MACBETH

Project deliverable D3.1

Energy consumption simulations

Co-funded by the European Union

DELIVERABLE ADMINISTRATIVE INFORMATION

Deliverable Administration					
Grant Agreement	101192466	Project name	MACBETH		
Deliverable no.	D3.1	Deliverable Name	Energy consumption simulations		
Status	Final	Due	M11	Date	13/02/2026
Editor/Lead author	Mikaela Ranta (VTT)				
Co-authors	Joel Anttila (VTT)				
Peer reviewers	Patrick Plötz (Fraunhofer), Frances Sprei (Chalmers)				
Dissemination level	PU - Public				

Quality Control				
	Version	Date	Submitted	Comments
Document history	V0.1	25/01/2026	Mikaela Ranta (VTT)	Provided the first draft for review
	V0.2	12/02/2026	Mikaela Ranta (VTT)	Revised version based on review
	V1	13/02/2026	Yancho Todorov (VTT)	Finalized and submitted the final version
	V2	27/03/2026	Mikaela Ranta (VTT)	Corrected table of contents, lists of figures and tables

Legal Disclaimer

This project has received funding from the European Union's Horizon Europe innovation programme under the Grant Agreement No.101192466

TABLE OF CONTENTS

List of figures

List of tables

EXECUTIVE SUMMARY

This deliverable presents the methodology, execution, and outcomes of largescale energy consumption simulations conducted within Task 3.1 “Energy consumption simulations” of the MACBETH project. The work provides essential input data to support the development of operational tools and strategies for Megawatt Charging Systems (MCS) energy consumption simulations conducted within -haul freight transport.

The MACBETH project aims to accelerate the deployment of MCS infrastructure across Europe by combining real-world demonstrations with data driven analytical tools. Since vehicle technology, charging behaviour, and logistics systems are tightly interconnected, realistic modelling of vehicle energy consumption is crucial. This deliverable responds to that need by quantifying how various vehicle, route, environmental, and operational parameters influence energy use across heavy-duty vehicle categories by demonstrations with data driven analytical tools. Since vehicle technology, charging behaviour, and logistics systems are tightly interconnected, realistic modelling of vehicle energy consumption is crucial. This deliverable responds to that need by quantifying how various vehicle, route, environmental, and operational parameters influence energy use across heavy-duty vehicle categories.-driven analytical tools. Since vehicle technology, charging behaviour, and logistics systems are tightly interconnected, realistic modelling of vehicle energy consumption is crucial. This deliverable responds to that need by quantifying how various vehicle, route, environmental, and operational parameters influence energy use across heavy-duty vehicle categories.

A set of N-category (cargo) and M-category (passenger) vehicle models were created, each with parameter variations based on real-world data. Over 1000 European long-haul routes were selected from a synthetic dataset using a mileage-weighted sampling method to ensure representation of both heavily trafficked and less frequented corridors. These routes were enriched with real elevation and speed limits based on open-source data.

Simulations were implemented using VTT’s Smart eFleet (SeF) platform, which dynamically constructs driving cycles based on speed limits, traffic lights, vehicle capabilities, and adjustable driving style parameters. Key environmental and operational factors including payload, temperature, maximum speeds, and regenerative braking behaviour—were varied using probabilistic sampling to reflect realistic operating conditions.

Across all vehicle types, more than ~130 million kilometres of driving were simulated. The results provide detailed energy consumption distributions and reveal strong relationships between consumption and total vehicle weight, speed, route gradients, and temperature levels. Notably, temperature effects are substantial for buses and rigid body vans due to their high HVAC demand. Driving style (specifically, avoiding unnecessary regenerative

braking) was shown to reduce energy consumption by up to 2.9%, especially for larger vehicles. Notably, temperature effects are substantial for buses and rigid-body vans due to their high HVAC demand.

A comprehensive dataset containing vehicle parameters, simulation inputs, route characteristics, and resulting energy use metrics has been generated for further use within MACBETH and other research initiatives. Additionally, a machine learning model (random forest) trained on this dataset achieved a prediction error of ~6.3%, demonstrating both the robustness of the simulation framework and the potential for data driven energy consumption estimation tools.

Overall, this deliverable provides validated, high-resolution energy consumption insights essential for planning MCS infrastructure, optimizing charging hub operations, and supporting broader electrification strategies for long-haul freight and passenger transport.

Key words

Energy consumption, heavy-duty vehicles, simulation, feature analysis

LIST OF ABBREVIATIONS AND ACRONYMS

Acronym	Meaning
HVAC	Heating, Ventilation and Air Conditioning
MCS	Megawatt Charging system
SeF	Smart eFleet (simulation platform)

1 INTRODUCTION

1.1 Project summary

MACBETH aims to support the deployment and scale-up of Megawatt Charging Systems (MCS) in logistics to electrify long-haul freight, through developing and showcasing multipoint MCS hubs combined with tools facilitating the scale-up. MACBETH intends to address many of the technical, social, and economic challenges of mass deployment of MCS by setting up two demonstration sites, one in Sweden and one in Belgium to address various operational conditions, users' needs, and business cases.

By exploring these diverse environments, the project will generate valuable insights into the practical integration of Megawatt Charging Systems within real-world logistics operations. This approach will not only demonstrate the feasibility of large-scale electrification for long-haul freight but also inform future deployments by identifying best practices and potential obstacles. Ultimately, the knowledge gained from these pilot hubs is expected to lay the groundwork for broader adoption, fostering collaboration among stakeholders and shaping policy recommendations to accelerate the transition towards sustainable freight transport across Europe.

1.1 Attainment of the objectives and explanation of deviations

The objectives related to this deliverable have been achieved in full. The deliverable is delayed by 4 weeks due to delay in receiving required data and needed additional time for internal review.

1.2 Objective of the deliverable

This deliverable is part of task **3.1 "Energy consumption simulations"**, the aim of which is to analyse the energy consumption of vehicles of categories N2/N3 as well as of category M2/M3 considering the payload, driving environment, and country-specific characteristics.

1.3 Intended audience

This deliverable is intended for researchers working within the MACBETH project and other stakeholders interested in the energy consumption of electric vehicles.

1.4 Structure of the deliverable and links with other work packages/deliverables

This deliverable is organized into 5 chapters. Chapter 1 gives the introduction and chapter 2 a short motivation and background. The actual work methodology is described in chapter 3, whereas the results are illustrated in chapter 4. The conclusion is given in chapter 5.

2 MOTIVATION AND BACKGROUND

The MACBETH project focuses on MW-charging, one of the key enablers of the roll-out of electrified heavy-duty transportation. Vehicle technology and vehicle performance is generally not in the core focus of MACBETH. However, the aim to support the development and uptake of MW-charging infrastructure cannot be achieved by analysing the charging only. A large-scale roll-out of electrified transportation requires a systemic approach considering the vehicle technology, charging infrastructure and the whole logistics system. One of the MACBETH objectives is to support the electrification through development of operational tools and management strategies for MW charging hubs. This includes predictive tools for charging demand and location optimization considering user behaviour, vehicle types and grid interactions. The main target of task 3.1, and this deliverable, is to provide input information for these tools. The energy consumption of vehicles varies due to multiple factors, such as payload, vehicle parameters, route characteristics, ambient conditions and driving styles. These factors are often overlooked in research on charging of electric vehicles, and values on the expected average consumption is used instead. Relying on average values is often very well justified when analysing the charging demand of large regions. Vehicles with high energy consumption can be assumed to be compensated by vehicles with a low energy consumption. Furthermore, the analysis becomes overly complicated if energy consumption of single vehicles on specific routes is modelled on a large scale. However, it is believed that further knowledge on the variance of energy consumption and its dependency on environmental factors is important to take into consideration particularly when analysing and planning local charging stations in more detail.

