both the vehicle’s curb weight and payload excluding the body; the geographical start and end positions (GPS coordinates); the start and end timestamps; the distance covered (in kilometres); the total energy consumption (in kilowatt-hours), measured directly from the vehicle – excluding charging losses; the average energy consumption (in kWh/km), derived from total energy and distance; and the battery’s State of Charge (SoC) at the beginning and end of the event.

Some relevant data are not available from the telematic system, such as the actual vehicle speed measured over the course of the event, the topography or the outside temperature. Yet, temperatures and altitudes of the start and end points could be retrieved from existing open databases as described in the following paragraph, enabling the partial analysis of these parameters effect.

2.2 Data Quality, Treatment and Limitations

2.2.1 Energy Consumption Analysis

The consumption as main dependent variable that will be explained by different parameters was taken directly from the telematic system. For each driving event, the average energy consumption per kilometres was calculated. Accordingly, each observation of the dependent variable corresponds to a single driving event and its associated mean consumption per kilometre, no matter its duration or distance. Consequently, this analysis focuses on identifying parameters and their influence on the mean energy consumption per driving event.

Some parameters influencing the consumption are not recorded by the telematic software and could hence not be examined, such as weather conditions (wind, rainfalls etc.), road conditions, tyres pressure, ambient temperature, the route topography, and the rated vehicle speed/driving style. The absence of this later value makes it practically impossible to analyse the effect of the drive cycle on consumption. It is however possible to calculate the average speed of the driving event (in km/h), to get a rough indication of the vehicle driving situation. The ambient temperature of the starting point was retrieved from the German weather service (DWD) open database, as an indicator of the exterior temperature during the BETs journey. For the topography, the exact route taken by the vehicle between the starting and ending point is not recorded by the system, only the GPS coordinates are available. Although the altitude difference between these points is not a perfectly reliable measure of the effect of the slope on consumption, it can nevertheless give an indication of the minimum difference in altitude travelled. The altitude of the starting and ending points were obtained using the EU-DEM digital surface model [7], enabling the calculation of the total altitude difference per driving activity. It is important to note that only one case study partner operates in a region characterised by consistent and substantial altitude variations. This may introduce a confounding effect, making it difficult to distinguish between the influence of altitude and the specific characteristics of the case study partner.

What's more, the software displaying only the total vehicle energy consumption, it is not possible to differentiate between the energy used for driving and that used for other purposes, such as heating the driver's cabin, controlling the tail-lift, using cooling units etc. Likewise, it is not possible to quantify the amount of energy recovered through recuperation. Because the presence/absence of cooling units, also known as vehicle temperature control units, has been specified by the study partners, this parameter could be nonetheless examined in greater detail. To summarize, this first part of the study investigates the effect of different parameters on overall energy consumption. If the effect of the tail-lift use can be considered negligible compared with other energy uses, as mentioned in the BETT final report [1], the overall energy consumption corresponds to the combination of the energy used for driving, including the recuperation effects, and the energy used for driver's cab heating/cooling, as well as the use of the temperature regulation unit.

Finally, it should be underlined that it is not feasible to verify the accuracy of the data transmitted by the software. Nevertheless, any missing or implausible data can be excluded from the dataset. After an initial check of the data, some inconsistencies were identified and attributed to sensor detection errors which occasionally led to invalid or erroneous values. For the energy consumption analysis, the data has been cleaned to address this issue. The cleaning process included omitting missing values from the dataset, as well as rows containing outliers such as exceptionally high average speed values (average speed of more than 90 km/h). To sum up, given the rather limited reliability of the primary data, and the limited ways to check their accuracy, it is possible that other incorrect values have not been detected during the data cleaning phase. As result data from 19 vehicles in 16 weeks, that is 37 weeks and 119 days across all vehicles and a total of 807 driving events were analysed.

2.2.2 Activity Pattern Analysis

For the activity pattern analysis, the charging times, and the duration of charging events for various vehicles are examined, along with their evolution over time. Due to the limited data quality of this dataset described below, the analysis has been primarily carried out using a qualitative approach, based on the visualization of each day's activity pattern. Additionally, some statistical figures were calculated for each day and vehicle.

Prior to the analysis, the dataset underwent a cleaning process that differed slightly from the approach used in the energy consumption analysis. While the latter focused exclusively on driving events, the charging pattern analysis required a comprehensive dataset encompassing all vehicle activities – driving, charging, and stationary periods – over the course of entire days. Due to uncertainties in the recorded start and end times of charging and standing events, the data cleaning process emphasised the reconstruction of realistic and plausible daily activity patterns, while eliminating anomalous or erroneous entries.

