Real-world data analysis of energy consumption, activity and charging patterns of battery electric trucks operating in Germany

Berlin, July 2025

2nd report of the research project "ELV LIVE - Accompanying research on the use of battery-electric heavy duty vehicles in day-to-day logistics operations" FKZ 16EM6003-1

Authors

Juliette Le Corguillé
Florian Hacker
Dr. Katharina Göckeler
Moritz Mottschall
Theresa Dolinga

Oeko-Institut e.V.
info@oeko.de
www.oeko.de

Office Freiburg
Merzhauser Straße 173
79100 Freiburg
Phone +49 761 45295-0

Office Berlin
Borkumstraße 2
13189 Berlin
Phone +49 30 405085-0

Office Darmstadt
Rheinstraße 95
64295 Darmstadt
Phone +49 6151 8191-0

Supported by:

Federal Ministry for Economic Affairs and Energy

on the basis of a decision by the German Bundestag

Erneuerbar mobil

Acknowledgments

The authors would like to thank the case study partners and the Daimler Truck AG for their cooperation and participation in this study. The ELV-LIVE research project is financed by the Federal Ministry for Economic Affairs and Energy with funds from the "Erneuerbar Mobil" funding programme (https://www.erneuerbar-mobil.de/projekte/elv-live).

Citation recommendation

Juliette Le Corguillé, Florian Hacker, Katharina Göckeler, Moritz Mottschall, Theresa Dolinga (2025): Real-world data analysis of energy consumption, activity and charging patterns of battery electric trucks operating in Germany. 2nd report of the ELV-LIVE research project. Öko-Institut.

Executive Summary

This study provides one of the first in-depth analyses of real-world operational and energy consumption data from battery electric trucks (BET) in Germany. As part of the ELV-LIVE research project, data were collected from 19 Daimler eActros 300 and 400 trucks between 2023 and early 2025. These vehicles were operated by five case study partners in various regional transport applications. The goal was to better understand actual energy consumption under real-world conditions, identify influencing factors, analyse charging patterns, and derive initial optimisation strategies for vehicle operation and infrastructure planning.

The motivation behind the study stems from the rapid, yet early-stage, deployment of electric trucks in response to European climate policies. Despite increasing sales, there remains considerable uncertainty about their real-world performance. Predictable energy consumption and charging behaviour are key parameters for logistics planning, infrastructure development, and vehicle fleet electrification strategies.

Methodology

The analysis was structured around two main axes:

1. **Energy Consumption**
2. **Activity and Charging Patterns**

To analyse energy consumption, more than 800 individual driving events were evaluated. Key parameters such as average speed, outside temperature, vehicle weight, and altitude difference were examined. Due to limited data availability, some potential influences – such as road gradient, wind, or driving style – could not be directly assessed.

A multi-variable **Ordinary Least Squares (OLS)** regression model was applied to quantify the influence of individual factors on average energy consumption. In order to ensure robust results, vehicles operating with a Temperature Control Unit (TCU) were initially excluded from the regression to avoid confounding temperature effects.

For the **activity and charging pattern analysis**, 688 full days of data were visually and statistically assessed. After extensive data cleaning to correct sensor errors, only realistic daily profiles were retained. A qualitative approach was used to understand usage patterns, while basic metrics like charging frequency, duration, and standing times were calculated to draw comparisons between one- and two-shift operations.

Key Findings

- **Energy Consumption**:
  - The average real-world consumption was **0.96 kWh/km** for a vehicle weight range between 11 to 18 tonnes, an outside temperature between 19 and 21°C, and altitude difference range lower than 200 m. This is closely aligning with the manufacturer's specification (0.97 kWh/km under these optimal conditions).

  - The OLS regression revealed statistically significant impacts from:
    - **Vehicle weight** (approx. +0.18 kWh/km per additional 10 tonnes),
    - **Ambient temperature** (approx. -0.13 kWh/km per additional 10 °C),
    - **Altitude difference**, and
    - **Average speed**, with disproportionately high consumption observed at low speeds due to start-up energy demand and limited recuperation.
  - Vehicles equipped with a **Temperature Control Unit (TCU)** showed an average additional consumption of **0.092 kWh/km** under the specified conditions (weight between 11 and 19 tonnes, altitude difference lower than 100 m and speed between 40 and 60 km/h), with no clear correlation to ambient temperature, likely due to preconditioning at the depot.
- **Activity & Charging Patterns**:
  - All trucks were used exclusively in **regional delivery**, mostly on weekdays, with predefined and relatively inflexible routes.
  - **Depot charging** was the predominant strategy, with **public charging used only in isolated cases**.
  - In **single-shift operations**, charging typically occurred once daily after return to the depot, often completed well before the next shift.
  - **Two-shift operations** required more complex strategies, including **intermediate charging during loading** and higher charging power.
  - Despite technological constraints, **vehicles demonstrated high reliability**, with few operational failures or downtimes.

Optimisation Potentials

The study identifies significant opportunities to improve energy and charging efficiency, especially through **load shifting** and **optimised scheduling**. For instance:

- Nighttime charging often occurs earlier than necessary, resulting in idle time after charging is complete. **Delayed charging** could avoid peak grid loads and reduce infrastructure costs.
- **Intermediate charging** at loading bays during the day can reduce night-time dependency, though this requires integration with logistics workflows and spatial planning.
- Case study partners anticipate that **next-generation BET with larger battery capacities** may allow more flexibility in vehicle deployment and reduce infrastructure strain.

Conclusion

This research provides valuable early insights into the operation of BET under real-world conditions. The findings confirm that manufacturer-reported consumption values are realistic under optimal conditions, but also highlight significant variability due to external factors such as speed, temperature, and payload.

Charging strategies remain conservative, with room for optimisation. As electric trucks make up only a small fraction of total fleets today, future challenges will arise from the **scaling of depot infrastructure**, **load management**, and **public charging availability** – particularly for long-haul operations. Addressing these challenges will require close coordination between fleet operators, vehicle manufacturers, infrastructure providers, and policymakers.

Future studies would benefit from **larger and more diverse datasets**, **additional vehicle types**, and **extended observation periods** to further refine energy consumption models and operational strategies. Nevertheless, this analysis offers a solid empirical foundation to support the transition to electric heavy-duty transport.

Table of Contents

Executive Summary 3

List of Figures 7

List of Tables 9

1 Introduction 10

2 Data availability, data treatment and limitations 11

2.1 Data availability 11

2.2 Data quality, data treatment and limitations 13

3 Method 15

3.1 Energy consumption 15

3.2 Activity and charging pattern 19

4 Results 20

4.1 Real world energy consumption 20

4.1.1 Average energy consumption 20

4.2 Real world activity patterns 32

4.2.1 Operating conditions and available charging infrastructure 32

4.2.2 Activity patterns and charging profiles 32

4.2.3 Flexibilities and approaches for optimization 34

5 Conclusion 35

List of References 37

Annex I. Analysed activity patterns for the vehicles of the respective case study partners A-E 39

List of Figures

Figure 2-1: Schematic representation of data available 12

Figure 3-1: Average total energy consumption (kWh/km) vs. distance covered (km) 16

Figure 3-2: Average total consumption (kWh/km) vs. average speed (km/h) for distances below 20 km (left). Point distribution (lighter point colour indicates a high density of points) and fitted curve f in yellow for a dataset without vehicles operating with a TCU (right). 17

Figure 3-3: Average total consumption (kWh/km) vs. temperature (°C), for 40<s<60 km/h, w=16 t, |a|<200 m and no TCU (left). Average total consumption (kWh/km) vs. weight (t), for 40<s<60 km/h, t=10 °C, |a|<200 m, and no TCU (right). 18

Figure 3-4: Plot of the average total consumption (kWh/km) vs. altitude difference (m), for 40<s<60 km/h, w=17 T, 0<t<20 °C, and no TCU. 19

Figure 4-1: Box plot of the energy consumption, measured for a sample of vehicles with vehicle weight range of 11 to 18 t, for an exterior temperature from 19 to 21 °C, altitude differences |a|<200 m, and vehicles without a TCU. 21

Figure 4-2: Expected fluctuations in average total consumption (kWh/km) for the minimum and maximum values of the parameter set excluding vehicles with TCU. 23

Figure 4-3: Average consumption in kWh/km vs. average speed in km/h, split into broad average speed categories. 24

Figure 4-4: Box plots of the four defined categories, mean values are marked by a green triangle, median values by a black central horizontal line. 26

Figure 4-5: Box plots of the four defined categories, mean values are marked by a green triangle, median values by a black central horizontal line. 28

Figure 4-6: Plot of average energy consumption vs. temperature for vehicles with weight range of 11 to 19 T, altitude differences |a|<100 m, 40 <s≤60 km/h (left). Fitted regression line for the same plot (right).
29

Figure 4-7: Average consumption (kWh/km) of the 19 vehicles in real operation (ELV-LIVE) compared to measured values from comparable current applications 30

Figure 4-8: Exemplary charging pattern for different use cases (one- and two-shift-operation) and different charging strategies 33

Figure 6-1: Case study partner A – Vehicle 1 (04.10.2023 to 04.01.2025) 39

Figure 6-2: Case study partner A – Vehicle 1 (04.10.2023 to 04.01.2025) 39

Figure 6-3: Case study partner A – Vehicle 1 (02.10.2023 to 04.01.2025) 40

Figure 6-4: Case study partner B – Vehicle 1 (04.10.2023 to 02.01.2025) 40

Figure 6-5: Case study partner B – Vehicle 1 (16.09.2024 to 03.01.2025) 41

Figure 6-6: Case study partner B – Vehicle 1 (18.11.2024 to 04.01.2025) 41

Figure 6-7: Case study partner C – Vehicle 1 (18.11.2024 to 04.01.2025) 42

Figure 6-8: Case study partner C – Vehicle 1 (27.11.2024 to 03.01.2025) 42

Figure 6-9: Case study partner D – Vehicle 1 (26.02.2024 to 13.12.2024) 43

Figure 6-10: Case study partner D – Vehicle 1 (26.02.2024 to 22.11.2024) 43

Figure 6-11: Case study partner D – Vehicle 1 (11.12.2023 to 12.12.2024) 44

Figure 6-12: Case study partner D – Vehicle 1 (04.06.2024 to 13.12.2024) 44

Figure 6-13: Case study partner D – Vehicle 1 (18.08.2024 to 13.12.2024) 45

Figure 6-14: Case study partner D – Vehicle 1 (04.06.2024 to 13.12.2024) 45

Figure 6-15: Case study partner E – Vehicle 1 (14.08.2024 to 03.01.2025) 46

Figure 6-16: Case study partner E – Vehicle 1 (12.08.2024 to 02.01.2025) 46

Figure 6-17: Case study partner E – Vehicle 1 (15.08.2024 to 12.12.2024) 47

Figure 6-18: Case study partner E – Vehicle 1 (16.07.2024 to 02.01.2025) 47

Figure 6-19: Case study partner E – Vehicle 1 (15.08.2024 to 03.01.2025) 48

List of Tables

Table 2-1: Case study partner activities and vehicles’ operating conditions. 11

Table 2-2: Characteristics of available data. 15

Table 3-1: Statistics of input variables. 17

Table 4-1: Descriptive statistics of the data sample. 21

Table 4-2: Output statistics of the performed OLS regression analysis. 22

Table 4-3: Descriptive statistics of samples for vehicles with weight range of 11 to 18 t, at outside temperatures between 19 and 21 °C, altitude differences |a|<200 m , excluding vehicles with TCU. 25

Table 4-4: Axle/vehicle configuration and vehicle weight 27

Table 4-5: Descriptive statistics of samples for vehicles with 20 km/h<s≤60 km/h, at outside temperatures between 19 and 21 °C, altitude differences |a|<200 m, excluding vehicles with TCU. 27

Table 4-5: Calculated average energy consumption depending on vehicle weight and deviation from measured values 28

1 Introduction

Under the influence of the European Union policies, sales of battery electric trucks (BET) are increasing gradually in Europe (IEA - International Energy Agency 2024). 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 kilometres (km), which is a key factor in determining whether their delivery tours will be feasible or not. BET 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 (IEA - International Energy Agency 2024). However, the range of an electric vehicle or, in other words, the vehicle total energy consumption is influenced by various parameters, as already observed in previous studies (Li et al. 2016), (Xu et al. 2023a).

The first objective of this study is to quantify the influence of several parameters on the total energy consumption of BET 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 is of a 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 BET 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 BET 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 (Xu et al. 2023a) (Xu et al. 2023b). Yet, as BET have only recently come onto the market, few studies based on real-world BET data are available. Two published studies are of particular interest: (1) 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 (Mao et al. 2023) and (2) Cenex analysed real-world data of 20 BET operating in the UK in 2022 and 2023 focusing on factors affecting energy consumption such as the drive cycle, ancillaries, weight, and temperature (Cenex 2024).

This 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 complement 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 BET operating in Germany has been collected and analysed[1]. 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 BET 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, used for regional delivery, belong to five case study partners of the ELV-LIVE research project, that operate in diverse market categories. To maintain the confidentiality of the case study partners 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 therefore carry goods on behalf of third parties. Finally, the partners have vehicles with different axle combinations: 4x2, 6x2, and lorry carrying a trailer. A summary of relevant information communicated by the study partners is shown in the following table.

Table 2-1: Case study partner activities and vehicles' operating conditions.

Case study partner	Topography	Transport type	Use of temperature control units (TCU)
A	Mostly flat	Hire and reward services	No
B	Mostly flat	Own goods	Sometimes
C	Mostly flat	Hire and reward services	Yes
D	Mostly flat/Hilly	Hire and reward services	No
E	Mountainous	Own goods	No

Source: own illustration

The data was collected between September 2023 and January 2025, at the frequency of approximately one week of 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 BET 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.