3 METHODOLOGY

3.1 Vehicle models

For the simulations, vehicle models within the N2, N3, M2, and M3 categories were created. The most common types of vehicles within these categories were selected for the analysis. Since vehicles of different brands and types are not the same even though they belong to the same category, several vehicles were created within each category. Parameters for the creation of vehicle profiles were collected based on existing vehicles[1], both conventional and zero-emission vehicle data. It was assumed that parameters that are not directly related to the powertrain (e.g. rolling resistance, physical dimensions) will remain similar to conventional vehicles. The mass of battery-electric vehicles was assumed to be similar to conventional vehicles except for the battery weight, which increases the unladen weight of battery-electric vehicles. The motor powers were set up based on vehicle data and to meet the driving requirements, i.e. each created vehicle was tested prior to the simulations to ensure that the powertrain was powerful enough for steep uphill. The battery capacity was set based on what could be expected for each vehicle type. In several vehicle categories, battery-electric vehicles are still very rare, and very little data was, therefore, available on the actual battery capacities. Battery technology development might enable larger battery capacities in the future without adding too much weight to the vehicle.

The main parameters for each vehicle category and their maximum and minimum values are illustrated in Table 1 and Table 2. The vehicle profiles were created by randomly sampling values for each parameter assuming uniform distributions. In total, 10 different vehicles for each vehicle category were created, except for the semi-trailer vehicles for which 5 of each were made.

[1] European Environment Agency, “Monitoring of CO2 Emissions from Heavy-Duty Vehicles - Regulation (EU) 2018/956.”

Table 1 – N category vehicles

Vehicle category	Chassis mass (kg)	GVW (kg)	Rolling resistance (-)	Air drag coefficient (-)	Frontal area (m^2)	Motor power (kW)	Battery capacity (kWh)
Van	2200-2900	5000	0.0055 – 0.008	0.35 – 0.5	4.6 – 5.7	90-110	50-150
Van with body	2300-4000	7500	0.0055-0.008	0.4-0.55	5.5-7.04	100-150	50-150
Delivery 2 axles	4500-15000	18000	0.0055-0.0075	0.5-0.7	7-10.2	210-230	75-550
Delivery 3 axles	10000-17000	28000	0.005-0.007	0.5-0.7	7-10.2	310-340	200-700
2 axle tractor with 3 axle semitrailer	14200-20500	40000	0.005-0.007	0.5-0.7	10.2	340-370	300-800
3 axle tractor with 5 axle semitrailer	18200-24700	68000	0.005-0.007	0.5-0.7	10.2	420-480	300-1000

Table 2 – M category vehicles

Vehicle category	Chassis mass (kg)	GVW (kg)	Rolling resistance (-)	Air drag coefficient (-)	Frontal area (m^2)	Motor power (kW)	Battery capacity (kWh)
Minibus	2500-3500	5000	0.0055-0.008	0.35-0.5	5.3-5.9	90-110	75-200
2 axle bus	11000-14000	18000	0.005-0.007	0.55-0.65	8.4-9.2	280-320	450-700
3 axle bus	12000-15000	26000	0.005-0.007	0.55-0.65	8.4-9.2	300-360	500-800

Double decker	20440	26000	0.007	0.75	10.7	450	800

3.2 Routes

The routes to be analysed were obtained from a synthetic dataset[2] provided by Fraunhofer based on previous projects. The dataset contains 1.5 million origin and destination pairs representing long-haul connections of trucks all over Europe. The dataset also includes traffic flow for each route. As all possible routes cannot be simulated within a reasonable time frame, a subset of routes had to be selected. The routes in the dataset showed a large variation in both length and traffic flow. Evaluating the travelled distance of each route as number of vehicles * length of the route further revealed, that approximately 20% of the routes represent 80% of the total mileage i.e., if routes would be randomly selected from the dataset, then the result would mostly include routes with a low traffic flow. To achieve a subset of routes that more evenly represents routes with a high traffic flow and routes with a low traffic flow, the sampling of routes was performed based on the share of mileage. A total of 1000 routes were sampled to form this subset.

The obtained subset of routes was further processed to include all the data required for the simulations. Data on route elevation, speed limits, as well as locations of traffic lights, tunnels and bridges were obtained from openly available data sources (OpenStreetMap, Open Topo Data). A few routes had to be removed from the data set due to missing elevation data, and some routes were split in parts as they contained segments using a ferry for crossing seas. As a result, a set of 1091 routes were prepared for the simulations covering all parts of Europe. The elevation data was further filtered to remove unrealistically high slope values.

The obtained routes are illustrated in

. Statistical data on some of the key features of the routes are presented in Table 3. The route lengths vary from 7.5 km up to 3162 km with an average of 636 km, as the focus is on long-haul operation. The total elevation gain is the sum of the elevation increase when going uphill, the value is always positive as going downhill is not included. The cumulative elevation gain is simply the elevation gain in meters divided by the total route length in kilometres. Together with the average slope and difference between the highest and lowest

[2] Speth et al., "Synthetic European Road Freight Transport Flow Data."

point on the route, these values give an indication on the hilliness of the routes. The average slope is mostly very close to zero, as the elevation of the starting and end points are often similar, and the positive and negative slopes eliminate each other. The difference between the highest and lowest points show that some routes include very high hills, as this value can be as high as 1800 m.