Two primary types of data quality issues were identified. First, certain vehicles exhibited implausible daily activity profiles, characterised by significant data gaps or evident measurement errors. To address this, entire days were excluded from the analysis if they met any of the following criteria: absence of any driving activity, total daily driving duration of less than one hour, presence of unassignable activity labels, or recorded activity durations summing to less than 10 hours or more than 35 hours. These thresholds were established for two reasons. First of all, a significant number of days exhibited missing data, particularly during nighttime hours, and in some cases, also during the day. Missing values occurring overnight were interpreted as prolonged stationary periods. In order to retain days with plausible, yet undetected, extended standing times – while simultaneously excluding days with excessive data loss – a lower threshold of 10 hours of total recorded activity was established. Secondly, many days contained overlapping activity entries extending over multiple hours, resulting in total daily activity durations significantly exceeding 24 hours. To avoid excluding otherwise plausible days affected by minor overlaps – particularly during nighttime transitions – a maximum threshold of 35 hours of cumulative activity duration per day was applied.

The second category of errors involved implausible or physically impossible events, such as unrealistic average speeds or overlapping activity labels. To correct these issues, all events lacking labels or reporting speeds exceeding 120 km/h were removed. Additionally, instances where stationary events overlapped with either charging or driving events were resolved by prioritising driving and charging activities. This was achieved by inspecting the three events preceding and following each instance of overlap and adjusting the activity labels accordingly.

Even though many days were excluded due to implausibility, it is still possible that days with data and measurement mistakes are left in the dataset and distort the analysis.

In view of the many changes apported to the dataset during this cleaning process, it was considered judicious to move away from a purely quantitative analysis, as the results could be biased. Instead, the decision was taken to employ a qualitative approach for the analysis, with a focus on the examination of daily activity patterns through visualization.

The resulting dataset contains 16 weeks of data, with a total of 166 weeks and 688 days across all 19 vehicles. Due to data availability and quality, for each vehicle a different number of days are analysed, with an average of 34 days per vehicle.

3 Methodology

The analysis focuses on two aspects: the vehicle energy consumption and vehicle activity patterns.

3.1 Energy Consumption

For the energy consumption analysis, a multi-parameter linear regression has been conducted for the selected parameters. To this end, the ordinary least squares (OLS) regression method of the "statsmodels" module was used.

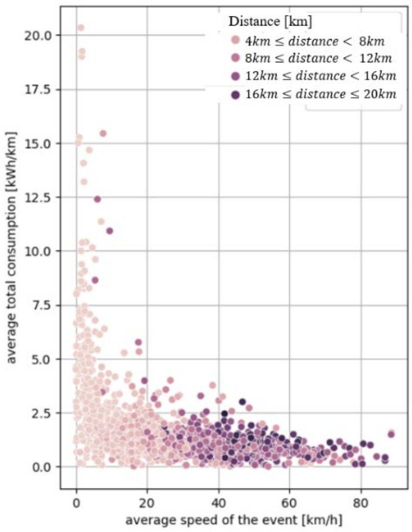

Figure 1: Vehicle speed vs. energy consumption scatter plot, with categories of distance for distances up to 20 km.

First observation suggests a notable correlation between the vehicle total energy consumption and the distance travelled, as shown in Figure 1. Indeed, the vehicle energy consumption (in kWh/km) are remarkably high for distances that remain below 5 km. Discussions with the manufacturer and case study partners revealed that this is mainly because the vehicle start-up process is highly energy intensive. When the vehicle starts, the system records a peak of energy consumption in kWh. As the average consumption is calculated in kWh/km, this peak is balanced out over longer distances. Consistently, high energy consumption values are associated with low average speed values: In the case of a vehicle trip that is subject to frequent stops, the average speed observed is likely to be low, whilst the multiple start-ups contribute to higher energy consumption. On top of this, the effect of recuperation is greater when the vehicle has a high rated speed, resulting in lower consumption values for high average speeds. Considering these observations, the average speed must be considered in the analysis alongside the other selected parameters.

Additionally, a minority of vehicles operates with temperature control units (TCU). The impact of TCUs on consumption remains uncertain, particularly with regard to the potential dependence of this effect on the other parameters listed below (Table 1). A temperature-dependent effect, for example, cannot be ruled out. As the regression can only be done with independent variables, we first exclude the vehicles with cooling units from the dataset. The reduced dataset contains 5,431 rows. The effects of the TCU are examined in more detail in section 4.1.3. Therefore, the parameters studied are listed in the table (Table 1).