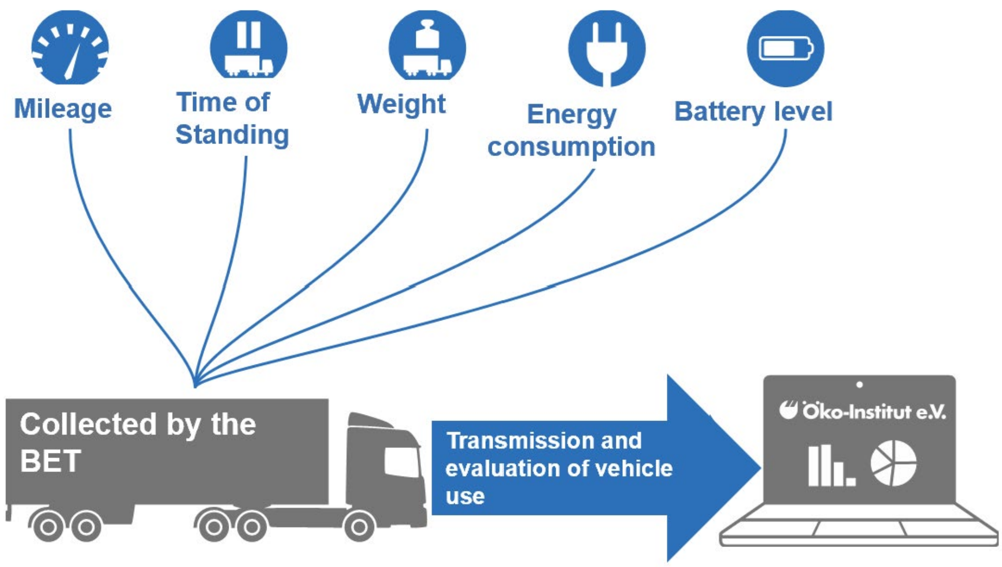
[1] https://www.erneuerbar-mobil.de/projekte/elv-live, last accessed on 2025-04-11

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 first BET 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 summary is available, containing the following information:

- the activity: vehicle driving, standing or charging
- the vehicle weight (in tonnes), that is the gross combination weight, including the vehicle body weight and payload without body
- the start and end positions (GPS coordinates)
- the start and end time
- the kilometres covered (in km)
- the total energy consumption (in kWh) measured directly on the vehicle, meaning that charging losses are not taken into account.
- the average energy consumption (in kWh/km) is derived from these latter values
- the battery Status of Charge (SoC) at the beginning and end of activity.

Figure 2-1: Schematic representation of data available



Source: own illustration

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, data treatment and limitations

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 kilometre 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 nominal 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 external air temperatures of the starting points were retrieved from the German weather service (DWD) open database[2], as an indicator of the outdoor temperature during the BET 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 of the start and end point 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[3], 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 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 summarise, this 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 (Cenex 2024), the overall energy consumption corresponds roughly 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 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

2 https://www.dwd.de/EN/ourservices/opendata/opendata.html
3 https://www.eea.europa.eu/en/datahub/datahubitem-view/d08852bc-7b5f-4835-a776-08362e2fbf4b

(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.

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 visualisation 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 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 prioritizing 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 visualisation.

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 quantity of days are analysed, with an average of 34 days per vehicle.

Table 2-2: Characteristics of available data.

	Energy consumption data	Activity pattern data
Number of vehicles	19	19
Total number of weeks	16	16
Number of vehicle weeks / days	37 / 119	166 / 688
Number of trips	807	-
Average number of trips per day	6.8	-

Source: own illustration

3 Method

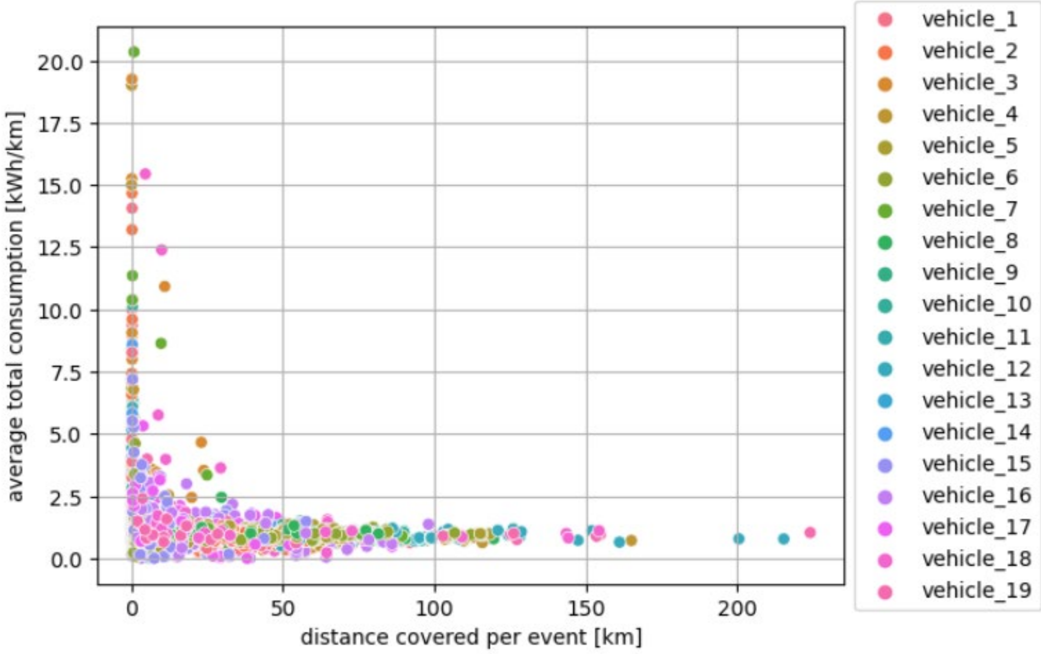
The analysis focuses on two aspects: the vehicle energy consumption and vehicle activity pattern.

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" python module was used.

Firsts observation suggests a notable correlation between the vehicle total energy consumption and the distance travelled, as shown in Figure 3-1. Indeed, the vehicle energy consumption (in kWh/km) are remarkably high for mileage that remain below 5 km.

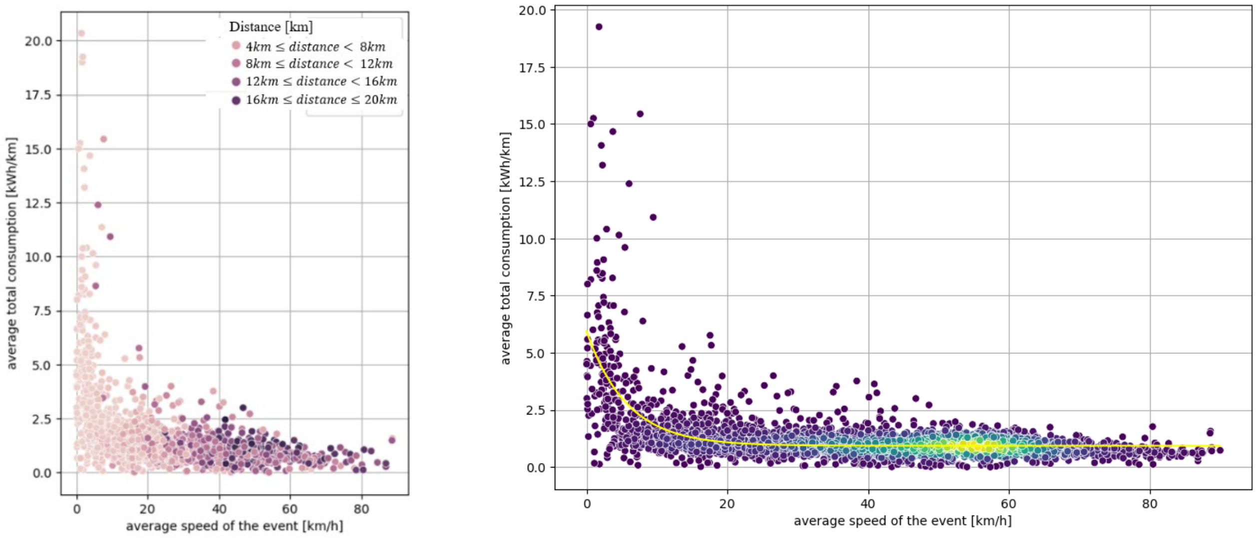
Figure 3-1: Average total energy consumption (kWh/km) vs. distance covered (km)



Source: own illustration

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. The manifestation of this effects can be further observed through the graphical representation of average consumption against average speed (see Figure 3-2). 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 nominal speed, resulting in lower consumption values for high average speeds.

Figure 3-2: Average total consumption (kWh/km) vs. average speed (km/h) for distances below 20 km (left). Point distribution (lighter point colour indicates a high density of points) and fitted curve f in yellow for a dataset without vehicles operating with a TCU (right).



Source: own illustration

Considering these observations, the average speed s must be included as a variable in the regression alongside the other selected parameters. Additionally, a minority of vehicles operate with temperature control units (TCU). The impact of TCU on consumption remains uncertain, particularly with regard to the potential dependence of this effect on the other parameters listed below. A temperature-dependent effect, for example, cannot be ruled out, as it could be expected that a high outside temperature would lead to an increase in energy consumption to cool the unit. Since the regression should not include any unaccounted dependencies, vehicles with cooling units were first excluded from the data set for the regression analysis.

To develop a robust yet parsimonious regression model with a clear focus on the most relevant explanatory variables, the analysis includes only independent effects. Consequently, data points involving a cooling unit are excluded to reduce complexity and potential confounding.

The reduced dataset contains 5.431 rows. The effects of the TCU are examined in more detail in section 4.1.5. Therefore, the parameters studied are as follows:

Table 3-1: Statistics of input variables.

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

Source: own illustration

As observed previously, the relation between consumption and average speed is not linear. By looking at the distribution of points, it is possible to recognise a trend line somewhat similar to the form of a function of the type:

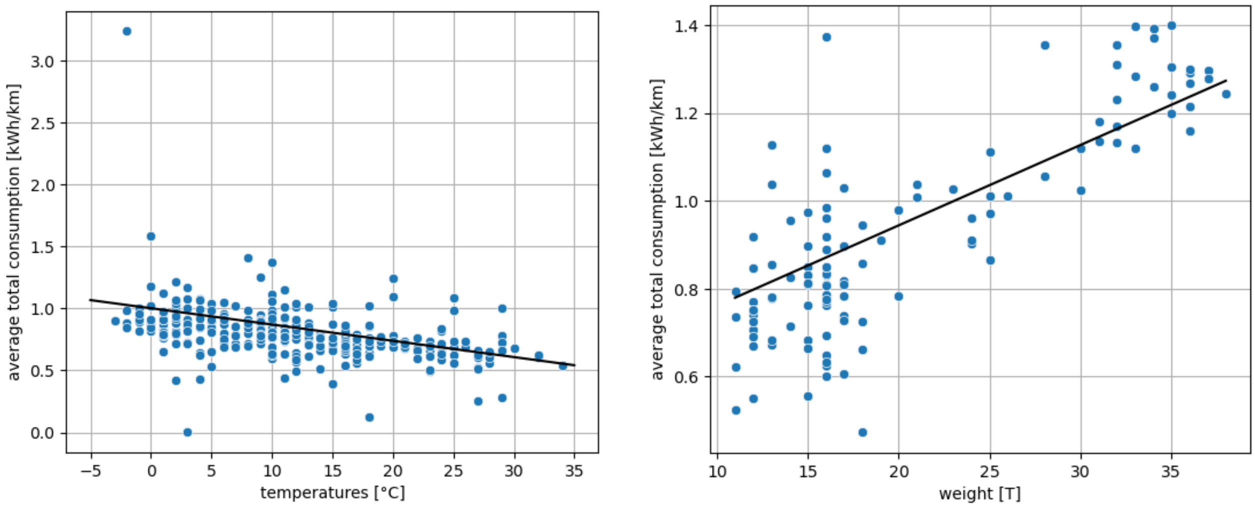
$$(1) \quad \boldsymbol{f(s) = a' \cdot e^{-b' \cdot s} + c'}$$

where a', b' and c' are constants, and s the average speed in km/h.

When fitting this function to the data, in yellow in Figure 3-2, the R^2 value obtained equals 0.42 which is relatively low. Nevertheless, given the influence of additional parameters (including those not examined in the scope of this study), this seems to be a satisfactory fit for an approximate description of the effect of the average speed on fuel consumption. Furthermore, Figure 3-2, which illustrates the density of points (light colour for a high density), demonstrates that they are predominantly concentrated at speeds between 40 and 60 km/h, indicating that the fit performs with optimal precision within this average speed range. However, between 0 and 20 km/h, some points deviate significantly from the curve, hereby signifying the presence of a substantial number of outliers within this particular range.

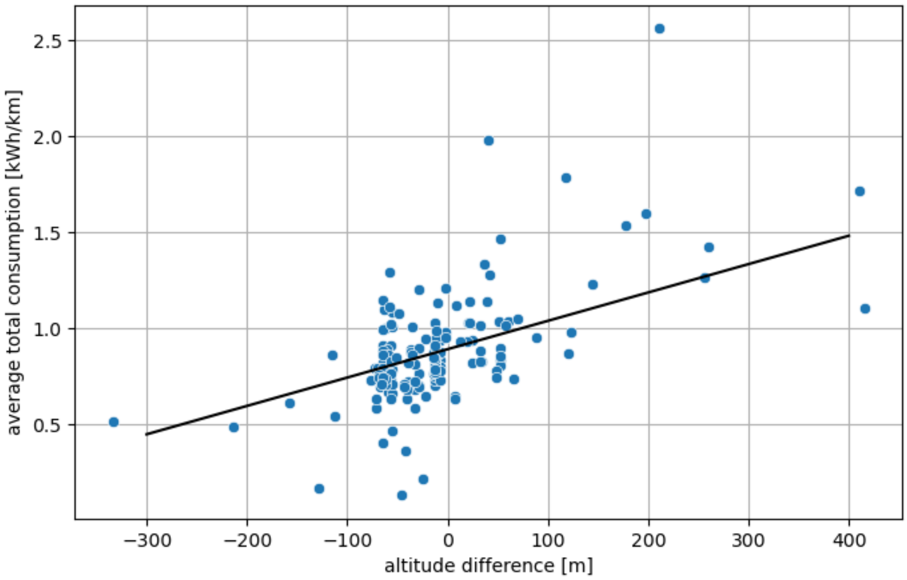
For the other parameters, observations show that, in principle, temperature t, weight w and altitude difference a seem to present a linear relationship with the average consumption, as illustrated in Figure 3-3 and Figure 3-4.