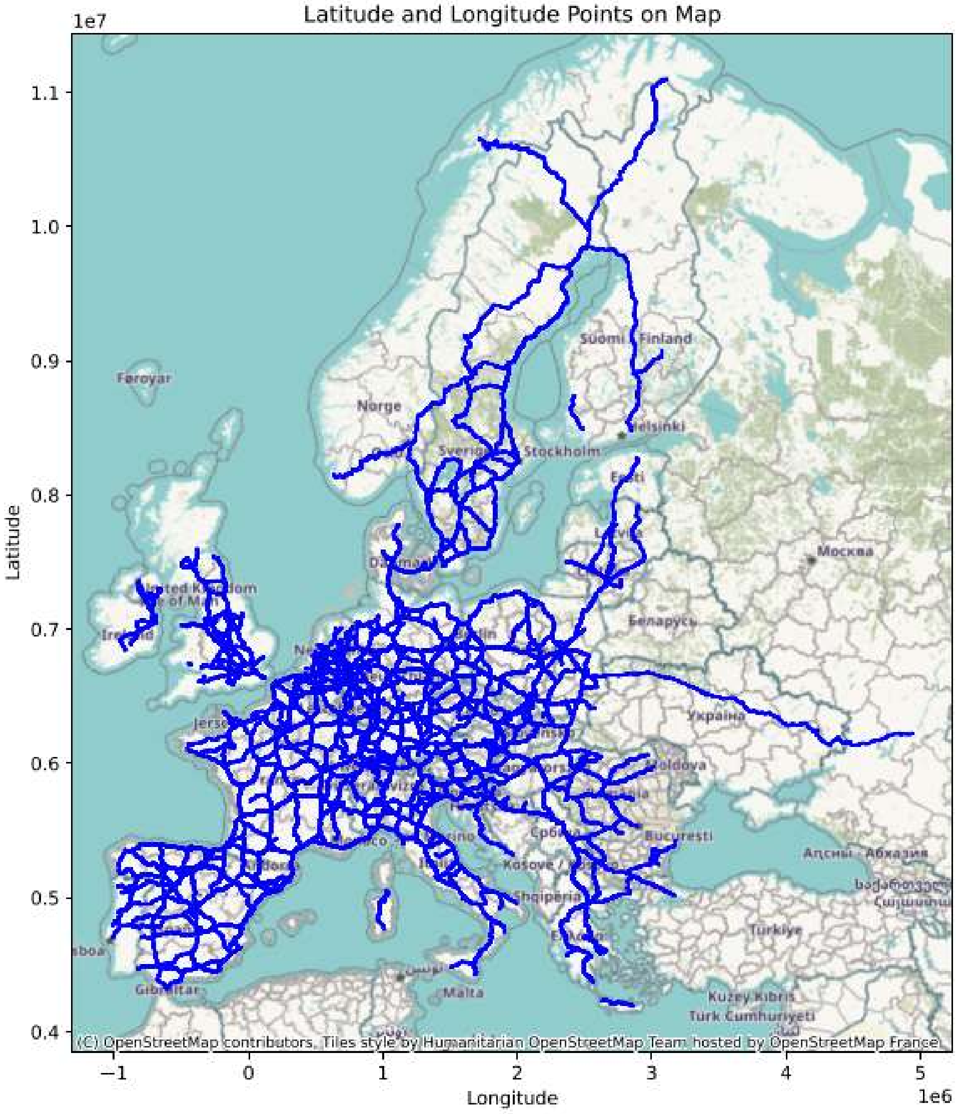

Figure 1 – Routes created for the simulation analysis.

The average speed limits are typically around 110 km/h, with a variation from 68 km/h to 140 km/h. Most routes include segments with low-speed limits, going down to 30 km/h, while some of the shortest routes stay at 140 km/h for the whole route. It should be noted that the speed limit is just a feature of the route itself. The vehicle speeds will be determined on other factors as well, and the actual speed will, therefore, deviate from the speed limits.

Routes are typically lengthy, requiring many hours or even several days to complete. The values presented in Table 3 are calculated based on the entire routes, but the simulation results will be presented dividing the routes into shorter segments. Therefore, the variance in route-related features such as cumulative elevation gain, average slope and speed are expected to be higher in the simulation results.

Table 3 – Statistical values on the obtained routes.

Route feature	Mean value	Median value	Minimum value	Max value	Standard deviation
Length	636.3 km	971.4 km	7.5 km	3162.0 km	637.6 km
Total elevation gain	5149.7 m	2805.5 m	22.8 m	32247.2 m	5416.9 m
Cumulative elevation gain	8.0 m/km	8.0 m/km	2.0 m/km	22.2 m/km	2.8 m/km
Difference between highest and lowest point	484.5 m	333.8 m	5.2 m	1799.7 m	395.0 m
Average slope	0.0019 %	-0.0001 %	-0.5206 %	0.9007 %	0.1006 %
Average speed limit	110.8 km/h	112.3 km/h	67.7 km/h	140.0 km/h	10.8 km/h
Minimum speed limit	30.8 km/h	30.0 km/h	5.0 km/h	140.0 km/h	13.0 km/h

3.3 Simulation model

The VTT Smart eFleet simulation platform (SeF)[3][4][5] was utilized for the actual simulation. SeF is a python-based simulation tool that has been extensively used in previous projects for various vehicle types. Similarly to other simulation tools, the core of the simulation consists of the longitudinal dynamics equation, which specifies the resistive forces and the traction energy required for a vehicle to travel at a given speed. The resistive forces (rolling resistance, air drag, gravitational force) primarily depend on the dimensions and weight of the vehicle, as well as the topography of the route. The ambient temperature is also considered in the resistive forces as it has an effect both on the rolling resistance due to temperature-dependency of the tyre dynamics and the air drag due to temperature-dependency of the air density. The ambient temperature further affects the cooling/heating need of the vehicle. The simulation platform includes a cabin model that defines the HVAC power required. The model considers multiple factors such as thermal flows with the structure of the cabin, metabolic heat from the driver and passengers, conduction and convection through the cabin shell etc. The total energy drawn from the battery is a combination of the traction energy need, the powertrain efficiency and the HVAC energy need.

Contrary to most other simulation tools, SeF does not rely on a ready-made speed profile, instead, the speed set point is dynamically formed during the simulation. The speed set point is determined based on route information, such as the speed limit and location of traffic lights. Driving style parameters are used to define the maximum acceleration and deceleration, as well as the behaviour of braking and regeneration of energy. Hence, the resulting speed will depend on characteristics of the route and the vehicle as well as the driving settings.

3.4 Simulation settings

To capture the variation of driving conditions seen in real life, a large set of simulations were carried out with variations of the inputs. A summary of the input parameters that are varied is given in Table 4. The total weight of the vehicle is one of the most decisive factors when it comes to the energy consumption. Hence, the payload of each vehicle was varied within boundaries set by the vehicle specifications, i.e., the payload was varied from no payload to the maximum payload permitted by the gross vehicle weight specification. For N-category vehicles, the maximum payload was specified simply based on the permitted

---

[3] Anttila et al., “System-Level Validation of an Electric Bus Fleet Simulator.”
[4] Lopez-Ibarra et al., “Electric Bus Forward and Backward Models Validation Methodology Based on Dynamometer Tests Measurements.”
[5] Vehviläinen et al., “Simulation-Based Comparative Assessment of a Multi-Speed Transmission for an E-Retrofitted Heavy-Duty Truck.”

weight. For M-category vehicles, both the number and weight of passengers affect the results, hence, the number of passengers was varied from 1 to the maximum number allowed, and, in addition, the weight of each passenger was varied based on the vehicle specification. The number of passengers has a direct impact on the heating/cooling need of the bus, and the maximum weight of each passenger was assumed to include the passenger as well as potential baggage.

Table 4 – Varied simulation input parameters.

Parameter	Value/distribution
Payload	Uniform distribution, vehicle-dependent maximum value
Temperature	Normal distribution with a mean value of 11 ℃ and the standard deviation 10 ℃
Maximum speed	80/90/100/120 km/h
Avoid excessive regeneration	True/False

The temperature varies greatly both spatially and temporarily, i.e. southern Europe experiences very high temperatures during the summer, whereas northern Europe experiences very low temperatures during the winter. Naturally, the temperature also varies with altitude and throughout the day, meaning that the driving conditions of the vehicle depend on the timing of the driving, the climatic conditions of the location and the type of route driven (mountainous area / lowland area). It is, however, not possible to analyse all potential driving routes within Europe as the simulations would then take too much time, which is why roughly 1000 routes were selected for the analysis. The selected routes cover all of Europe, but no area of Europe is extensively covered, e.g. only a few routes are in the northern-most parts of Europe. To avoid misleading results, it was decided to separate the climatic condition settings from the routes, i.e., the temperature settings did not depend on the location of the route. Instead, the temperature was randomly sampled from a Gauss distribution that was designed to capture the most typical European weather conditions as well as extremes both in low and high temperatures. In this manner, most results represent typical driving conditions, but also very high and very low temperatures are represented regardless of the other characteristics of the route.