Table 1: List of parameters and statistical information

Variable name	Unit	Range	Mean	Standard deviation
Average speed s	km/h	$0.02 - 90$	44	17.6
Exterior temperature t	°C	-7 $-$ 36	11.8	8.5
Vehicle gross combination weight w	tonnes	$11 - 40$	20.4	7.5
The altitude difference a	m	-785 $-$ 786	-0.2	94.9

As observed previously, the relation between consumption and average speed is not linear. Consequently an exponential function was fitted to the data, yielding three constants ($f(s) = a' * \exp(-b' * s) + c'$). Considering an R^2 of 0.42 the performance of this fit is relatively low, but it is satisfactory to represent the non-linear effect and performs even better around 40 – 60 km/h, whereas it performs not really good from 0 – 20 km/h. For the other parameters, observations show that, in principle, temperature *t*, weight *w* and altitude difference a seem to present a linear relationship with the average consumption, as illustrated in Figure 2.

Finally, we get the following expression for the average consumption *C* in kWh/km:

$$(1)\quad C = m_1 * e^{-k_1 * s} + m_2 * t + m_3 * w + m_4 * a + m_5$$

where $m_1, k_1, m_2, m_3, m_4, m_5$ are constant coefficients.

The regression is performed, utilising $k_1 \cong 0.17$ found when fitting (1) to the dataset without TCU.

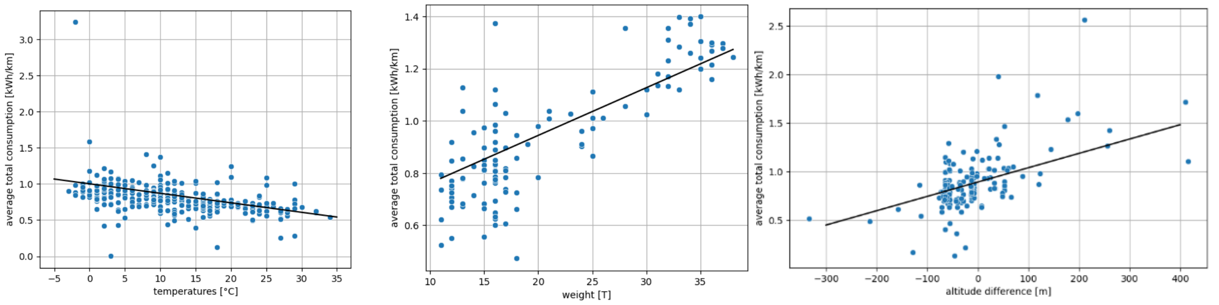

Figure 2: Scatter plots and corresponding regression lines for three combinations:
each parameter (temperature (left), weight (middle), altitude difference (right)) plotted against the dependent variable, average total consumption. Each point in the scatter plots represents a single driving event.

3.2 Activity and Charging Pattern

The activity patterns of each day and vehicle were plotted and visually analysed using start and end times. Following a qualitative approach, the patterns were clustered, and the discussion was enriched by additional information collected during visits to case study partners.

For the statistical analysis, each day was examined, and the mean, minimum, and maximum values for the length and frequency of the activities driving, charging and standing were calculated. To analyse the duration and frequency of activities per day, each day was defined as ending at 12:00 p.m. Events that extended beyond this cutoff were split into two separate entries: one assigned to the day before midnight and one to the following day. For the purpose of counting the number of events per day, each event was attributed to the day on which it began. Only charging events lasting more than 5 minutes were considered for the number of charging events, the total length of all “standing” events (including “standing while charging”) per day was calculated by subtracting the total “driving” time from 24. For each vehicle, statistics were calculated based on its observed days. However, days with fewer than one charging event or one hour of driving or, fewer than 10 kilometres of driving, or a longest charging event exceeding 10 minutes were excluded. This was done to prevent significant distortion due to unusual day patterns. As mentioned above (see section on data limitations), only days with driving and charging events were included, i.e. holidays, weekends, and other days without driving events were not examined, such as days in workshops. As a result, 688 days were analysed, yielding an average of 34 days per vehicle. It is important to note that the statistical analysis should be interpreted with caution, in consideration of the numerous modifications made to the dataset during the cleaning process.

4 Results

4.1 Real-world Energy Consumption

4.1.1 Average Energy Consumption

The objective of this section is to compare the energy consumption observed in real-world data with the values reported by the vehicle manufacturer. To ensure comparability, data collected under conditions similar to those used in the manufacturer’s testing were selected.

According to Mercedes-Benz, the eActros 300 achieves a range of up to 300 km with a usable battery capacity of 291 kWh (installed capacity of 336 kWh), corresponding to an average energy consumption of approximately 0.97 kWh/km. This value is reported to have been measured "under optimal conditions, after preconditioning, for a partially loaded vehicle operating in regional delivery transport without a trailer, with a 4x2 axle configuration, and at an ambient temperature of 20 °C." [8]. A similar specification is given for the eActros 400, which achieves a range of up to 400 km with a usable battery capacity of 388 kWh (installed capacity of 448 kWh).