Figure 3-3: Average total consumption (kWh/km) vs. temperature (°C), for 40<s<60 km/h, w=16 t, |a|<200 m and no TCU (left). Average total consumption (kWh/km) vs. weight (t), for 40<s<60 km/h, t=10 °C, |a|<200 m, and no TCU (right).



Source: own illustration

Figure 3-4: Plot of the average total consumption (kWh/km) vs. altitude difference (m), for 40<s<60 km/h, w=17 T, 0<t<20 °C, and no TCU.



Source: own illustration

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

$$(2) \qquad \boldsymbol{C = m_1 \cdot e^{-k_1 \cdot s} + m_2 \cdot t + m_3 \cdot w + m_4 \cdot a + m_5}$$

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

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

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 pm. 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 km 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 (chapter 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 spent by vehicles 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

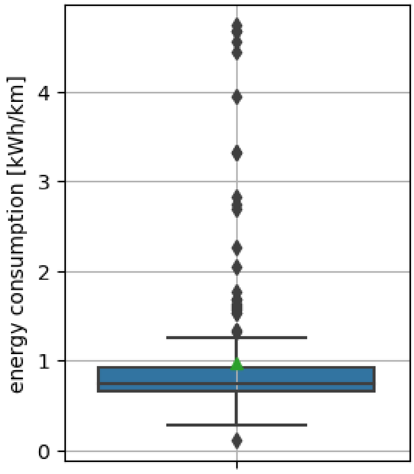
The objective of this section is to compare the energy consumption observed in real-world data with the values reported by the vehicle manufacturer. To ensure comparability, data collected under conditions similar to those used in the manufacturer’s testing were selected.

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 at an ambient temperature of 20°C” [4]. 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).

From the data collected, we can calculate the consumption values obtained under similar conditions. However, it should be noted that not all the vehicles in the studied sample are equipped with a 4x2 configuration. In order to obtain sufficient data points for a reliable statement, the values of all 19 vehicles were taken into account, regardless of their axle configuration. To this end, we selected the consumption data for events with a total vehicle weight corresponding to these of a 4x2 configuration: The manufacturer technical information indicates these have a “maximal technically permissible gross combination weight of 19 t” and a “payload without body of approx. 10,6 t” (Mercedes Benz, 2024). As the manufacturer’s measures were obtained for “a partially loaded vehicle [..] at an ambient temperature of 20°C”, we selected energy consumption values obtained for events with a vehicle weight range of 11 to 18 tonnes. As there are not enough data points in the dataset to produce reliable results with t=20°C, so the temperature range is expended to 19 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 4-1, which is very close to the manufacturer’s stated value. The discrepancy between the manufacturer's figure and the observed value is -1.03 %.

4 https://hub.mercedes-benz-trucks.com/de/de/trucks/eactros-300-400.html#actros300-400_technical-data, last accessed on 2024-10-31

Figure 4-1: Box plot of the energy consumption, measured for a sample of vehicles with vehicle weight range of 11 to 18 t, for an exterior temperature from 19 to 21 °C, altitude differences |a|<200 m, and vehicles without a TCU.



Source: own illustration

The mean value is signalised by a green triangle, the median value by a black central horizontal line

Table 4-1: Descriptive statistics of the data sample.

Parameter type	Value
Mean energy consumption	0,96 kWh/km
Sample dimension	211 values
Standard deviation	0.75
First quartile (25 %-percentile)	0.66
Median (50 %-percentile)	0.74
Third quartile (75 %-percentile)	0.92

Source: own illustration

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 4-1**. This can partly be explained by the high consumption values observed for low average speed values.

4.1.2 Influence of parameters on the vehicle average consumption

In consideration of the limitations outlined in section 2.2, 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 ordinary least square (OLS) regression are shown below in Table 4-2.

Table 4-2: Output statistics of the performed OLS regression analysis.

General statistics	
N	5.431
Df residuals	5.426
R^2	0.474
Adj. R^2	0.473
Prob (F-statistics)	0.00

Coef. name	Corresponding variable	Coef. value	Std err	t	P>|t|	Confidence interval [0.025 ; 0.975]	
m_1	Speed $e^{-k_1 \cdot s}$	5.1304	0.076	67.181	0.000	4.981	5.280
m_2	Temperature t	-0.0132	0.001	-12.071	0.000	-0.015	-0.011
m_3	Weight w	0.0183	0.001	14.752	0.000	0.016	0.021
m_4	Altitude difference a	0.0015	9.76e-05	15.150	0.000	0.001	0.002
m_5	Constant	0.7091	0.029	24.453	0.000	0.652	0.766

Source: own illustration

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 0.463 which can be considered as low. Nevertheless, considering the limitations exposed in section 2.2., 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 roughly 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 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 outside temperature instead of 20°C, this could mean that the vehicle could cover 358 km instead of 400.

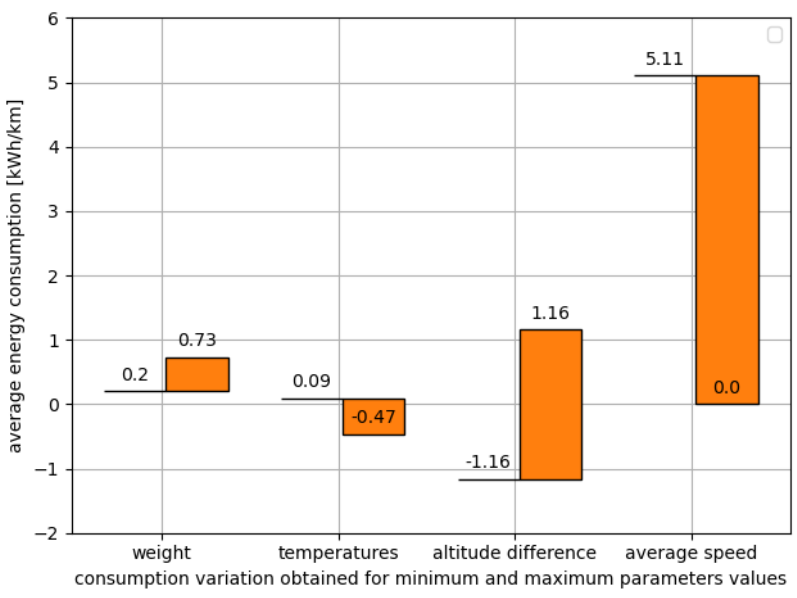
Figure 4-2 illustrates the variation in energy consumption corresponding to the minimum and maximum values of each parameter within the analysed dataset (see Table 3-1 for value ranges). This provides a realistic depiction of consumption variability and the potential impact of each parameter. Specifically, assuming a baseline consumption constant m5=0.70 kWh/km, the first bar indicates that a lorry with the minimum recorded weight (11 t) contributes an additional 0.20 kWh/km, while a lorry with the maximum weight (40 t) adds approximately 0.73 kWh/km to the baseline.

Similarly, temperature shows notable effects: the highest recorded temperature (36 °C) decreases the baseline consumption by 0.47 kWh/km, whereas the lowest temperature (-7 °C) results in a modest increase of 0.09 kWh/km. The greatest observed altitude gain (786 m) increases energy consumption by 1.16 kWh/km, while a comparable descent (-785 m) decreases it by the same amount. These results should be interpreted with caution, as altitude is recorded only as net elevation change, which may not fully capture the actual elevation profile along a route.

Among all parameters, average speed exhibits the most pronounced variation in energy consumption (5.11 kWh/km). This can be attributed to its strong correlation 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.

In summary, all four parameters - vehicle weight, ambient temperature, altitude difference, and average speed - demonstrate significant influence on energy consumption within realistic, real-world parameter ranges.

Figure 4-2: Expected fluctuations in average total consumption (kWh/km) for the minimum and maximum values of the parameter set excluding vehicles with TCU.



Source: ow illustration

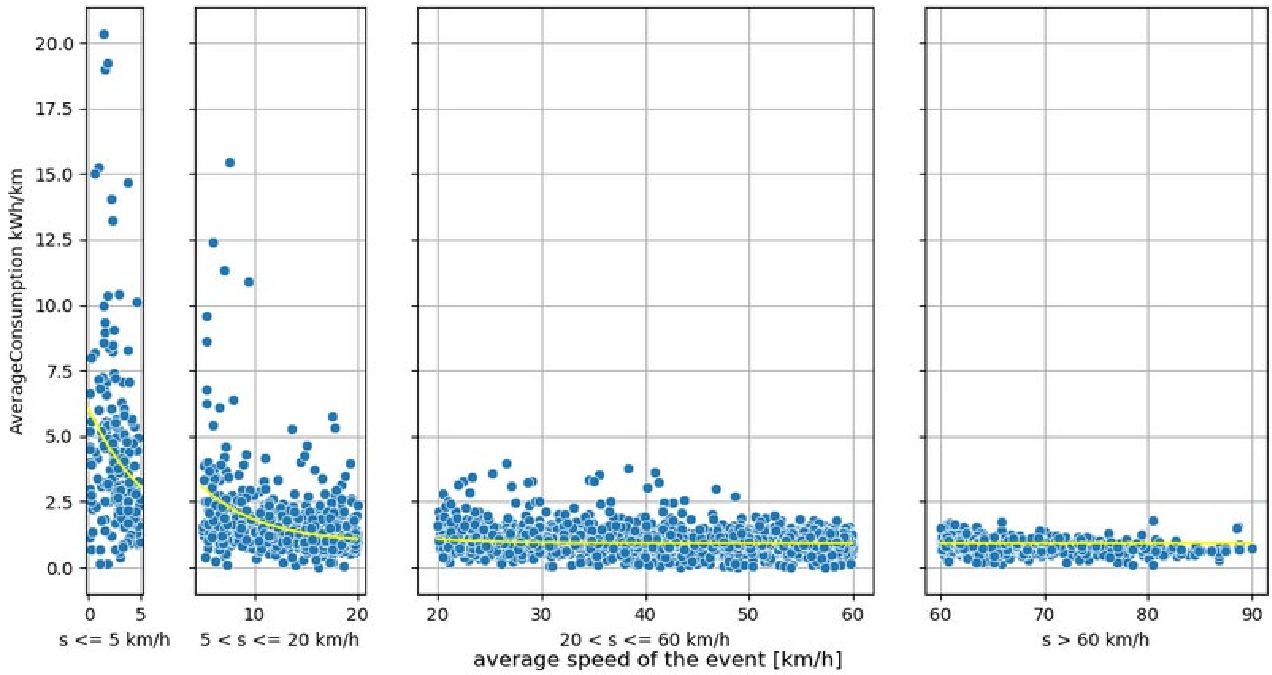
4.1.3 Average energy consumption for different speed categories

As the average speed has a major impact on the energy consumption, average consumption values can be calculated for different speed ranges.

Determining precisely the drive cycle solely on the basis of average speed is not feasible, as explained in section 2.2. In addition, the software does not record the route taken between the start and end points, which makes it impossible to determine the exact nature of the road taken (highway, urban road, etc). However, it is possible to identify broad categories based on the average speed s and distance covered d in km:

- $s \leq 5\ km/h$ and $d \leq 1\ km$: This corresponds most probably to a situation in which the vehicle is in idling mode. For instance, stuck in a traffic jam in town, or moving slowly between different stations at the depot.
- $km/h < s \leq 20\ km/h$ and $d > 1\ km$: It is not possible to make any reliable statements about the driving situation. The vehicle could be moving at low average speed in an urban or rural environment, or at higher speed but with a large number of stops. In an urban environment, when the vehicle is subject to repeated decelerations, the effects of regenerative braking should be significant. However, this effect is impossible to detect precisely here, since only the total consumption per trip is analysed.
- $20\ km/h < s \leq 60\ km/h$ - The vehicle's operating condition remains uncertain. For example, the vehicle could be moving at a constant low speed between 20 and 60 km/h or at a high speed but with frequent stops.
- $s > 60\ km/h$ - Above the average speed of 60 km/h, the vehicle is very likely to be moving on a motorway or at high speed on a road in a rural area, with few stops.

Figure 4-3: Average consumption in kWh/km vs. average speed in km/h, split into broad average speed categories.



Source: own illustration

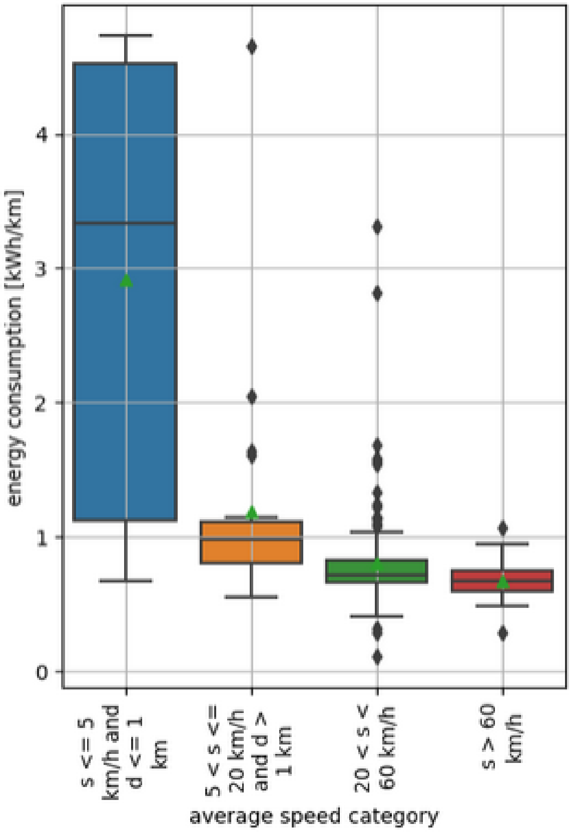
Thereafter, it is possible to recalculate the mean consumptions obtained for these four categories, for similar conditions to those described in section 4.1.1. However, there are not enough values in these reduced datasets to produce reliable results, so the temperature range is expanded to 19 and 21 °C (instead of solely 20°C). The results shown in Table 4-3 are obtained.

Table 4-3: Descriptive statistics of samples for vehicles with weight range of 11 to 18 t, at outside temperatures between 19 and 21 °C, altitude differences |a|<200 m , excluding vehicles with TCU.