Another aspect affecting the energy consumption is the driving speed and driving style. The driving speed is mainly determined by the speed limitations along the route. However, heavy-duty vehicles have additional speed limitations, and these limitations are country specific. In most European countries, heavy-duty trucks are allowed to travel at maximum 80 km/h, while e.g. France allows speeds up to 90 km/h. Therefore, an additional speed limitation was set for trucks to 80 km/h in 80% of the simulations, and to 90 km/h in 20% of the simulation runs. The smallest vehicles analysed, i.e. the vans and minibuses are not limited by additional speed limits, and their maximum speed is set to 120 km/h in all cases. The maximum speed limit for coaches was set to 100 km/h. Driving style can be characterized in multiple ways, including factors such as aggressiveness of accelerations, over-speeding, utilisation of regenerative braking etc. Since mostly long-haul routes are of interest in this task, acceleration patterns are not expected to have a big impact on the results as the vehicles travel at a fairly constant speed most of the time. However, braking behaviour when travelling downhill has been observed to affect the energy consumption in previous projects. Even though electric vehicles can utilize regeneration when going downhill, there is always an energy loss as the efficiency of the powertrain is less than 100%. If not strictly necessary to slow down, it is energy-wise more economical to maintain the kinetic energy instead of circulating it through the battery. Therefore, a parameter controlling the braking was introduced. The parameter is designed to avoid excessive regeneration and, hence, prioritize maintaining the kinetic energy. Consequently, the vehicle is allowed to slightly overspeed when going downhill, the over-speeding is always kept withing reasonable limits, thought, and the regenerative braking is activated if necessary. The parameter can be considered a driving style settings, as it either makes the vehicle strictly follow the speed limitations when set to False, or allow slight over-speeding when going downhill to avoid losing kinetic energy when set to True.

4 RESULTS

4.1 Simulation results

Simulations with each generated vehicle were run on all routes using the input sampling method described in Chapter 3. To gain enough results for the analysis, some vehicles were simulated several times on each route with different settings for ambient temperature and payload. The total number of kilometres simulated for each vehicle category is illustrated in Table 5. The simulation outcomes were recorded with a 4.5 hour interval. The simulation itself runs at a 0.1s interval, and it is possible to analyse the outcomes with detail. However, recording the results with high granularity would increase the simulation time, as storing the results to memory takes a relatively long time. The choice of 4.5 hours also reflects the fact that drivers are allowed to drive a maximum time of 4.5 hours before taking a break. In addition to the 4.5 hours intervals, the outcomes of the whole route were included in the final results. The number of results for each vehicle category is shown in Table 5.

Table 5 – Summary of simulated distances for each vehicle category.

Vehicle category	Simulated distance (km)	# of results
Van	$13.88 \cdot 10^{6}$	52695
Van with body	$6.94 \cdot 10^{6}$	30618
Delivery 2 axles	$20.82 \cdot 10^{6}$	91750
Delivery 3 axles	$20.82 \cdot 10^{6}$	91676
2 axle tractor with 3 axle semitrailer	$17.35 \cdot 10^{6}$	76502
3 axle tractor with 5 axle semitrailer	$17.35 \cdot 10^{6}$	76700
Minibus	$7.35 \cdot 10^{6}$	28077
2 axle bus	$6.94 \cdot 10^{6}$	27386
3 axle bus	$20.79 \cdot 10^{6}$	82108
Double decker	$0.69 \cdot 10^{6}$	2736

The distributions of the energy consumptions for each vehicle category are illustrated in Figure 2 and Figure 3. The total weight of the vehicle is one of the most important factors influencing the energy consumption, this is illustrated in Figure 4 and in Figure 5 showing the energy consumption as a function of the weight. Statistical data on the energy consumption for each vehicle category is given in Table 7. As comparison, empirical data on the energy consumption of trucks of 11-18 tons show an average value of 0.96 kWh/km[6], whereas empirical data of tractor-trailers with varying payload has been reported in the range of 0.92 – 1.5 kWh/km[7]. All these values lie within the range of the simulated results obtained. Statistical features of the routes calculated from the results are shown in Table 7. These values are different from the values in Table 3 as the routes are split into parts of 4.5 hours driving in the results. The results also include the values recorded for the whole route, hence, the maximum distance is the same as in Table 3, but the mean and median distances are not. There is greater variation in the cumulative elevation gain and average slope, as some results correspond to travelling mostly downhill or uphill.

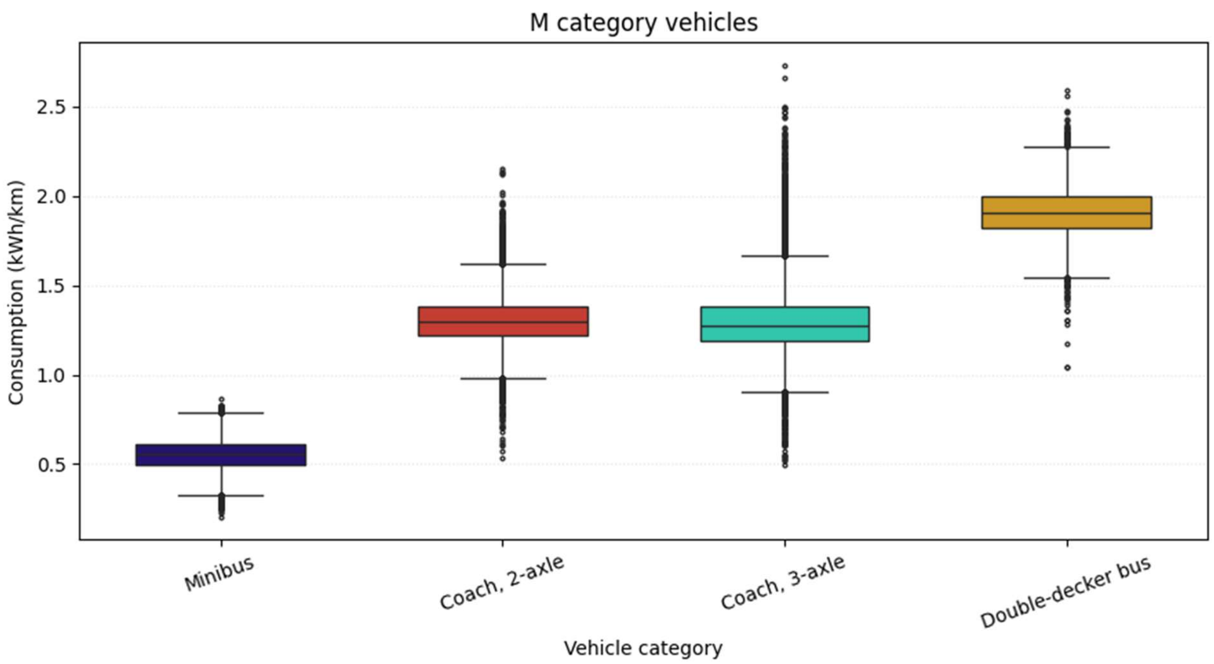

Figure 2 – Statistical distribution of energy consumption of passenger vehicles.

[6] Le Corguillé et al., *Real-World Data Analysis of Energy Consumption, Activity and Charging Patterns of Battery Electric Trucks Operating in Germany*.
[7] Ragon Pierre-Louis, *Real-World Use Cases for Zero-Emission Trucks*.