Parameter type	Value
Mean energy consumption	0.96 kWh/km
Sample dimension	211 values
Standard deviation	0.75 kWh/km
First quartile (25 %-percentile)	0.66 kWh/km
Median (50 %-percentile)	0.74 kWh/km
Third quartile (75 %-percentile)	0.92 kWh/km

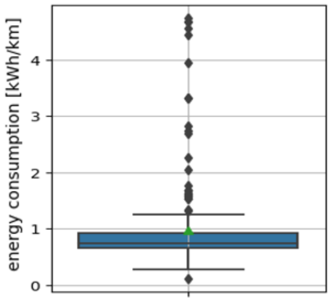

Figure 3: Box plot and statistical summary of the dependent variable, average energy consumption, in the dataset

To obtain a sufficient number of data points for analysis, all 19 vehicles in the case study were included, even though not all were configured with a 4x2 axle layout. The maximum technically permissible gross weight of the vehicles is 19 t. To approximate the "partially loaded" condition described by the manufacturer, only trips made with a vehicle weight between 11 and 18 t were considered. Additionally, to increase the sample size, the temperature range was slightly broadened to include data collected at ambient temperatures between 19 °C and 21 °C. Given that the manufacturer did not provide indications on topography, we selected trips with a recorded absolute altitude difference range lower than 200 m, which minimise the effect of topography on final results. The mean consumption value measured under these conditions is of 0.96 kWh/km, as shown in Figure 3, which is very close to the manufacturer's stated value. The discrepancy between the manufacturer's figure and the observed value is -1.03 %.

Results show that the median deviates considerably from the mean value, a discrepancy that is attributable to the observed heterogeneity in the data sample, see Figure 3. This can partly be explained by the high consumption values observed for low average speed values.

4.1.2 Influences of Parameters on the Vehicle Average Consumption

In consideration of the limitations outlined in section 2.2.1, the objective of this section is to provide an approximate estimation of the impact of the parameters on the vehicle's total energy consumption. Results of the OLS-regression are shown below in Table 2:

Table 2: Output statistics of the performed OLS regression analysis. The independent variables – speed, temperature, weight, and altitude difference – explain the variance in the dependent variable, average total energy consumption.

General Statistics		**Variable**	**Corresp. Variable**	**Coef value**	**Std err**	**t**	**P>|t|**	**Confidence interval [0,025; 0,975]**	
N	5431	m_1	Speed $\exp(-k_1 * s)$	5.130	0.076	67.181	0.000	4.981	5.280
Df residuals	5426	m_2	Temperature t	-0.013	0.001	-12.071	0.000	-0.015	-0.011
R^2	0.474	m_3	Weight w	0.018	0.001	14.752	0.000	0.016	0.021
Adj. R^2	0.473	m_4	Altitude difference a	0.002	9.76e-05	15.150	0.000	0.001	0.002
Prob (F-stats)	0.00	m_5	Constant k	0.709	0.029	24.453	0.000	0.652	0.766

Results show that all P-values associated with each parameter are null, which means that all coefficient obtained are statistically significant, that is, that the independent variables *s, t, w*, and *a* all have an effect on the average consumption C, as expected. The confidence interval indicates that the true coefficient falls within the specified range, with 95 % confidence. Intervals obtained are minimal, with the exception of the interval related to speed, and, to a lesser extent, to the constant.

R^2 of this multivariable regression equals 0.473 which can be considered as low. Nevertheless, considering the limitations exposed in 2.2.1, that is, the presence of additional factors that could not be taken into account in this study, the inherent uncertainty related to the calculated parameter used to study the effects of topography, the possible remaining incorrect values in the dataset, the obtained coefficients appear to provide a reasonable first estimate of the order of magnitude of the effect of parameters on the average consumption. Furthermore, given the fit of the exponential function presented in section 3.1, the coefficients can be expected to predict more accurately the results for a range of speeds from 20 to 90 km/h.

In concrete terms, the results indicate that for a vehicle without a TCU, a weight increase of 10 t, the energy consumption is expected to rise by 0.18 kWh/km ($m_3 \cdot 10$). An increase in temperature by 10°C is predicted to yield a decrease in energy consumption of -0.13 kWh/km, and a variation in altitude of 100 metres results in a difference in energy consumption of 0.15 kWh/km. For a mean energy consumption of 0.96 kWh/km (see section 4.1.1), these effects are not negligible and should not be overlooked by users. Whereby the determined additional energy consumption when the altitude difference changes must be viewed critically, since no statement can be made on the basis of the available data in connection with the more meaningful gradient. Due to its non-linear nature, the effect of speed is more complex to interpret. For this reason, an exemplary case is examined: when the average speed of a trip increases from 20 km/h to 30 km/h, the average energy consumption decreases by 0.138 kWh/km. However, this effect should be interpreted with caution, as speed is strongly correlated with route length and trip type. In this dataset, low average speeds are typically associated with short-distance trips and start-up phases, which involve frequent acceleration and are therefore linked to disproportionately high energy consumption.