Categories	$s \leq 5\ km/h$ and $d \leq 1\ km$	$5 < s \leq 20\ km/h$ and $d > 1\ km$	$20 < s \leq 60\ km/h$	$s > 60\ km/h$
Mean energy consumption	2.9	1.18	0.80	0.67
Sample dimension	10	22	131	33
Standard deviation	1.75	0.85	0.37	0.14
First quartile (25 %-percentile)	1.13	0.80	0.66	0.60
Median (50 %-percentile)	3.34	0.97	0.72	0.67
Third quartile (75 %-percentile)	4.53	1.11	0.83	0.74

Source: own illustration

Figure 4-4: Box plots of the four defined categories, mean values are marked by a green triangle, median values by a black central horizontal line.



Source: own illustration

The elevated standard deviation obtained for the categories $s \leq 5\ km/h$ and $d \leq 1\ km$ and $5 < s \leq 20\ km/h$ and $d > 1\ km$ indicate a high degree of variance in the observed data, as already noted previously. The average consumption value obtained for $s > 60\ km/h$ is the lowest. In this category, it can be assumed that the vehicles are travelling long distances with a limited number of stops. As the vehicle's speed increases, the recuperation effect becomes more pronounced, which contributes to a reduction of energy consumption.

The theoretical expected value can also be calculated using the function previously defined in $(\mathbf{2})$. Given the fit's limitations, a speed of 40 km/h is chosen, since it is known that the model performs best in this speed range.

$$\boldsymbol{C = m_1 \cdot e^{-k_1 \cdot s} + m_2 \cdot t + m_3 \cdot w + m_4 \cdot a + m_5}$$

$$\boldsymbol{C = 5,13 \cdot e^{-0,174 \cdot 40} - 0.0131 \cdot 20 + 0.0183 \cdot 14,5 + 0,001 \cdot 0 + 0 + 0.710}$$

$$\boldsymbol{C \simeq 0.72}$$

The comparison of the results of the function previously calculated based on the whole dataset with the data sample between 40 and 60 kWh/km above confirms the relatively good model fit in this speed range, as the median value of 0.72 kWh/km is met and the deviation from the mean value is relatively low at 10 %.

4.1.4 Average energy consumption for different weight categories

The case study partners have vehicles with different combinations: 4x2, 6x2 axle combination, lorries with a trailer.

Table 4-4: Axle/vehicle configuration and vehicle weight

Axles / configuration	2 Axles	3 Axles	Lorry carrying a trailer
Maximum permissible weight	19 t	27 t	40 t

Quelle: own illustration

According to these specifications, the following four weight categories are established:

- $w \leq 19\ t$
- $20 \leq w \leq 27\ t$
- $28 \leq w \leq 34\ t$
- $34 \leq w \leq 40\ t$

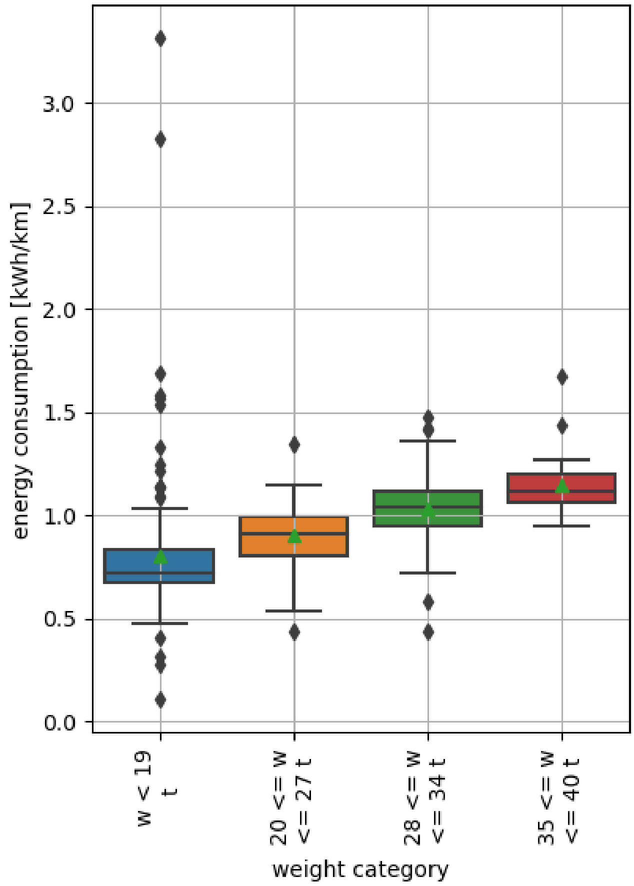
Subsequently, recalculation of the mean consumptions obtained for these four categories is possible. For similar conditions to those described in section 4.1.1, with a temperature range that is expanded to 19 and 21 °C and an average speed between 20 and 60 km/h, the following results shown in Table 4-5 are obtained.

Table 4-5: Descriptive statistics of samples for vehicles with 20 km/h<s≤60 km/h, at outside temperatures between 19 and 21 °C, altitude differences |a|<200 m, excluding vehicles with TCU.

Categories	$w \leq 19\ t$	$20 \leq w \leq 27\ t$	$28 \leq w \leq 34\ t$	$35 \leq w \leq 40\ t$
Mean energy consumption	0.80	0.90	1.03	1.14
Sample dimension	137	72	77	32
Standard deviation	0.36	0.15	0.17	0.14
First quartile (25 %-percentile)	0.67	0.80	0.95	1.06
Median (50 %-percentile)	0.72	0.91	1.04	1.12
Third quartile (75 %-percentile)	0.83	0.99	1.12	1.67

Source: own illustration

Figure 4-5: Box plots of the four defined categories, mean values are marked by a green triangle, median values by a black central horizontal line.



Source: own illustration

The theoretical expected value can also be calculated using the function previously defined in (**2**). In this way, for a speed of 40 km/h, and a temperature of 20 °C.

Table 4-6: Calculated average energy consumption depending on vehicle weight and deviation from measured values

Weight (t)	14,5	23,5	31	37
Calculated theoritical average consumption value (kWh/km)	0.72	0.88	1.02	1.13
Deviation from measured mean values of Table 4-4	-10 %	-2 %	-1 %	-1 %

Quelle: own illustration

In these cases, the regression also performs relatively well. The result of the regression formula only deviates from the mean of the data sample being more than 2 % in the lowest weight category (14.5 t), which is also characterised by the greatest variance of the individual values.

4.1.5 Effect of temperature control unit on vehicle energy consumption

Vehicles with a temperature control unit (TCU) were not included in the previous analyses due to concerns about potential dependence on temperature, as described above (see Section 3.1).

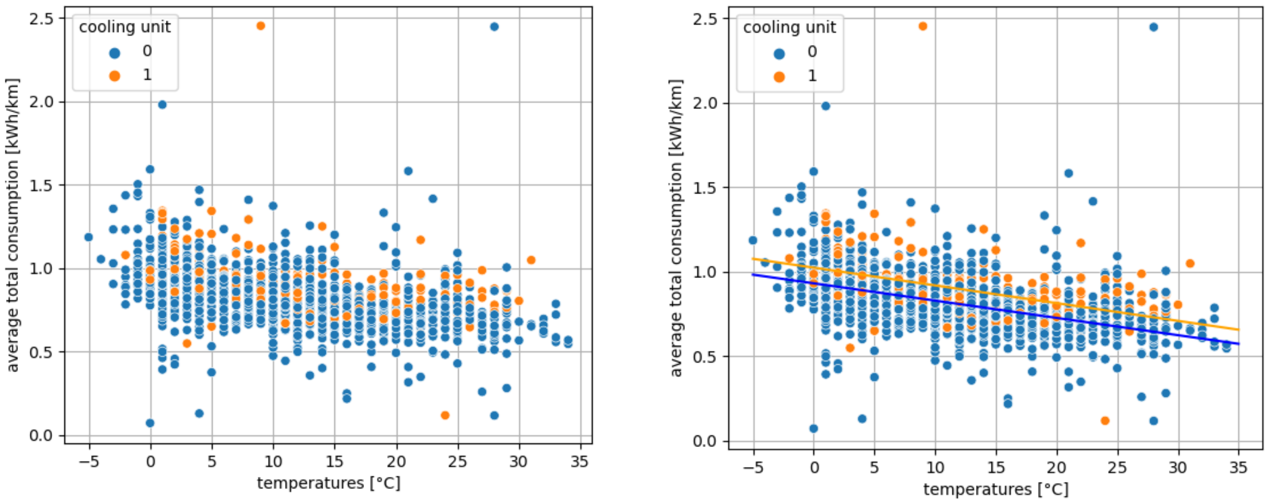
Thus, in order to study the effect of the cooling unit, the energy consumption of vehicles with a cooling unit was analysed separately. The presence of the cooling unit can be represented by a dummy variable, as follows:

$$\begin{cases} u = 1 & \text{if there is a cooling unit installed} \\ u = 0 & \text{if there is no cooling unit} \end{cases}$$

Despite not performing a regression analysis including u as a variable, it is still possible to compare the energy consumption obtained with and without a TCU for parameters set to specific values. This could provide preliminary information regarding the effect of TCU on energy consumption and, if any, allow for the estimation of the order of magnitude of the change.

Figure 4-6 shows the average total consumption of all vehicles weighing between 11 to 19 tonnes, with an average speed range of 40 to 60 km/h and an altitude difference of less than 100 meters.

Figure 4-6: Plot of average energy consumption vs. temperature for vehicles with weight range of 11 to 19 T, altitude differences |a|<100 m, 40 <s≤60 km/h (left). Fitted regression line for the same plot (right).



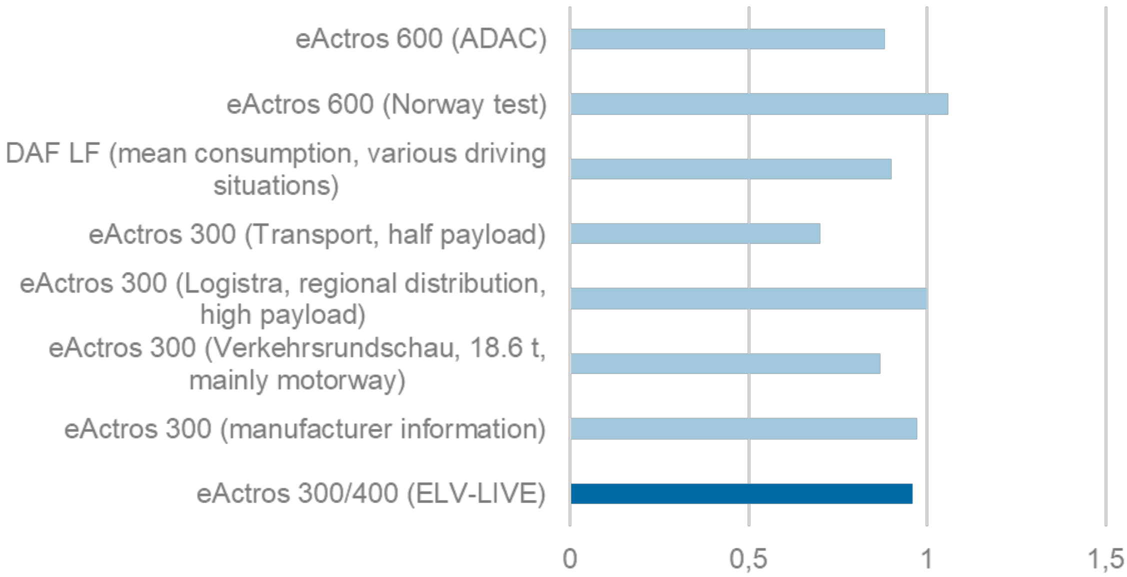
Source: own illustration

These results show that the presence of a temperature control unit increases the average energy consumption of the vehicle. Indeed, the linear regression performed on this sub-dataset suggests that vehicles with a TCU have an average increase in energy consumption of 0,092 kWh/km compared to vehicles without TCU. The magnitude of the additional consumption is confirmed by the manufacturer's own unpublished measurement series. Compared to the range of variations caused by the other parameters discussed above, this appears to be a relatively small effect. Surprisingly, at first it seems that temperature has no visible effect on the energy consumption of vehicles with TCU (where we might have expected a vehicle to consume more energy in summer, for example, to cool the unit down more). However, the effect of the presence of a cooling unit on energy consumption remains constant across varying temperatures, as both regression lines show similar slopes. One potential explanation for this phenomenon is that the temperature control units are preconditioned in the depot. Indeed, the case study partners have indicated that the units are already cooled down when the vehicle starts the tour. Since the units are insulated, the vehicle would not require a significant amount of energy to maintain the desired temperature throughout the journey. Further analysis would be required to better understand the relationship between cooling unit, outside temperature and vehicle energy consumption.

4.1.5.1 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. When interpreting the results, however, it should be noted that the other available data on energy consumption was obtained under conditions that differed significantly in some cases and therefore cannot be compared directly with the results from the 19 vehicles analysed in the ELV-LIVE project. Nevertheless, preliminary trends can be identified.

Figure 4-7: Average consumption (kWh/km) of the 19 vehicles in real operation (ELV-LIVE) compared to measured values from comparable current applications*



*Data from other sources with significantly deviating conditions and therefore only comparable to a limited extent (see text).
Quelle: own illustration

For instance, the eActros 300, the vehicle examined by the ELV-LIVE project, was tested by the German magazine “Verkehrsrundschau” (Faehrmann 2023) in year 2023. 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 (Reichel 2024) also reports on a test of the eActros300 with a total 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. 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 (Transport - Die Zeitung für den Güterverkehr 2023), 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.

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 (Cenex 2024). 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) (Vogt-Möbs und Schuhmacher 2022).

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 (Schaal 2024).

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 (ADAC 2024).

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 (Scania 2024).

In summary, it can be concluded that the consumption values determined in this section from real-world operation of 19 vehicles are within the range of the published test consumption values. 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 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 km 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 km.