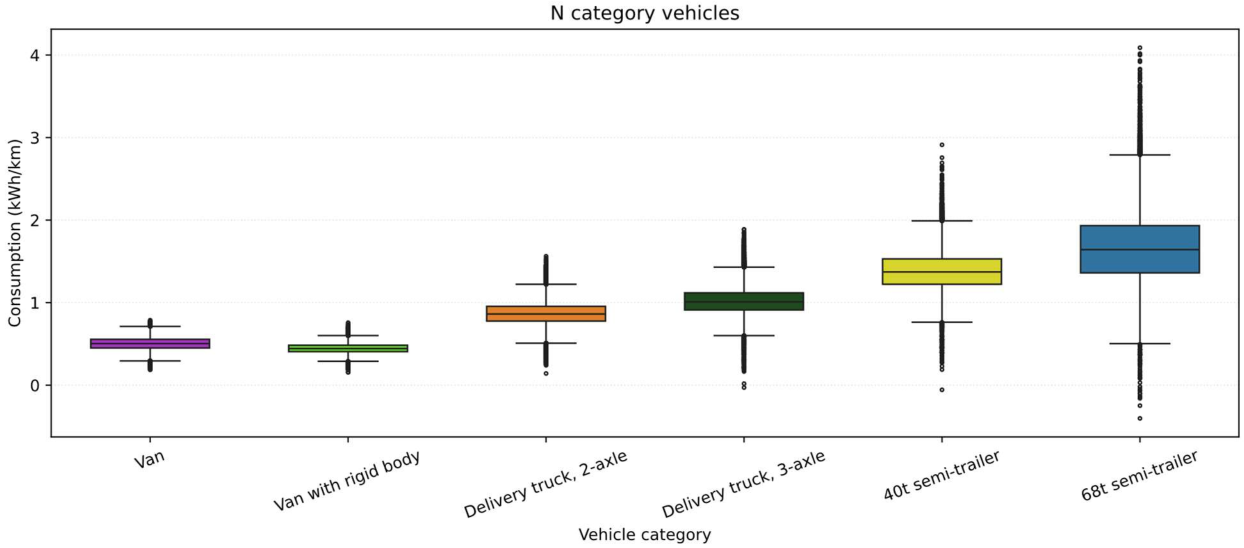

Figure 3 – Statistical distributions of energy consumption of cargo vehicles.

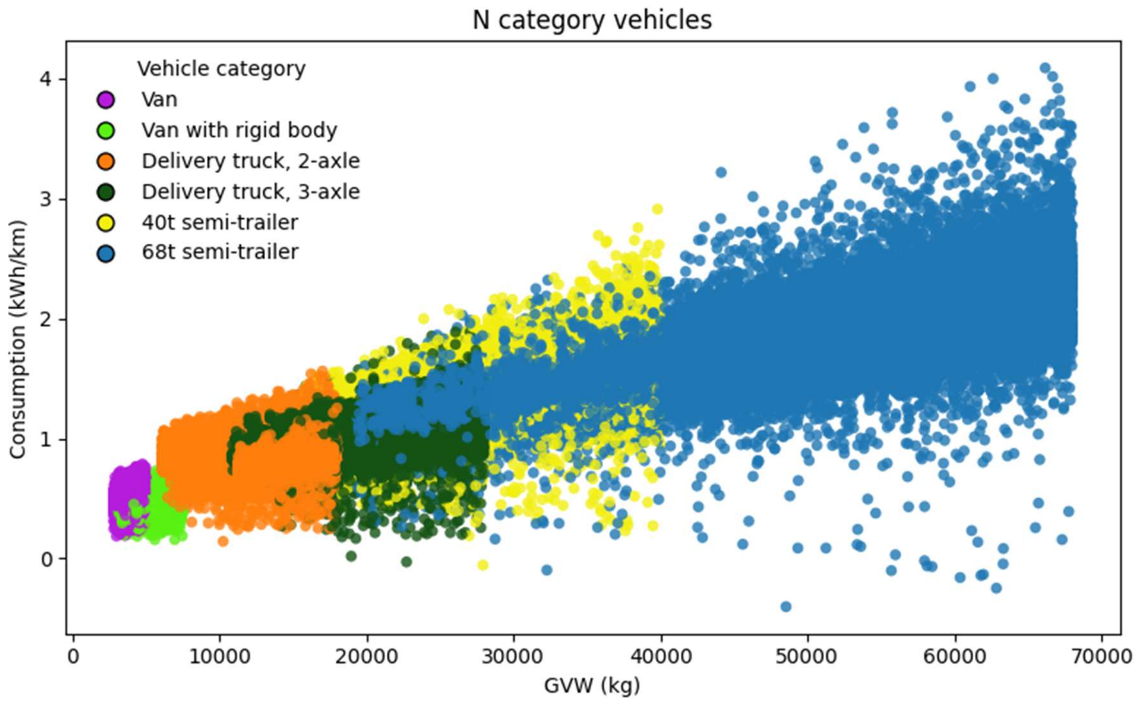

Figure 4 – Energy consumption as a function of Gross Vehicle Weight (GVW) of N-category vehicles.

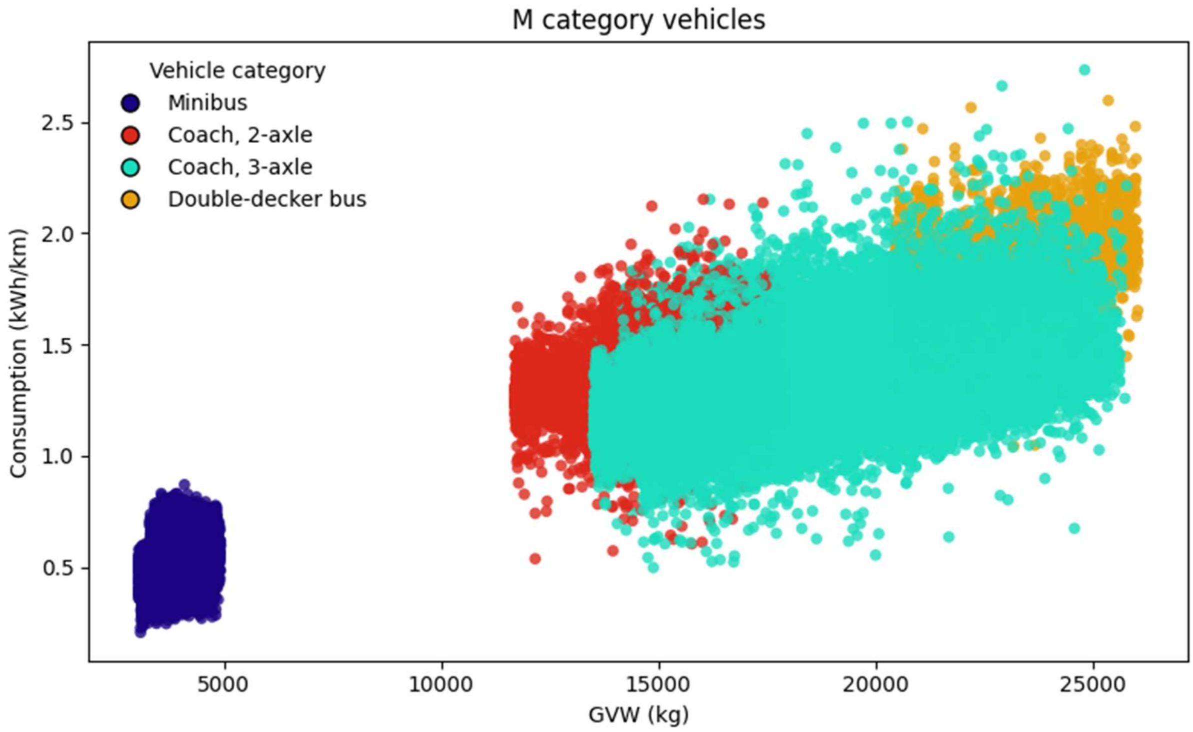

Figure 5 – Energy consumption as function of Gross Vehicle Weight (GVW) of M-category vehicles.