These results show that a user who is on the road in a region where the average temperature is low, for example at high altitudes, must consider that their vehicles will be able to cover substantially fewer kilometres than in a region where the average temperature is higher. For an eActros400 vehicle travelling in conditions as described in section 4.1.1, but with 10°C external temperature instead of 20°C, this could mean that the vehicle could cover 358 km instead of 400.

4.1.3 Accuracy of the Model and Deeper Insights into Parameters

To evaluate the accuracy and robustness of the model developed in the previous section, individual parameters were analysed in isolation. For this purpose, the dataset was segmented into different ranges of each parameter under investigation, while keeping the remaining variables constant within predefined bounds: ambient temperature between 19–21 °C, vehicle weight between 11–18 t, and average driving speed between 20–60 km/h. The average energy consumption for each parameter range was calculated and compared with the model predictions. This allowed identification of the parameter ranges where the model shows the best fit.

For vehicle speed, a high degree of variation can be observed at very low speeds (below 5 km/h). As speed increases, energy consumption decreases, following a predictable trend. The best model performance is observed at a speed of 40 km/h, where the predicted consumption deviates by only 10 % from the actual average consumption of the corresponding data subset.

In contrast to speed, weight does not exhibit extreme outliers. A general trend is observed in which energy consumption increases with vehicle weight. The best agreement between model and empirical data was found at a weight category centred around 14.5 t, where the deviation from the measured average consumption is just 2 %.

A separate analysis was conducted to examine the effect of cooling units on energy consumption. Comparing datasets with and without cooling units reveales that vehicles equipped with a cooling unit consumed, on average, 0.092 kWh/km more energy. Notably, this increase appeares to be independent of ambient temperature, as both regression lines show similar slopes.

4.1.4 Comparison with other Energy Consumption Data of Electric Trucks

A comparison with other published consumption figures for trucks can be useful to facilitate a more profound comprehension of the specific energy consumption figures presented in section 4.1. Consumption figures can be found, for example, in tests in the specialised press, in automotive magazines or on internet portals focusing on electromobility.

For instance, the eActros 300, the vehicle examined by the ELV-LIVE project, was tested by the German magazine “Verkehrsrundschau” in year 2023 [9]. In this test, the 4x2 vehicle, with a total weight of 18.6 tonnes, was driven over a distance of 171 km on Italian roads. The specific consumption of the vehicle was determined via the on-board computer, and was found to be 0.87 kWh/km. The majority of this test was conducted on the motorway, characterised by relatively flat terrain and a speed of 85 km/h. The test consumption is marginally higher than the median consumption of 0.8 kWh/km determined in section 4.1.4 for the weight class ≤19t and significantly higher than the median consumption of 0.67 kWh/km determined in section 4.1.3 for journeys over 60 km/h.

The magazine Logistra also reports on a test of the eActros300 with a payload of 6.9 tonnes by the company Cargo-Partner in regional distribution transport. It is reported that the vehicle, operating regional distribution transport operations in the vicinity of Vienna Airport, consumed 1 kWh/km. The slightly smaller Fuso eCanter, with a payload of 3.1 tonnes, has also been cited as consuming 1 kWh/km, but for a driving profile that includes both inner-city journeys in Bratislava and long-distance journeys [10]. It is noteworthy that the testing phase started in March/April, so there were probably no challenging winter weather conditions.

The eActros 300 has also been tested by “Transport” magazine, with a test consumption of 0.70 kWh/km. In this case, however, the test is only carried out with half the maximum payload, i.e. 7.5 tonnes [11]. This test consumption roughly corresponds to the median consumption of 0.72 kWh/km for average speeds between 20 and 60 km/h (see section 4.1.3).

The effect of speed and vehicle mass has been demonstrated by the evaluation of the journeys of 20 DAF

Electric LFs in the UK over a total of 287,000 km. The average consumption for motorway journeys was between 0.8 and 0.9 kWh/km, depending on the payload, and between 0.7 and 0.8 kWh/km for rural traffic. The highest energy consumption was observed in urban traffic, ranging from 0.9 to 1.3 kWh/km [1]. The mean consumption across the three weight classes is 0.9 kWh/km, which is significantly higher than the mean consumption of the weight class <19 tonnes determined in this study of 0.8 kWh/km and the median consumption of 0.72 kWh/km. It is noteworthy that the discrepancy in consumption varies considerably between drive cycles, urban, rural and motorway. It is important to note that this analysis based on the drive cycle could not be conducted using the data collected in ELV-LIVE, as the nominal speed was not available in the dataset (see section 2.2).