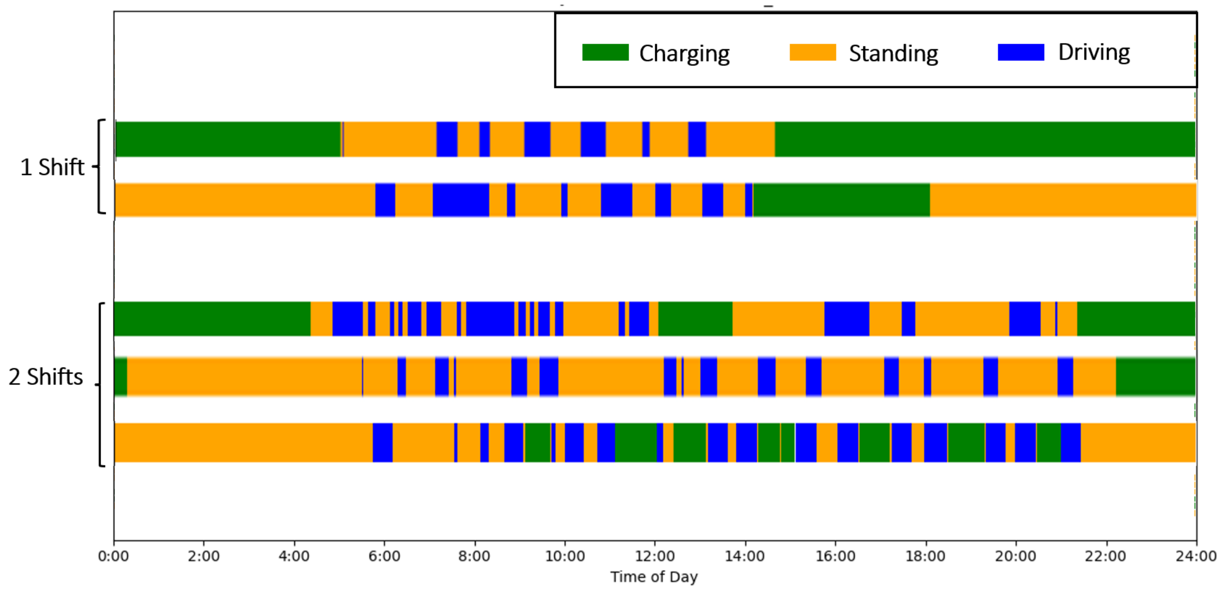
Visits to the case study partners have revealed that current vehicle use mainly follows a predetermined plan and is in principle inflexible, which explains the similar patterns over time. This can be explained by the constraint of the range, meaning that the partners have at least checked the feasibility 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. A comprehensive overview of the activity patterns of all vehicles at the five case study partners is provided in the annex. The vehicles are used exclusively during the day and start at around 5 a.m.

Figure 4-8: Exemplary charging pattern for different use cases (one- and two-shift-operation) and different charging strategies



Source: own illustration

However, a clear difference can be seen between vehicles in one-shift and two-shift operation (see Figure 4-8). 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 partner 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 units 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.

5 Conclusion

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 outside temperature and vehicle weight. For example, consumption decreases by 0.132 kWh/km in average when the outside 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 BET 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.

List of References

ADAC (Hg.) (2024): Mercedes eActros 600: Mit 40 Tonnen elektrisch unterwegs. Online verfügbar unter https://www.adac.de/rund-ums-fahrzeug/autokatalog/marken-modelle/mercedes-benz/mercedes-benz-eactros-600/#verbrauch-rund-88-kwh-auf-100-kilometer, zuletzt geprüft am 10.04.2025.

Cenex (Hg.) (2024): BETT – Battery Electric Truck Trial Final Report. Online verfügbar unter https://bett.cenex.co.uk/assets/reports/BETT---End-of-trial-report.pdf, zuletzt geprüft am 10.04.2025.

Faehrmann, Fabian (2023): Elektro Lkw: So viel Strom verbraucht der eActros 300. Hg. v. Verkehrsrundschau Plus. VerkehrsRundschau. Online verfügbar unter https://www.verkehrsrundschau.de/e-lkw/elektro-lkw-so-viel-strom-verbraucht-der-eactros-300-3381338, zuletzt aktualisiert am 30.05.2023, zuletzt geprüft am 10.04.2025.

IEA - International Energy Agency (Hg.) (2024): Trends in heavy electric vehicles. Electric truck and bus sales. Global EV Outlook 2024. Online verfügbar unter https://www.iea.org/reports/global-ev-outlook-2024/trends-in-heavy-electric-vehicles, zuletzt geprüft am 11.04.2025.

Li, Wen; Stanula, Patrick; Egede, Patricia; Kara, Sami; Herrmann, Christoph (2016): Determining the Main Factors Influencing the Energy Consumption of Electric Vehicles in the Usage Phase. In: *Procedia CIRP* 48, S. 352–357. DOI: 10.1016/j.procir.2016.03.014.

Mao, Shiyue; Zhang, Yichen; Rodriguez, Felipe; Wang, Shuo; Hao, Chunxiao (2023): Real-world performance of battery electric heavy-duty vehicles in China. Energy consumption, range, and charging patterns. Hg. v. ICCT - The International Council on Clean Transportation. Online verfügbar unter https://theicct.org/wp-content/uploads/2023/04/HDV-BEVs-real-world_final2.pdf, zuletzt geprüft am 10.04.2025.

Reichel, Johannes (2024): Cargo-Partner testet Elektro-Lkw europaweit. In: *logistra. Das Praxismagazin für Nfz-Fuhrpark und Lagerlogistik* (online). Online verfügbar unter https://logistra.de/news/nfz-fuhrpark-lagerlogistik-intralogistik-cargo-partner-testet-elektro-lkw-europaweit-323268.html, zuletzt geprüft am 10.04.2025.

Scania (Hg.) (2024): Sweden to Turkey: top insights from a 4,500 km BEV road trip. Online verfügbar unter https://www.scania.com/group/en/home/electrification/e-mobility-hub/sweden-to-turkey-top-insights-from-a-4500-km-bev-road-trip.html, zuletzt geprüft am 10.04.2025.

Schaal, Sebastian (2024): Letzte Testfahrten: Mit dem Mercedes eActros 600 quer durch Norwegen. Hg. v. electrive.net. Online verfügbar unter https://www.electrive.net/2024/06/20/letzte-testfahrten-mit-dem-mercedes-eactros-600-quer-durch-norwegen/, zuletzt geprüft am 10.04.2025.

Transport - Die Zeitung für den Güterverkehr (Hg.) (2023): Gut geworden. Online verfügbar unter https://transport-online.de/fachzeitung/fachartikel/fahrzeug-und-technik-lkw-test-gut-geworden-111838.html.

Vogt-Möbs, Gerfried; Schuhmacher, Stefanie (2022): DAF Elektro-Lkw im Leistungstest. Hg. v. VerkehrsRundschau. Online verfügbar unter https://www.verkehrsrundschau.de/e-lkw/daf-elektro-lkw-im-leistungstest-3197343, zuletzt geprüft am 10.04.2025.

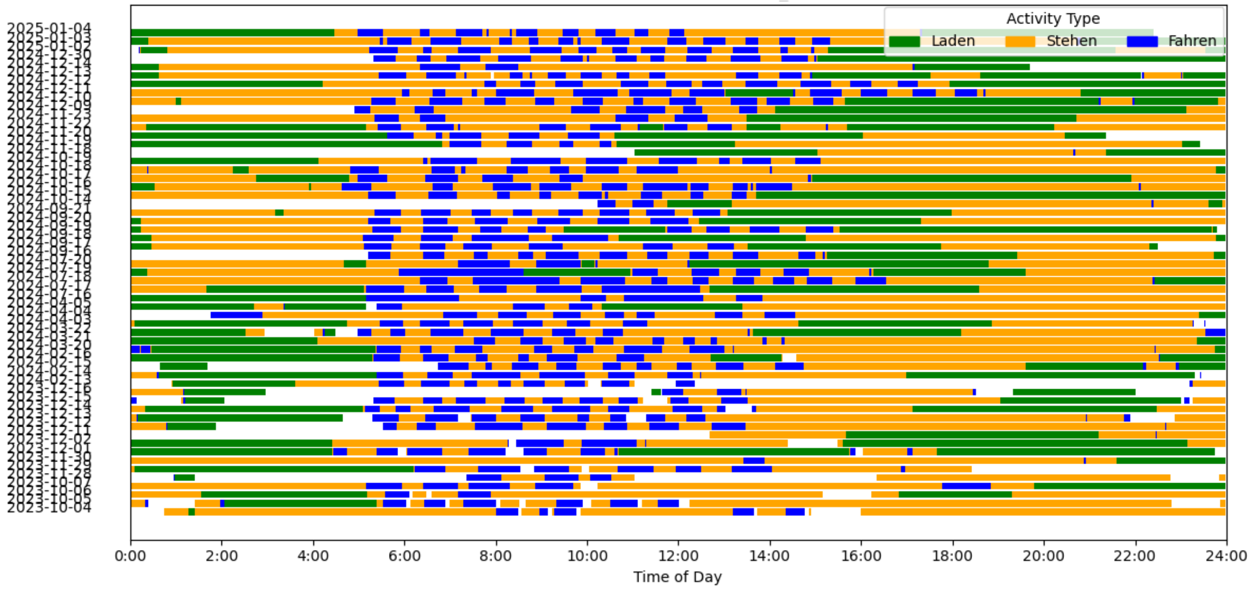
Xu, Hang; Liu, Yu; Li, Jingyuan; Yu, Hanzhengnan; An, Xiaopan; Ma, Kunqi et al. (2023a): Study on the influence of high and low temperature environment on the energy consumption of battery electric vehicles. In: *Energy Reports* 9, S. 835–842. DOI: 10.1016/j.egyr.2023.05.120.

Xu, Zhicheng; Wang, Jun; Lund, Peter D.; Zhang, Yaoming (2023b): Analysis of energy consumption for electric buses based on low-frequency real-world data. In: *Transportation Research Part D: Transport and Environment* 122, S. 103857. DOI: 10.1016/j.trd.2023.103857.

Annex

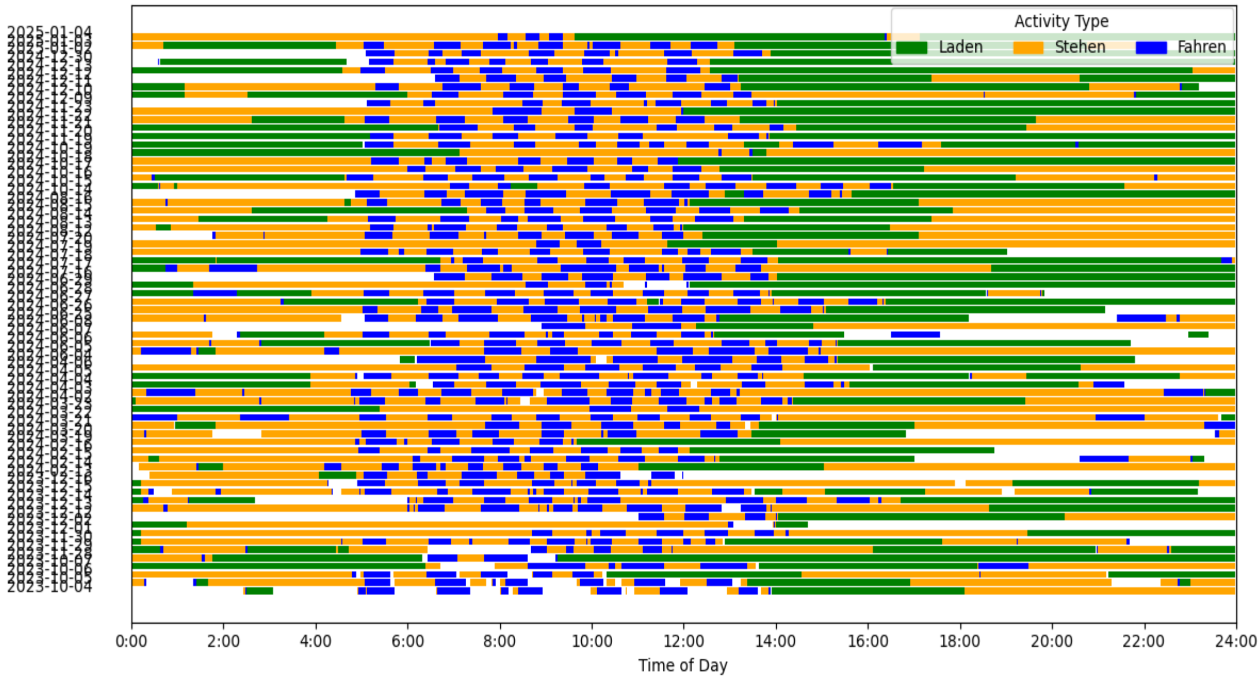
Annex I. Analysed activity patterns for the vehicles of the respective case study partners A-E

Figure 6-1: Case study partner A – Vehicle 1 (04.10.2023 to 04.01.2025)



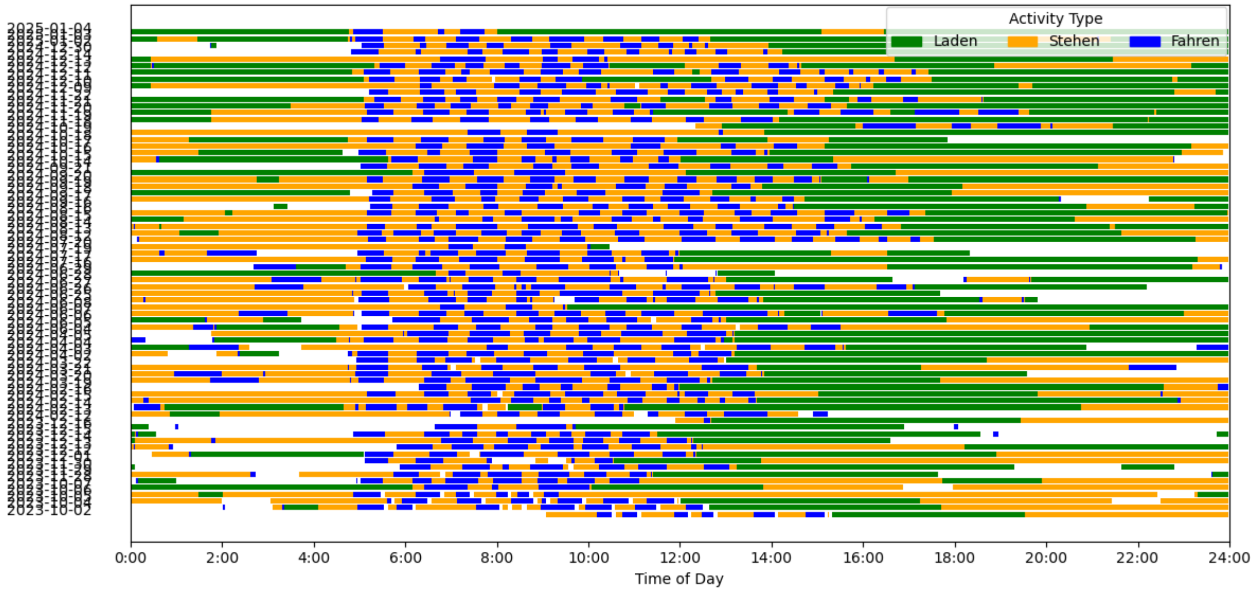
Source: own illustration

Figure 6-2: Case study partner A – Vehicle 1 (04.10.2023 to 04.01.2025)