Table 6 – Statistical data on the energy consumption of each vehicle category

Vehicle category	Mean value (kWh/km)	Median value (kWh/km)	1st quartile (kWh/km)	3rd quartile (kWh/km)	Standard deviation (kWh/km)
Van	0.5	0.5	0.45	0.55	0.08
Van with body	0.45	0.44	0.40	0.48	0.07
Delivery 2 axles	0.87	0.86	0.77	0.95	0.16
Delivery 3 axles	1.02	1.01	0.91	1.12	0.19
2 axle tractor with 3 axle semitrailer	1.38	1.37	1.22	1.53	0.26

3 axle tractor with 5 axle semitrailer	1.66	1.64	1.35	1.93	0.46
Minibus	0.55	0.55	0.50	0.61	0.09
2 axle bus	1.3	1.29	1.22	1.38	0.16
3 axle bus	1.29	1.28	1.19	1.38	0.2
Double decker	1.91	1.91	1.81	2.0	0.22

Table 7 – Statistical route parameters derived from the results.

Route feature	Mean value	Median value	Minimum value	Max value	Standard deviation
Length	439.8 km	355.6 km	0.0 km	3162.0 km	427.6 km
Total elevation gain	3438.7 m	2556.2 m	0.0 m	31108.1 m	3554.0 m
Cumulative elevation gain	7.78 m/km	7.58 m/km	0.00 m/km	52.31 m/km	3.05 m/km
Average slope	-0.0035 %	0.0001 %	-3.77 %	5.23 %	0.13 %

4.2 Feature analysis

To better understand the variability of the energy consumption observed in the results, a statistical analysis was performed on the dataset. The mutual information of random variables can be utilized to describe how much knowing one variable gives information about another variable. In this work, the energy consumption is of main interest, therefore, the mutual information of various variables in the dataset in respect to the energy consumption was calculated. The results are presented separately for each vehicle category, since vehicles of different types have somewhat different characteristics. The results of N-category vehicles are shown in Figure 6, Figure 7, and Figure 8, and the results of M-category vehicles in Figure 9 and Figure 10. The weight of the vehicle is the total weight, i.e. the weight of the vehicle itself and the payload (goods and/or passengers). The weight has a high impact on the energy consumption, and for several vehicle categories, it is the most influential parameter. However, in the case of vans (Figure 6) and minibuses (Figure 9), the influence of the weight is very small. This does not mean that the weight of these vehicles does not affect the energy consumption, rather, it reflects the fact that the variance of the weight of these vehicles does not vary very much in this dataset, and other factors explain the variance in the observed energy consumption more than the weight. The average speed and the maximum speed have a relatively much higher influence on the energy consumption of the smallest vehicles. This is partly because the speed of these vehicles varies more than the speed of the other vehicles, since their maximum speed is set to 120 km/h. Hence, the dataset includes records of relatively high speed of vans, but also lower speeds, since the speed limit of the routes are sometimes much lower than 120 km/h.

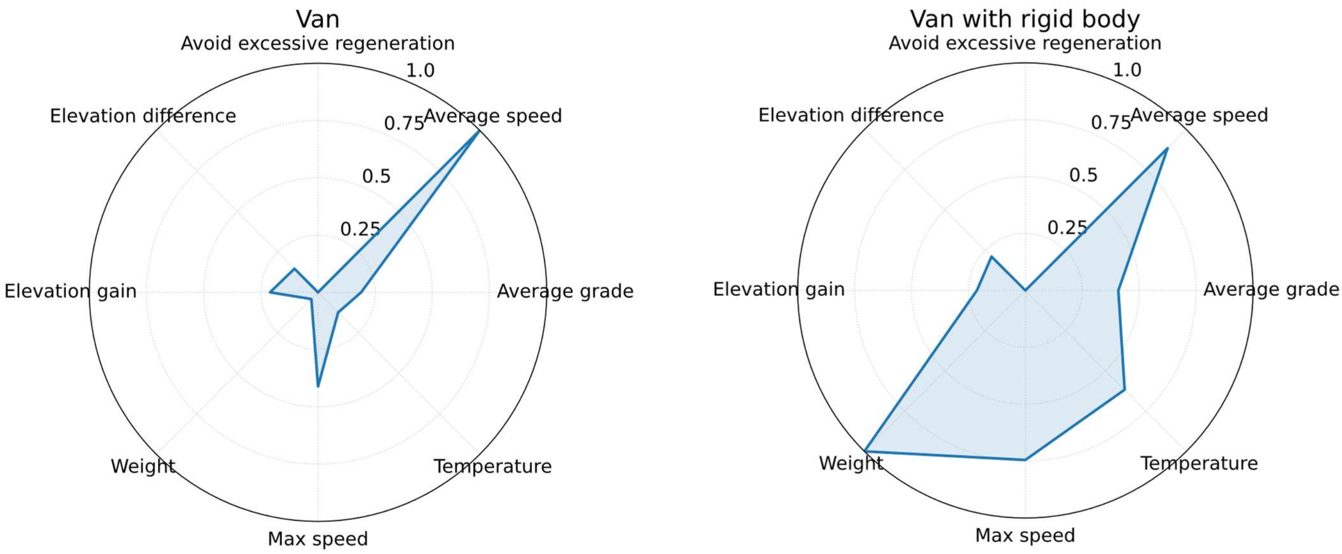

Figure 6 – Feature analysis of vans.

Besides the speed, the elevation gain, average grade and elevation difference are route specific characteristics. The impact of these variables ranges from relatively low to medium level. The importance of these features can be expected to somewhat correlate with the weight of the vehicle. Driving uphill with a heavy vehicle requires a lot of energy, while going uphill with a lighter vehicle does not necessarily increase the energy consumption so much compared to a flat route. It can, indeed, be observed, that the importance of these route-characteristics is quite low for the smallest vehicles (vans and minibuses). In the case of semi-trailer vehicles, which have the highest weights, the impact of the elevation-related features are relatively small, though, as can be seen in Figure 8. The direct impact of the overall weight and the maximum speed are of greatest importance in these vehicle categories.

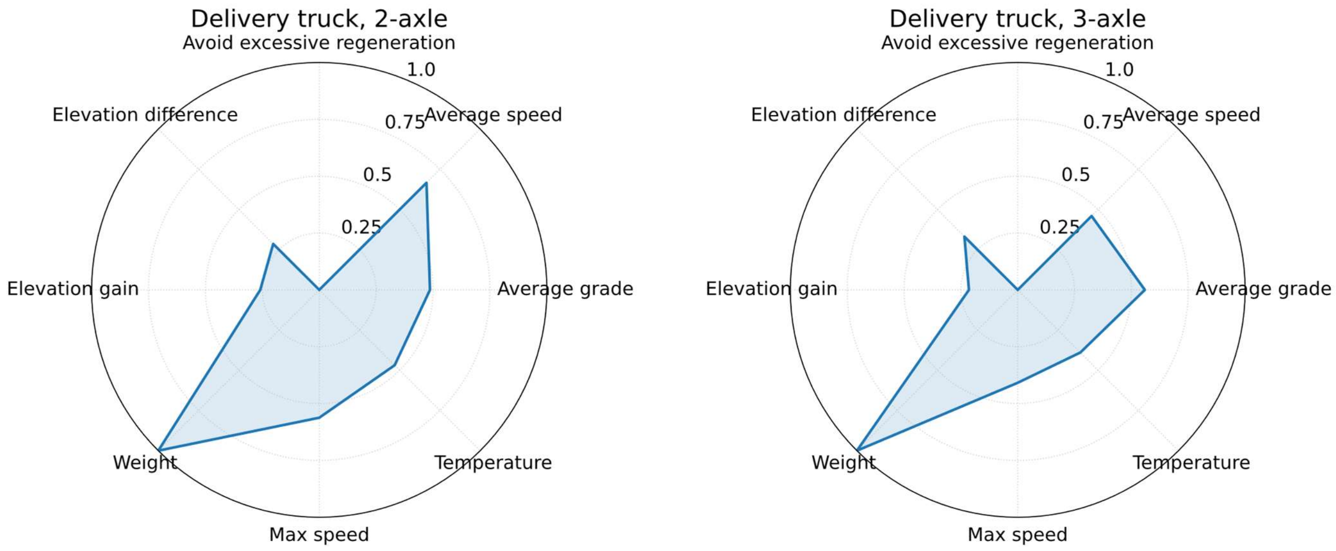

Figure 7 – Feature analysis of delivery trucks.