As discussed in section 4.1.2, the topography exerts a significant influence on energy consumption. This assertion is in line with the observations made during a test drive of a fully electric DAF CF with trailer and 8-tonne payload (total weight around 26 tonnes). The test route ran from Salzburg via the motorway, country roads and the Grossglockner High Alpine Road and back, covering a total of 302 km. The total altitude covered was approximately 3,400 metres. The consumption was measured at 1.77 kWh/km on the 117 km long route with a slight incline (730 metres in altitude), and 2.7 kWh/km on a second, significantly steeper section (69 km, 2,664 metres in altitude) [12].

A test drive with the eActros 600 tractor in Norway at 20°C showed a similar result. When travelling uphill, the vehicle consumed 1.24 kWh/km, compared to an average of 1.06 kWh/km. In contrast, during downhill driving, the consumption was observed to be as low as 0.84 kWh/km, which is approximately one-third of the consumption levels recorded during uphill driving [13].

The German automobile club ADAC also conducted a test of the eActros 600, reporting a consumption of 0.88 kWh/km for a 350-kilometre test drive from Munich to Wörth [14].

In 2024, an electric tractor unit from Scania, with a trailer (total weight 38 tonnes), was driven from Södertälje in Sweden to Istanbul in Turkey as part of a marketing campaign. Scania has stated that the average fuel consumption for this 4,439-kilometre journey was 1.15 kWh/km. The stated 108 hours of driving time results in an average speed of 41 km/h [15].

In summary, it can be concluded that the consumption figures determined in section 4.1 are within the range of published test consumption figures. Furthermore, trends such as increased consumption due to demanding topography are also confirmed. Additionally, the consumption figures derived from the driving tests confirm that consumption is subject to large variations and that factors such as usage patterns (regional distribution/ motorway), topography and payload have a significant influence on the electricity consumption of electric trucks.

4.2 Real-World Activity Patterns

4.2.1 Operating Conditions and Available Charging Infrastructure

The battery electric vehicles considered are used by the five case study partners exclusively in regional transport. In most cases, the vehicles are used only on weekdays. In particular, in the use cases for transporting one's own goods, they are also used on Saturdays (e.g. to supply retailers with fresh produce). In these cases, Saturdays were also included in the analyses. The specified requirements for state funding in Germany associated with vehicle procurement incentivise the highest possible degree of utilization of the vehicle, that is a high mileage. The intensity of vehicle use is correspondingly high, taking into account the range imposed by the battery capacity. On average, the vehicles cover 220 kilometres per day on days when they are used (one shift operation: 160 km; two shift operation: 280 km). The range of an average trip varies – depending on the vehicle – from 115 to 350 kilometres.

Visits to the case study partners have revealed that current vehicle use mainly follows a predetermined plan and is in principle inflexible, which explains the similar patterns over time. This can be explained by the constraint of the range, meaning that the partners have at least checked the feasibility of their trips and, if necessary, selected in advance the trips that can be made. Furthermore, the partners of the case study who have only a few charging stations have indicated that they currently have a ‘charging plan’ that determines which vehicle is charged when and where. All vehicles return to the depot at the end of a trip or day. All vehicles have access to depot charging infrastructure and are usually charged via this. Charging at public charging stations only takes place for some vehicles and then only in a few exceptional cases.

The charging infrastructure is positioned differently depending on the conditions in the depots and the operational requirements and has different capacities depending on the location. For example, the charging infrastructure is sometimes positioned so that the battery can be charged while the vehicle is being loaded and unloaded in the depot. In other cases, the charging infrastructure is located centrally in the depot and the vehicles have to be moved to it for battery charging, meaning that they cannot be loaded or unloaded during this time. The available charging capacity at the respective charging stations varies considerably among the project partners.

4.2.2 Activity Patterns and Charging Profiles

The analysis of the activity patterns shows that the vehicles under consideration typically operate in regional transport. All deployment patterns are characterised by a high number of short trips and frequent stops for loading and unloading goods. The vehicles are used exclusively during the day and start at around 5 a.m.