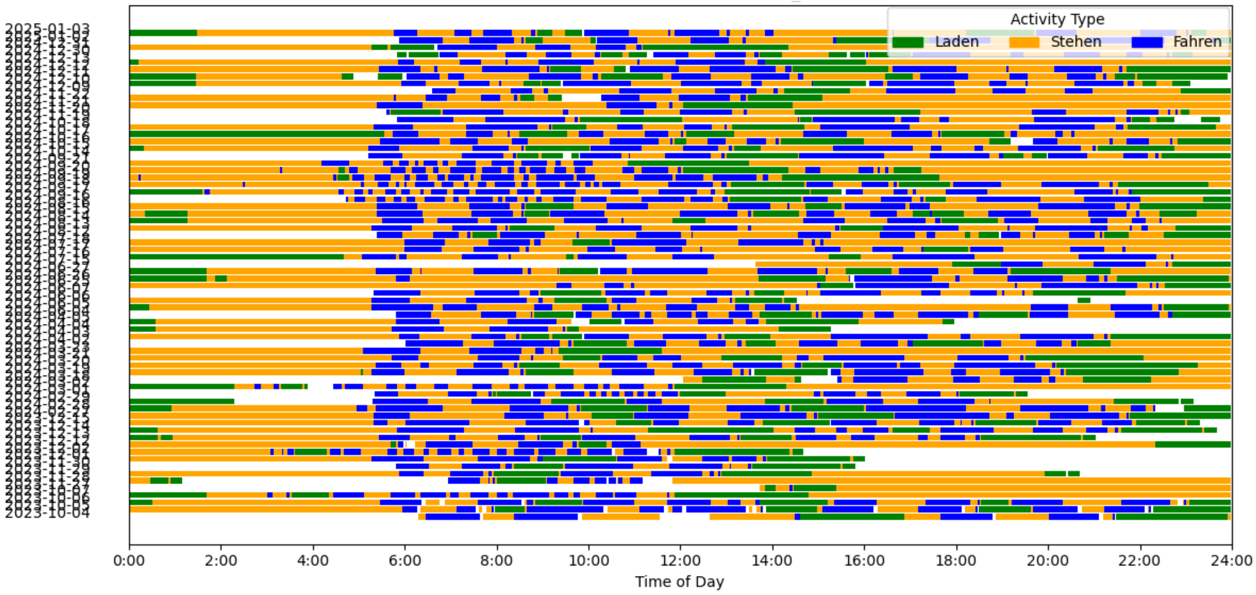
Source: own illustration

Figure 6-3: Case study partner A – Vehicle 1 (02.10.2023 to 04.01.2025)



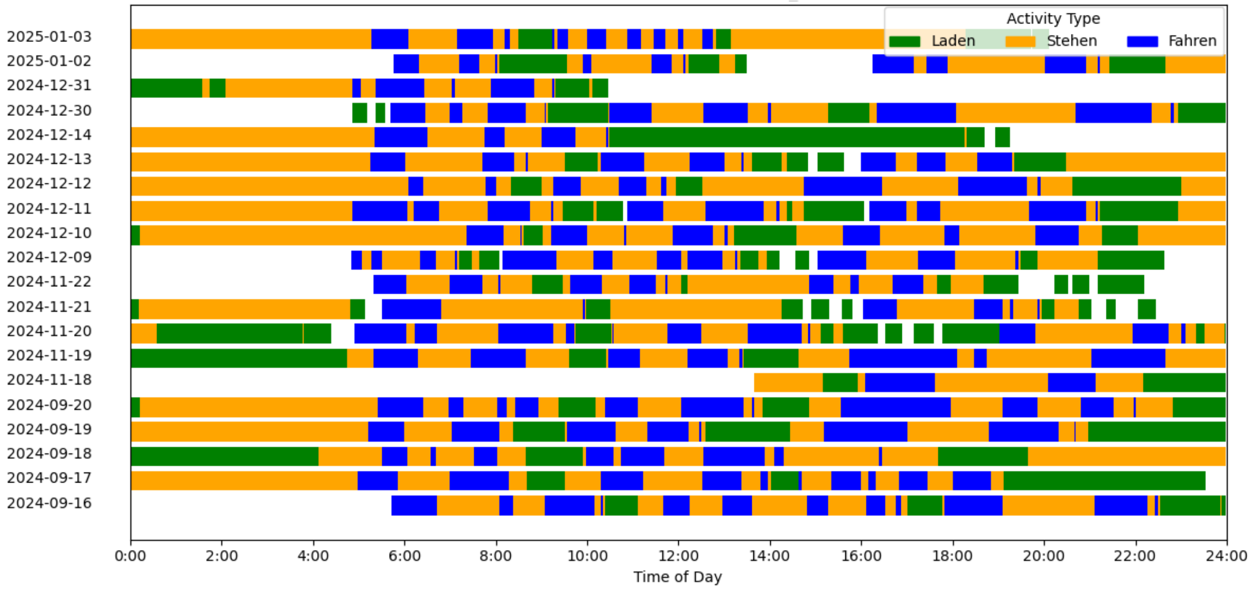
Source: own illustration

Figure 6-4: Case study partner B – Vehicle 1 (04.10.2023 to 02.01.2025)



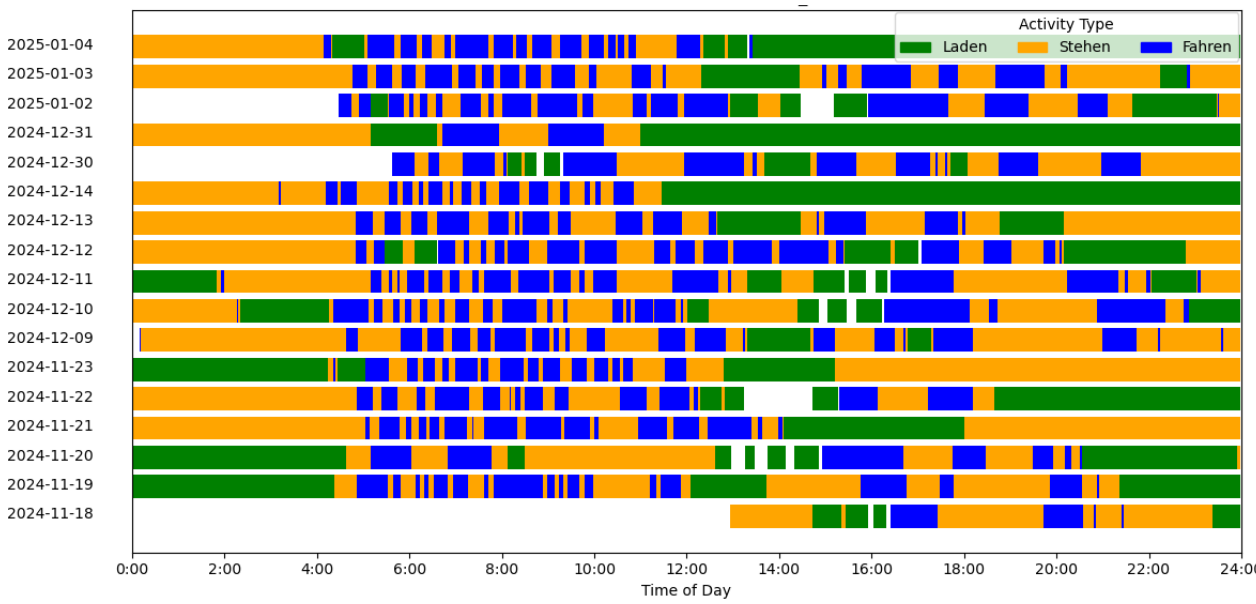
Source: own illustration

Figure 6-5: Case study partner B – Vehicle 1 (16.09.2024 to 03.01.2025)



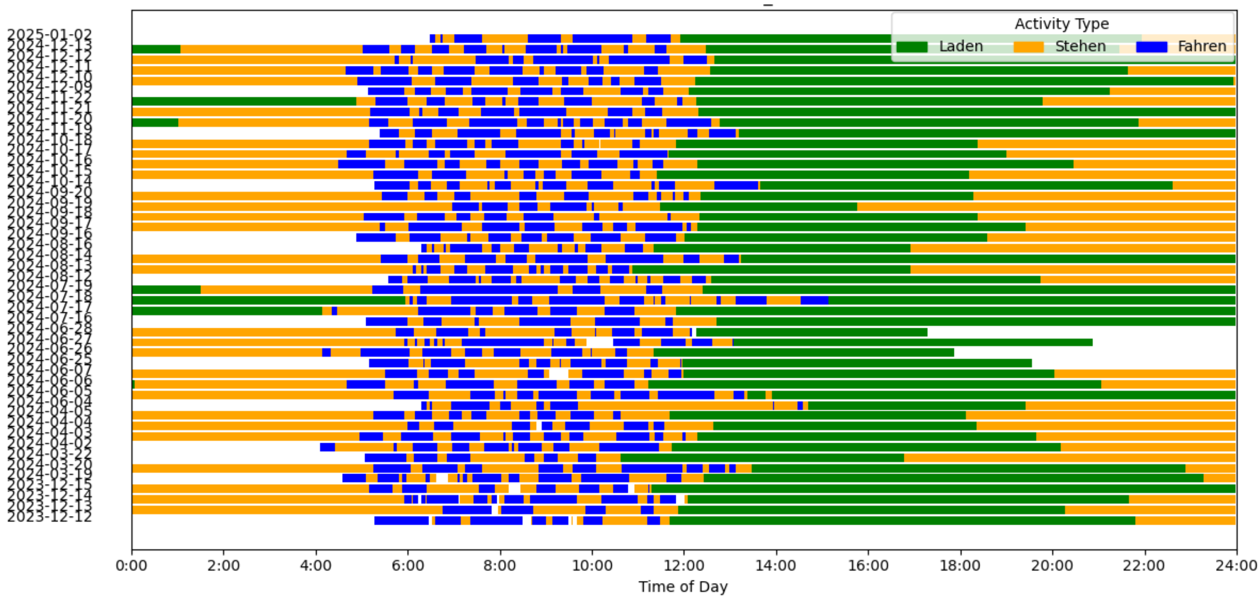
Source: own illustration

Figure 6-6: Case study partner B – Vehicle 1 (18.11.2024 to 04.01.2025)



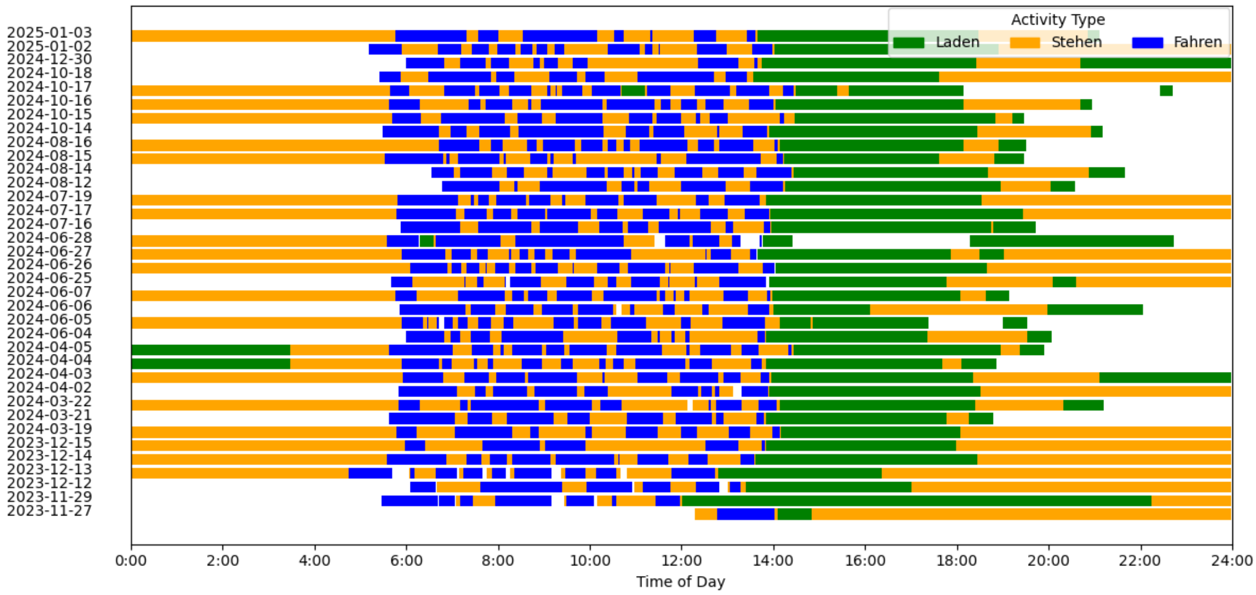
Source: own illustration

Figure 6-7: Case study partner C – Vehicle 1 (18.11.2024 to 04.01.2025)