The temperature affects the energy consumption in multiple ways. The need for cooling/heating depends on the temperature, but also the rolling resistance and the air drag are partly dependent on temperature (lower temperatures increase the rolling resistance as well as the air density). Hence, the impact of temperature reflects the impact of HVAC energy consumption and the relative importance of the temperature on the resistive forces. From Figure 10, it can be seen that the temperature is among the most important features in the case of coaches. This is natural, since the coaches have a large volume of air that requires temperature control. The temperature also affects the rigid body vans and delivery trucks to a quite great extent. In the simulations, it was assumed that only the cabin of these vehicles requires temperature control, hence, the impact of temperature is probably mostly related to the influence on driving resistances. In case the cargo space would also be temperature controlled, the importance of the temperature would probably be even higher.

The feature introduced to control the regenerative braking (avoid excessive regeneration) does not seem to have almost any impact at all as it is close to zero for all vehicle categories. This can be expected, as is it is a categorical variable that is either True or False, and the variation in energy consumption is mostly affected by other parameters. But this feature is not totally to be ignored. The mean value of the energy consumption when the feature was set to True was lower than the mean value of the energy consumption when it was set to False in all vehicle categories. The difference between the mean values was up to 2.9%, and it showed a tendency to increase with vehicle size. In most cases, it also led to a slightly higher average speed. Hence, it can be concluded that the driving style has an impact on energy consumption even in long-haul operation, and avoiding unnecessary regeneration when possible can bring savings both energy-wise and time-wise.

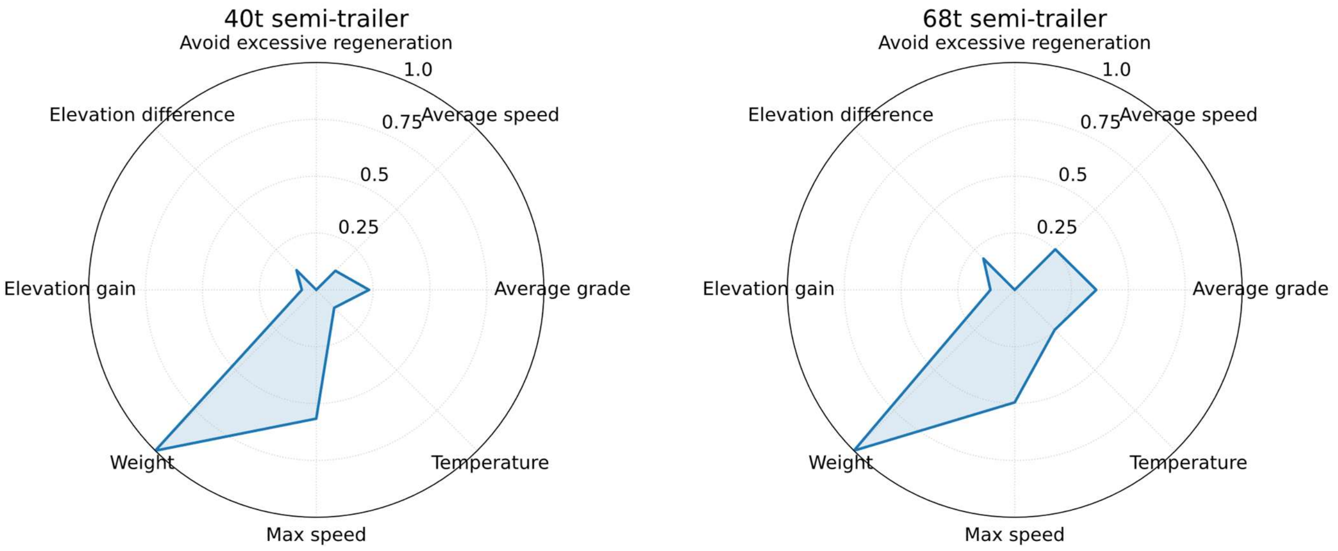

Figure 8 – Feature analysis of semi-trailer vehicles.

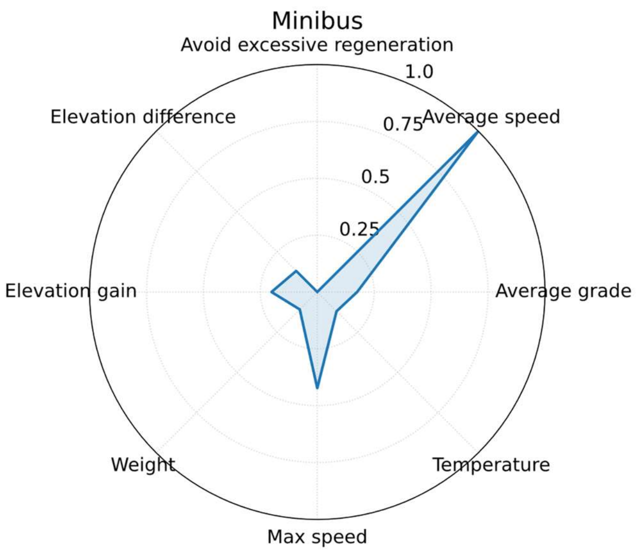

Figure 9 – Feature analysis of minibuses.

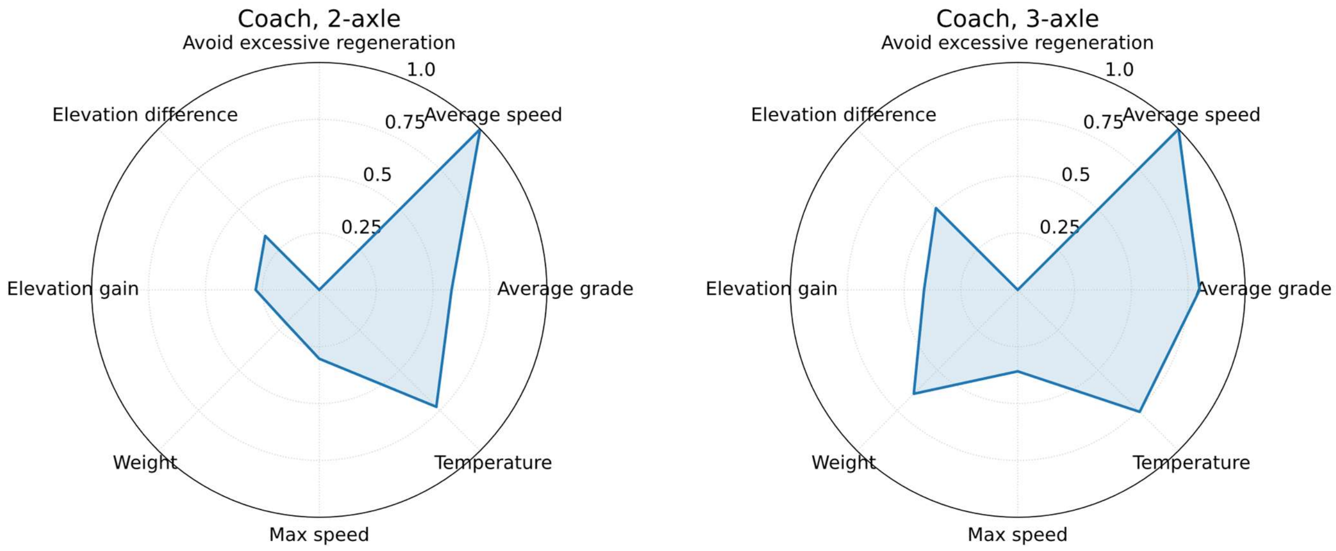

Figure 10 – Feature analysis of coaches.