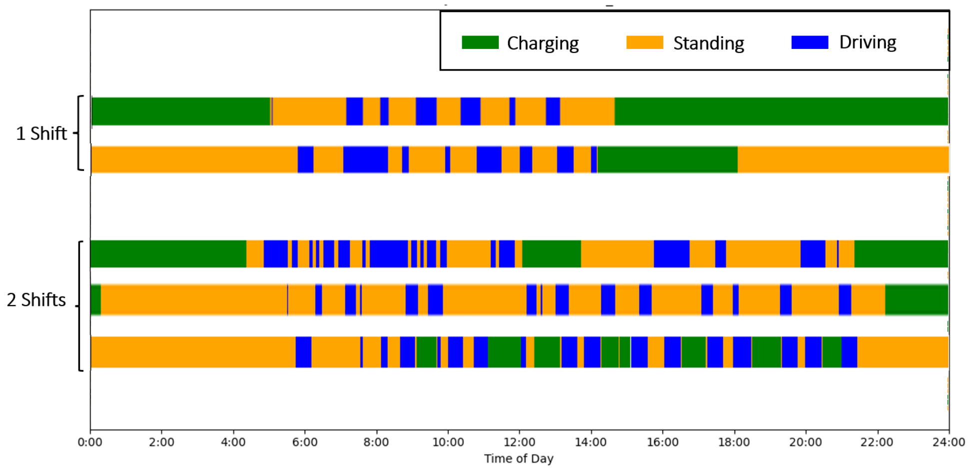

Figure 4: Exemplary charging pattern
for different using cases and charging strategies.

However, a clear difference can be seen between vehicles in one-shift and two-shift operation. For example, the battery of vehicles in one-shift operation is usually only recharged at the end of the tour. Often, the charging process begins immediately after the last trip and the battery is charged in the early afternoon (from around 1 p.m.). In some cases, the battery is already fully charged by the afternoon, while others take significantly longer to charge, mostly due to the different charging capacities. In other cases of single-shift operation, the charging process does not start until a few hours after arriving at the depot and ends during the night or just before the start of the next morning. This could indicate a limited number of charging points or the strategic use of electricity at night. However, it is also partly due to operational reasons. For example, in some cases, the trucks are loaded with goods in the evening for the first trip the next morning and then driven to the charging station on the company premises at the end of the working day for overnight battery charging. Finally, in single-shift operation, there are an average of 1.4 charging events and an average charging time of 9 hours. However, there is a high variance, which is illustrated by a standard deviation of more than two hours. The long charging times could be due to the different charging capacities in the respective depots, but also to measurement errors and incorrectly measured charging activities.

In the case of two-shift operation, the operating time of the vehicle is significantly longer and extends until after 8 p.m. To ensure the higher daytime driving distances, in some cases the battery is recharged after the vehicle returns to the depot in the middle of the day during the next loading and unloading process, so that it can cope with the second shift. This is particularly the case where a charging point has been set up in the immediate vicinity of the goods handling point in the depot. The feasibility of this option depends on the specific circumstances of the company and the infrastructure available at the customers' depots. While some case study partners reported the ability to charge at every customer location, others indicated that this option is not available to them. In some cases, the entire charging activity of a vehicle is limited to the intermediate charges; in others, the longer nightly charge of the battery begins after 8 p.m. Depending on the available charging power, the charging process is often completed well before midnight. Compared to single-shift operation, there are an average of 4.1 charging events per day and a significantly shorter total charging time of 4 hours with a standard deviation of almost 2 hours. The shorter charging times may be due to higher available charging power, but may also be partly due to higher measurement errors, as mentioned above.

There were no fundamental changes in the activity patterns over the observation period. The basic deployment patterns at the case study partners sites were determined when the vehicles were put into operation and optimised for the vehicles' characteristics, so that they could be maintained unchanged over the observation period. The available charging infrastructure also remained unchanged during the observation period. In individual cases, however, adjustments were made to the battery charging strategy. For example, one case study partner reduced the night charging to 90 % of the battery capacity because the trips in the relevant depot start with a longer descent due to the high altitude and this seems a good way to use the recuperation of the vehicle.

Multi-day idle times on weekdays could be traced in the data, but were excluded from the analysis. During the observation period, these were mainly associated with workshop stays. These occurred rarely overall. Particularly in the early test period, these were associated with longer downtimes due to processes in the repair shops that had not yet been established or long delivery times for spare parts. However, these were significantly reduced during the course of the trials, which was also confirmed by the case study partners.

Overall, the case study partners reported only a few technical failures, which were also no more frequent than for diesel trucks.

4.2.3 Flexibilities and Approaches for Optimization

The application profiles considered are generally adapted to the properties – in particular the range – of the currently available battery-electric trucks. Furthermore, it can be seen, that the requirements for the charging infrastructure in two-shift operation are significantly higher. However, particularly with regard to charging periods, flexibilities and optimisation potentials can be identified.

In the current implementation, different charging strategies are used. Some start – presumably mainly for practical reasons – with the battery charging process after the last daytime trip, although the battery charging time is usually significantly shorter than the vehicle's overnight standing time, even at low charging power. As a result, vehicles in single-shift operation stand in the depot overnight for 14 to 18 hours and charge for an average of half to one-third of that time. Even in two-shift operation, an average downtime of 7 to 8 hours is still achieved.