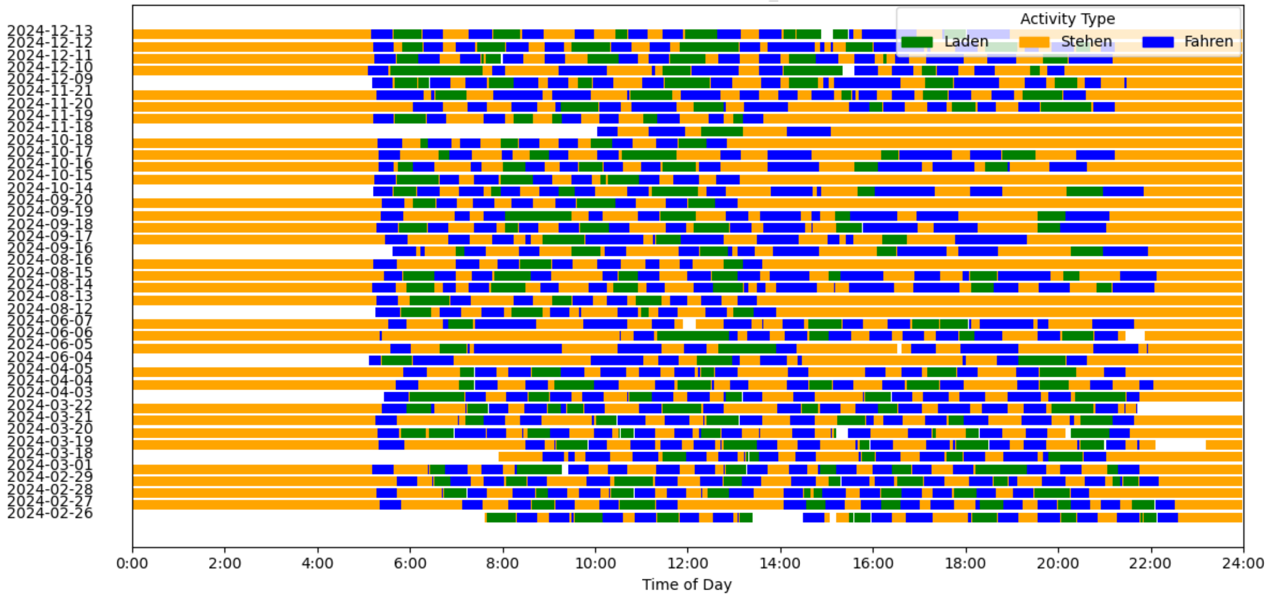
Source: own illustration

Figure 6-8: Case study partner C – Vehicle 1 (27.11.2024 to 03.01.2025)



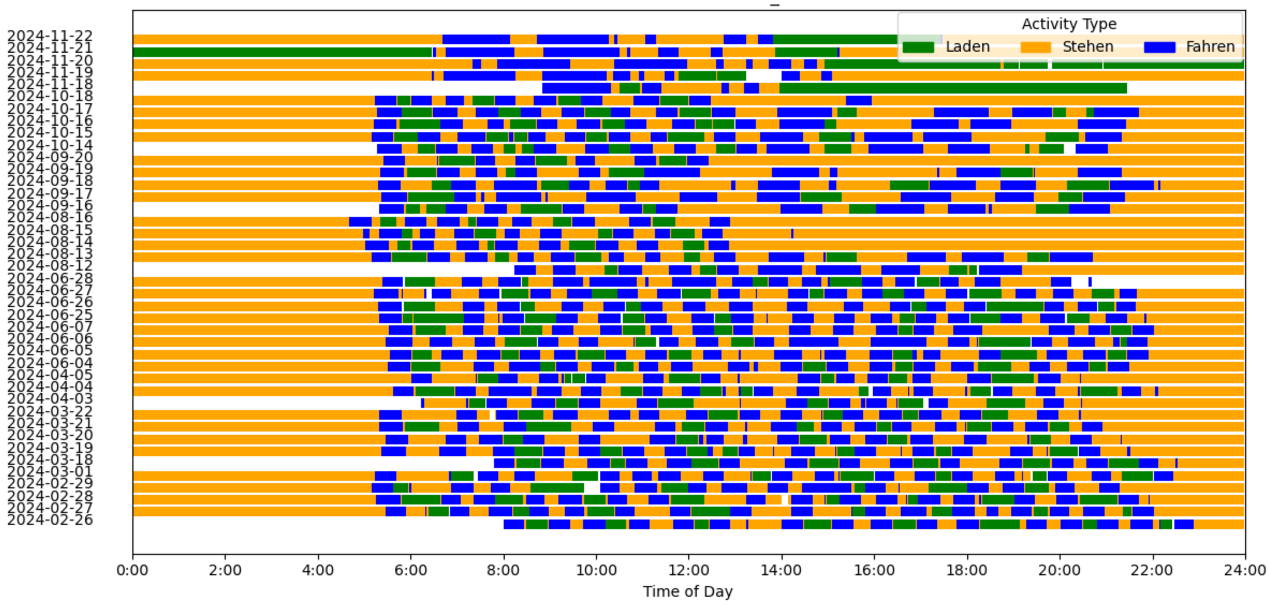
Source: own illustration

Figure 6-9: Case study partner D – Vehicle 1 (26.02.2024 to 13.12.2024)



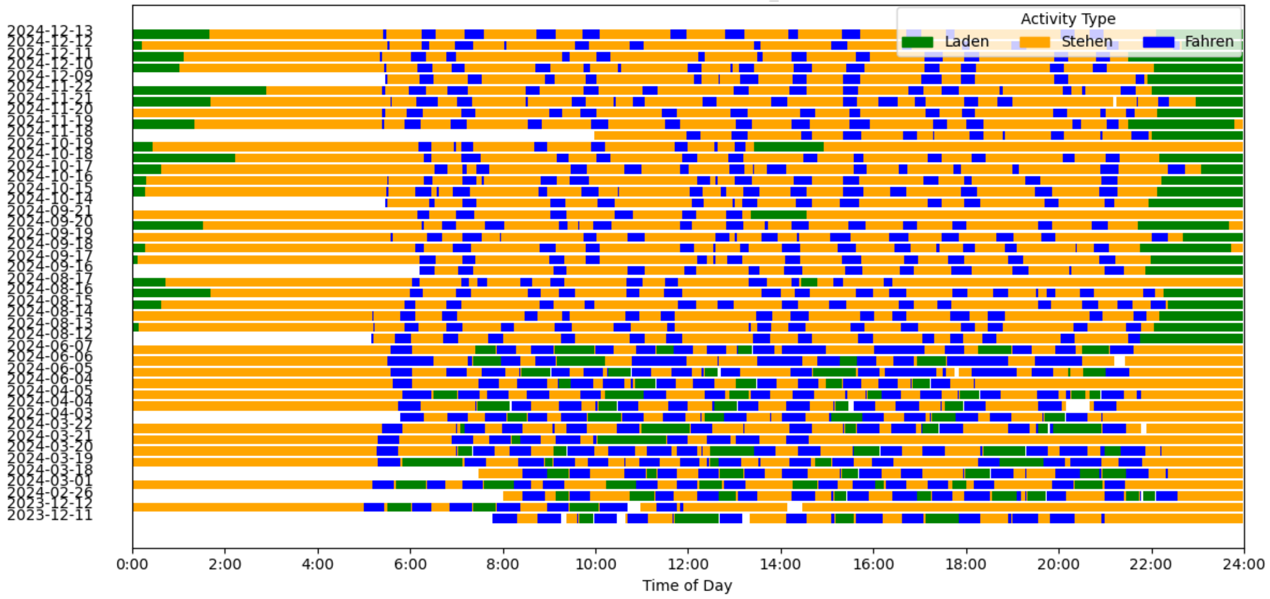
Source: own illustration

Figure 6-10: Case study partner D – Vehicle 1 (26.02.2024 to 22.11.2024)



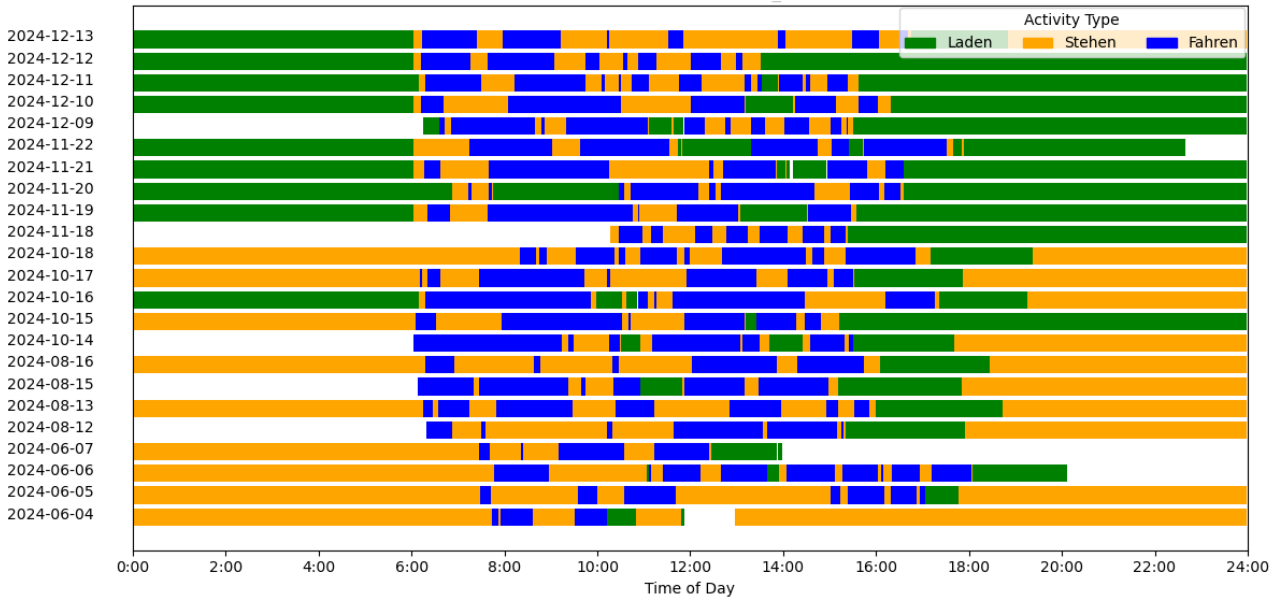
Source own illustration

Figure 6-11: Case study partner D – Vehicle 1 (11.12.2023 to 12.12.2024)



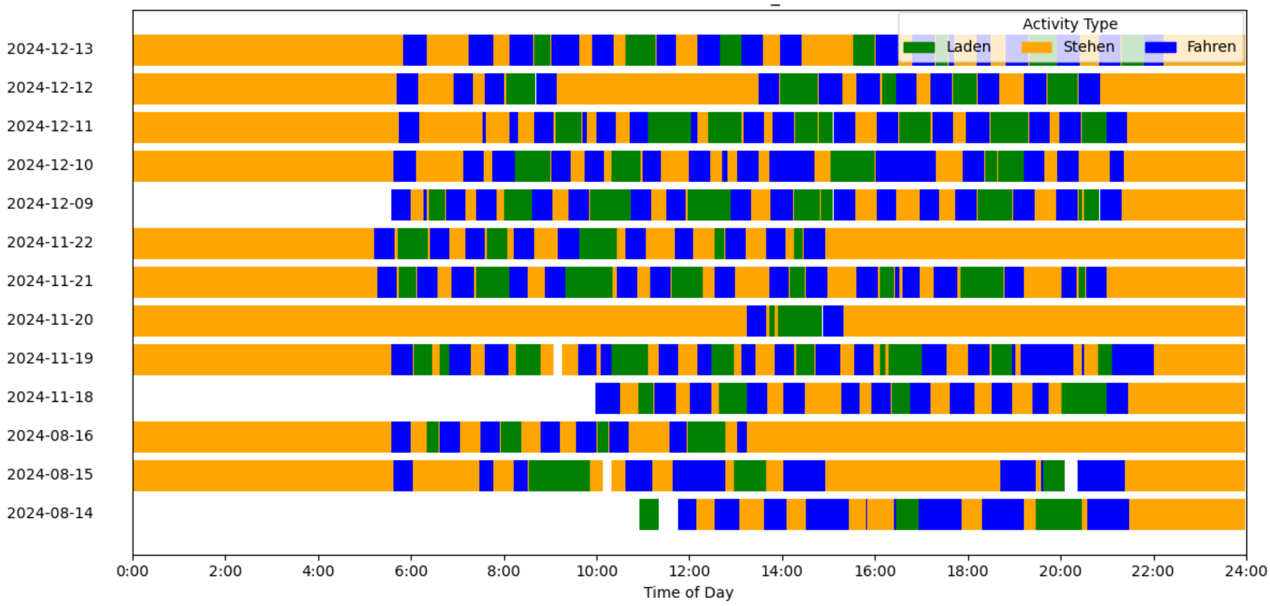
Source: own illustration

Figure 6-12: Case study partner D – Vehicle 1 (04.06.2024 to 13.12.2024)



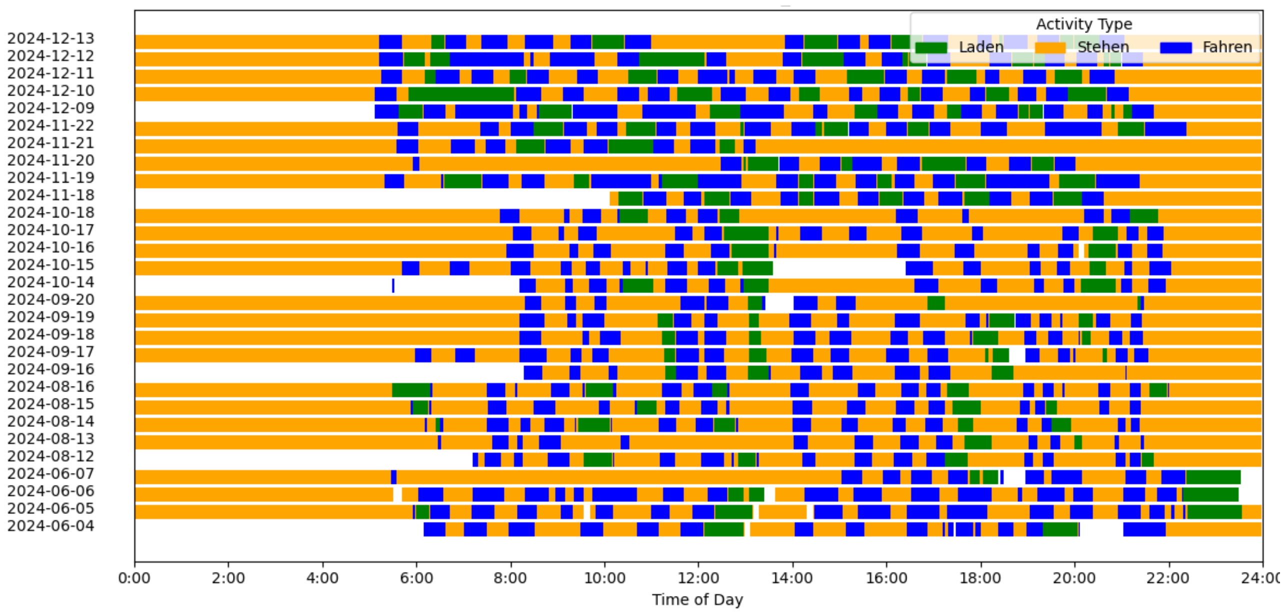
Source: own illustration

Figure 6-13: Case study partner D – Vehicle 1 (18.08.2024 to 13.12.2024)



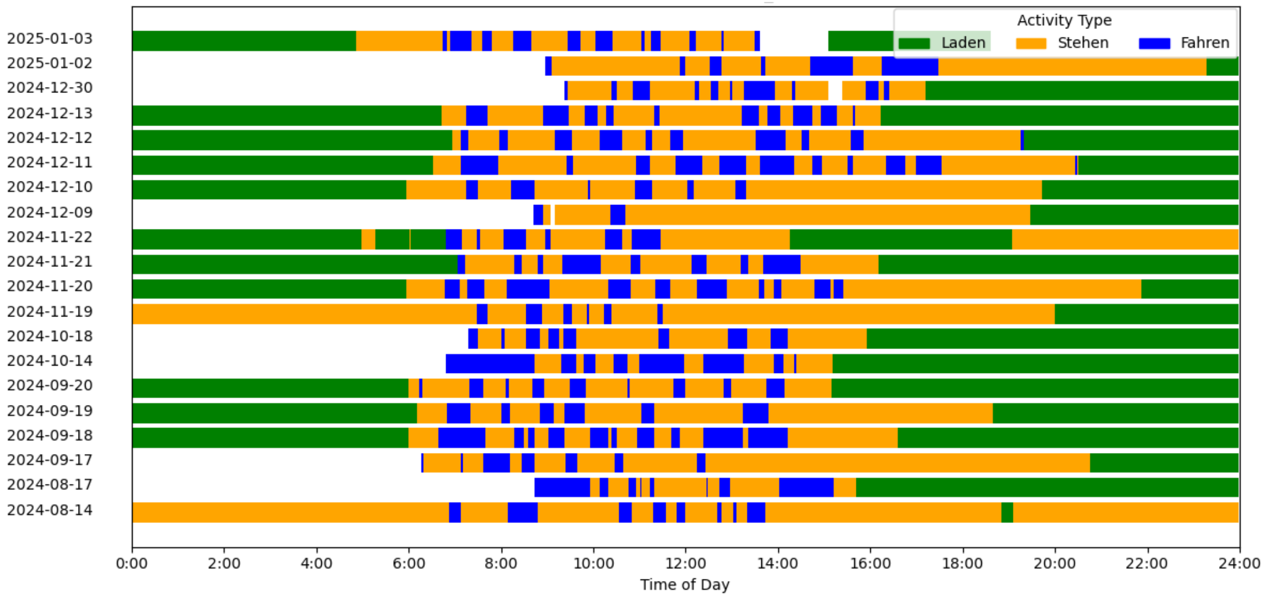
Source: own illustration

Figure 6-14: Case study partner D – Vehicle 1 (04.06.2024 to 13.12.2024)



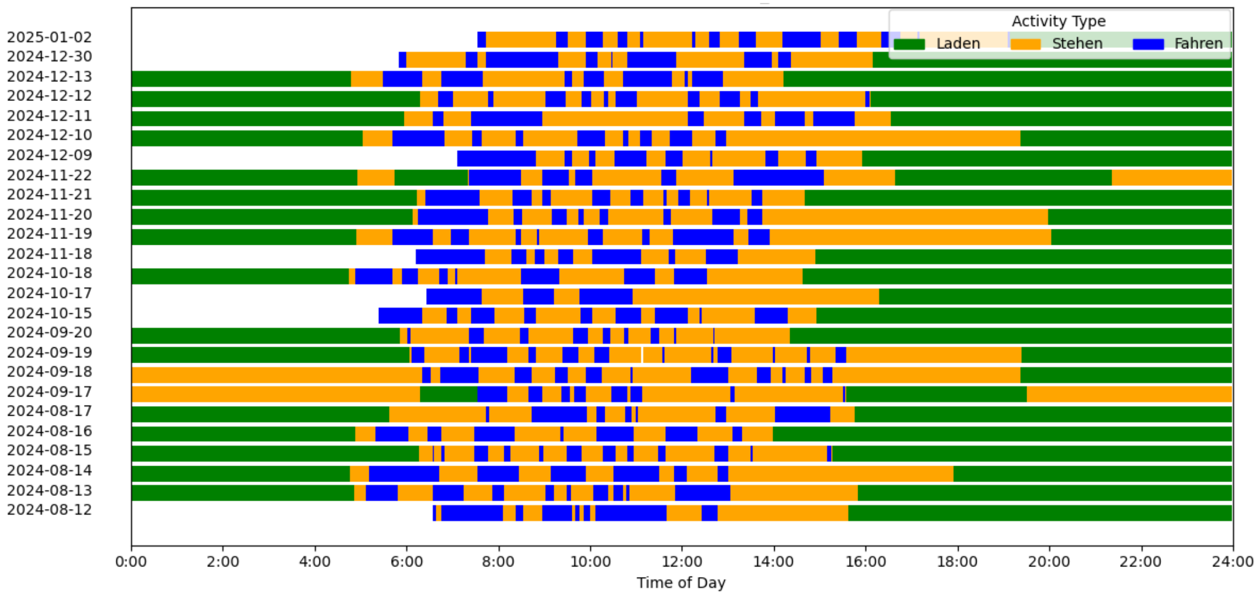
Source own illustration

Figure 6-15: Case study partner E – Vehicle 1 (14.08.2024 to 03.01.2025)



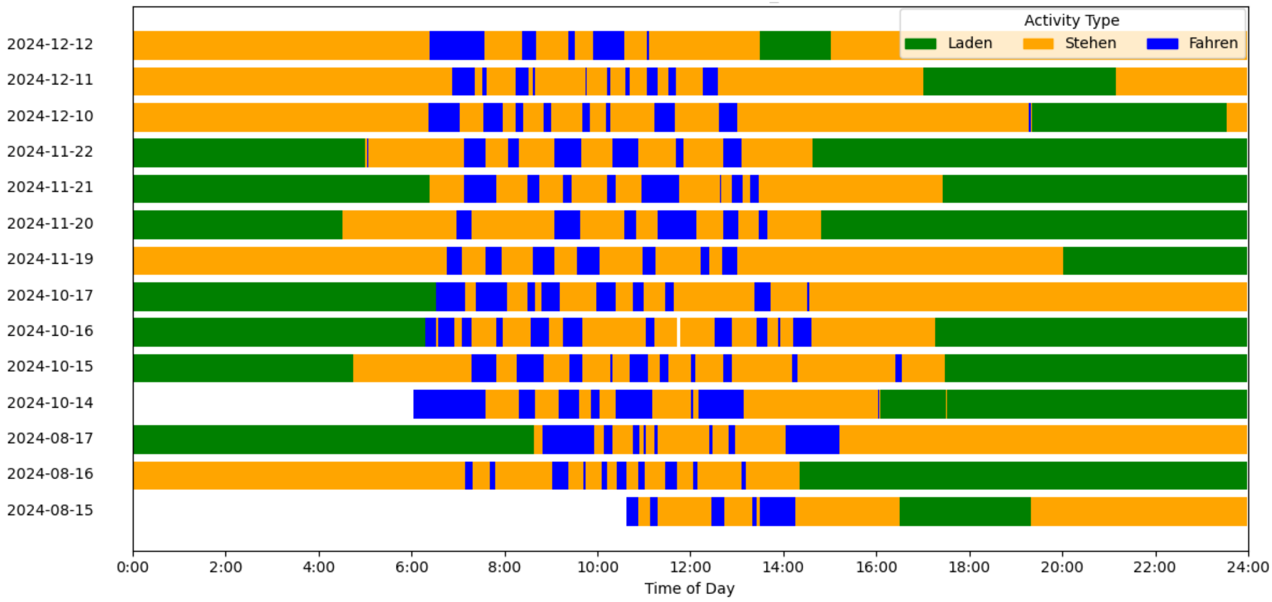
Source: own illustration

Figure 6-16: Case study partner E – Vehicle 1 (12.08.2024 to 02.01.2025)



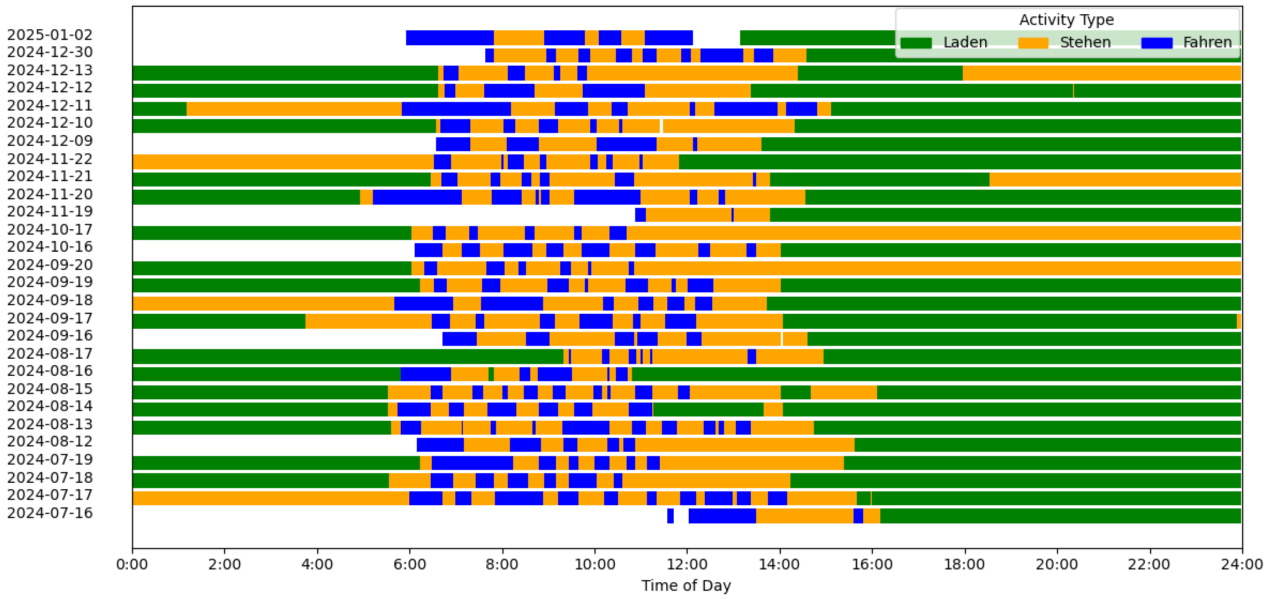
Source: own illustration

Figure 6-17: Case study partner E – Vehicle 1 (15.08.2024 to 12.12.2024)



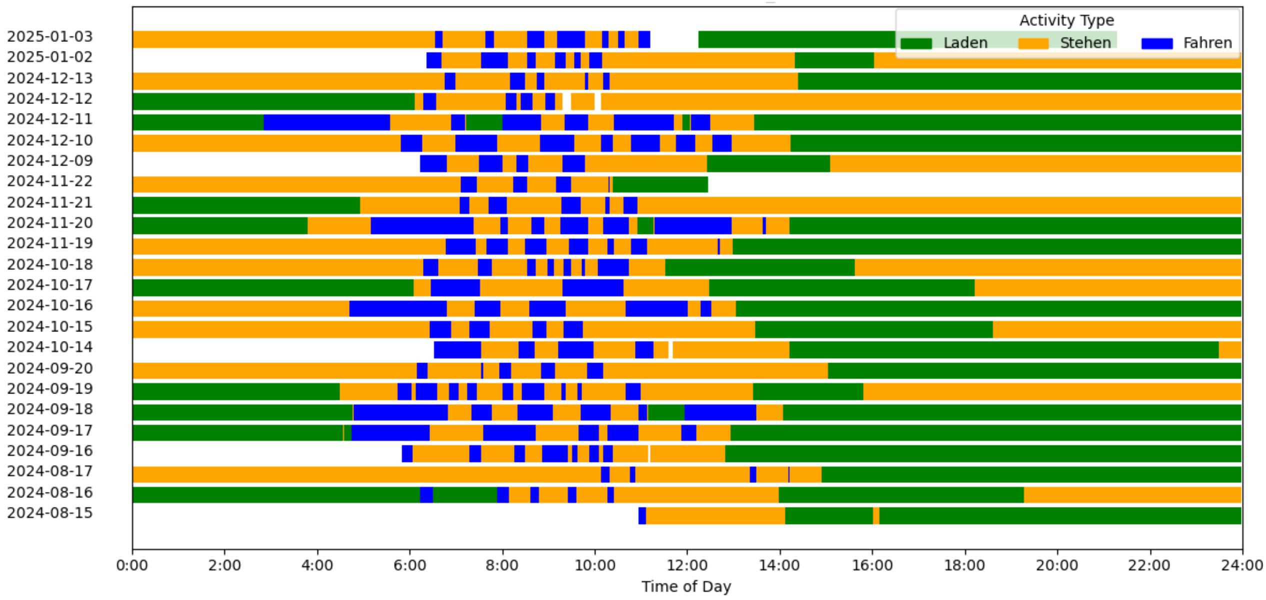
Source own illustration

Figure 6-18: Case study partner E – Vehicle 1 (16.07.2024 to 02.01.2025)



Source: own illustration

Figure 6-19: Case study partner E – Vehicle 1 (15.08.2024 to 03.01.2025)



Source own illustration