With a view to avoiding peak loads in the afternoon and early evening, which are also unfavourable from a cost perspective, a modified charging strategy could be implemented, as has already been done by some, which, for example, includes a later or more evenly distributed battery charge for the electric vehicles. If it is possible to move the vehicles at night, the number of charging points required per vehicle could also be reduced.

On the other hand, the more demanding two-shift operations show that the requirements for battery charging during the day can be reduced less easily, since the available time window for the loading and unloading process often requires parallel battery charging at the loading bay with the usual charging capacities. If such a technical solution is not feasible (e.g. lack of space for installing a charging station at the loading bay), vehicles with larger battery capacities or central charging stations with very high charging capacity and thus shorter battery charging times are possible alternatives, but these tend to be associated with higher costs. In such cases, charging may take place at public charging stations or at semi-private infrastructure provided by the customer. Some use cases already show the successful full utilization of opportunity charging, in which no charging events are necessary at night.

In view of the mostly low levels of electrification in the fleets of the case study partners under consideration, the optimisation solutions outlined have so far only been partially implemented. However, with a view to the further electrification of the fleets, it is already foreseeable that technical bottlenecks and considerable costs will increasingly be associated with the provision of further depot charging infrastructure and the increased power demand, and that the outlined optimisation approaches will therefore probably gain in relevance in the future. At the same time, several case study partners plan to reduce flexibility in vehicle deployment and battery charging in the depot by procuring battery-electric trucks from the next generation of vehicles with higher battery capacity.

For the operation of long-distance vehicles, several case study partners see a strong need for public high-power charging infrastructure, since, in their estimation, these additional charging requirements can only be met to a very limited extent in the depot. The application profiles considered are generally adapted to the properties – in particular the range – of the currently available battery-electric trucks. Furthermore, it can be seen that the requirements for the charging infrastructure in two-shift operation are significantly higher. However, particularly with regard to charging periods, flexibilities and optimisation potentials can be identified.

5 Conclusions

As part of the evaluation of energy consumption and activity data from current e-truck series vehicles in regional transport, important insights into energy consumption and usage patterns were obtained from 19 vehicles.

The calculated average energy consumption per driving event of 0.96 kWh/km for this particular dataset shows a very small deviation of -1.03 % from the manufacturer's specification and also fits in well with other published data on e-truck energy consumption. The calculated regression provides only a satisfactory fit over the entire data set. However, a good fit is achieved in the medium speed range. The analyses of the influencing variables show a strong correlation between average speed and energy consumption. Particularly high energy consumption is obtained for very low speeds. These are probably mainly associated with starting processes and are usually connected with short driving distances. From an average driving speed of about 20 km/h, a relatively stable level of energy consumption is achieved.

A strong influence on energy consumption can also be demonstrated for the other influencing variables ambient temperature and vehicle weight. For example, consumption decreases by 0.132 kWh/km in average when the ambient temperature increases by 10°C. If the vehicle weight is increased by 10 tonnes, consumption increases by an average of 0.183 kWh/km.

The influence of topography and the use of a cooling unit on vehicle energy consumption also provides plausible correlations. However, a more detailed analysis would be necessary for robust results.

The analysis of the activity patterns illustrates the typical current use of BETs in regional transport. The different types of use are striking, differing between one-shift and two-shift operation as well as intermediate charging during the day and long night-time charging processes. The operating and charging strategies are already being adapted to the given operational framework conditions. With a view to further optimization options for battery charging, it can be seen on the one hand that intermediate charging during the day can greatly reduce the need for night charging. Additionally, the analyses show significantly longer standing times than charging times, which allows charging to be shifted to more favourable periods.

At the same time, however, it should also be noted that in the majority of the vehicles considered, the current e-trucks only make up a very small proportion of the total fleet. For further analyses, it is therefore important to examine the effects of a larger proportion of electrified vehicles in the fleet and the increasing use of vehicles in long-distance transport. For in-depth analyses of energy consumption and the influencing variables, larger samples with longer data series, which are characterised by fewer data gaps and include more vehicle models could represent a significant improvement.

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Presenter Biography

Florian Hacker holds a degree in Geoecology and joined Oeko-Institut in 2007. He is Deputy head of the Resources & Transport Division. His research activities focus on technology assessment from different perspectives and the development of CO_2 reduction strategies for the transport. His special expertise lies in the examination of alternative propulsion technologies with a particular focus on electric mobility. He is currently project leader of several projects on the electrification of heavy-duty vehicles.

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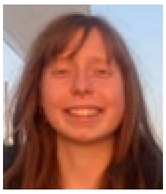

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