4.3 Usage of dataset

A dataset based on the simulations carried out is created to be available for usage in other tasks in this project and other research projects. The dataset includes the features listed in Table 8 and it can be accessed from https://doi.org/10.5281/zenodo.18431851. The elevation difference, elevation gain and average grade are purely characteristics of the route. The exact values vary between the simulation runs, as the recording is done at a 4.5-hour interval, and the speed of the vehicles depend not only on the route, but also on the vehicle characteristics. Besides the route characteristics, the temperature and the driving style settings are inputs to the simulation. The temperature is kept constant throughout each simulation run, but it is resampled before each run. Hence, multiple rows have the exact same temperature, but the overall temperature distribution should be close to the Gauss distribution used for sampling. The most important outcome is the energy consumption, but also the average speed and the max speed can be considered outcomes of the simulation. The driving cycle is not determined before the simulation, rather, the speed is formed during the simulation as previously described. The vehicle characteristics affect the vehicles' ability to follow the speed setpoint, hence, vehicles with a high payload tend to have a lower average speed than vehicles with a lower payload, especially if the route includes a lot of uphill driving.

Table 8 – Summary of the parameters included in the database.

Parameter	Parameter type	Parameter	Parameter type
Vehicle category	Vehicle parameter	**Avoid excessive regeneration**	Simulation setting
Total weight	Vehicle parameter	**Duration**	4.5 hours /Simulation outcome
Elevation gain	Route parameter	**Average speed**	Simulation outcome
Elevation difference	Route parameter	**Distance**	Simulation outcome
Average slope	Route parameter	**Energy consumption**	Simulation outcome
Temperature	Simulation setting	**Max speed**	Simulation outcome

The dataset can be used to extract the energy consumption of vehicles based on desired features such as vehicle type, vehicle weight, ambient conditions, and geographical information. It is not possible to directly filter the data based on e.g. country or location, as this information is not specifically included. But, if for instance, energy consumption of vehicles in a specific country is required, one can filter for route characteristics typical of that country in combination with typical temperatures and driving speeds. The filtering of the dataset can then give a range of energy consumption values that can be expected for the specific case.

Instead of direct filtering, the dataset can also be used to train machine-learning algorithms. For demonstrative purposes, a random forest model was trained on the dataset. In this training, all parameters in Table 8 were considered input values except the energy consumption, which is the output of the model. The model's ability to predict the energy consumption is illustrated in Figure 11. The root mean square error of the model is 0.088 kWh/km, and the average error around 6.3%. Hence, the model can predict the energy consumption relatively well, but it is also clear, that the provided data does not capture all features and variability that affects the energy consumption in the simulations.

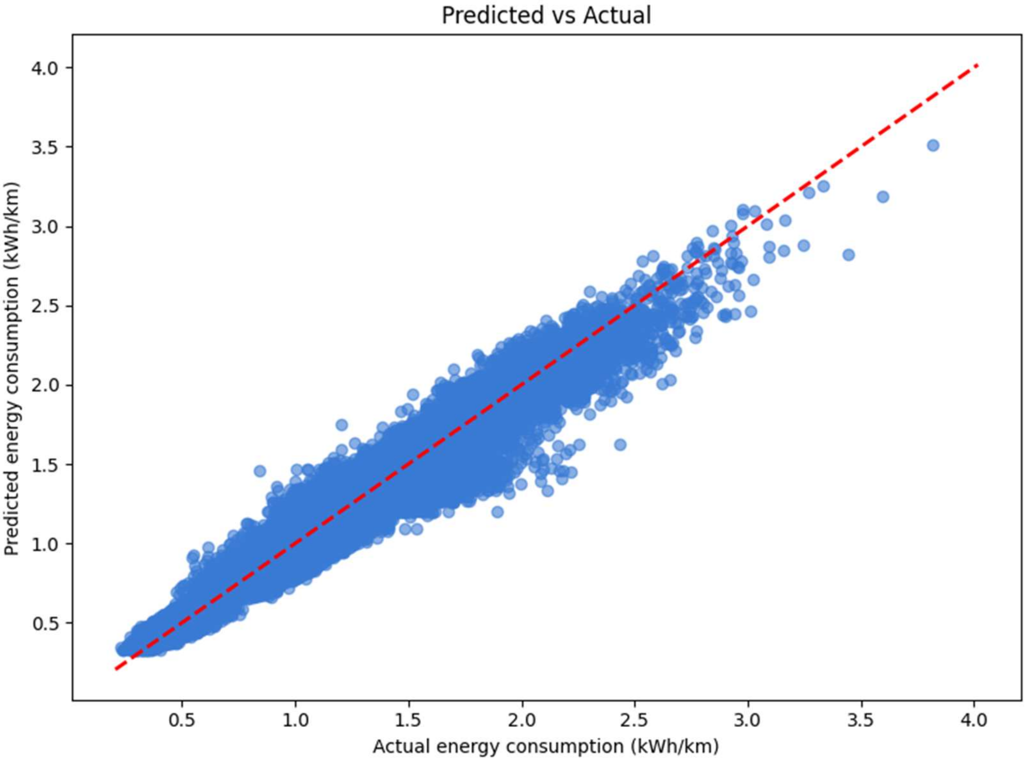

Figure 11 – Prediction of energy consumption using a random forest algorithm.

5 CONCLUSIONS

The largescale energy consumption simulations carried out in Task 3.1 provide a comprehensive and high-resolution foundation for understanding how vehicle, route, environmental, and operational factors influence the energy use of heavy-duty electric vehicles across Europe. By modelling a wide range of vehicle categories, diverse long-haul routes, and realistic variations in payload, temperature, speed limitations, and driving styles, the work offers valuable insights for the development of Megawatt Charging System (MCS) infrastructure and related operational strategies. The outcomes of the task will be utilized in the upcoming tasks developing future interactive charging demand as well as site selection and optimal locations tools.

The results confirm that total vehicle weight, speed, temperature, and route gradients are the dominant drivers of energy consumption. While lighter vehicles show lower sensitivity to elevation related features, heavier trucks and coaches exhibit strong relationships between consumption and both vehicle mass and thermal conditions. The simulations also demonstrate that small adjustments in driving style—particularly reducing unnecessary regenerative braking—can yield measurable efficiency improvements even in long-haul operations.

Beyond the analysis, the work has produced a rich dataset suitable for further research, scenario analysis, and machine learning applications. The demonstrated performance of the random forest model highlights the potential for data driven tools to support planning, prediction, and optimization tasks within MACBETH and related initiatives. The demonstrated performance of the random forest model highlights the potential for data driven tools to support planning, prediction, and optimization tasks within MACBETH and related initiatives.

Overall, this deliverable strengthens the analytical foundation for MCS deployment by providing validated, scalable, and versatile energy consumption data. These insights will support better infrastructure planning, enable more accurate charging demand forecasting, and contribute to the broader acceleration of electrified long-haul transport across Europe.

6 REFERENCES

Anttila, Joel, Yancho Todorov, Mikaela Ranta, and Mikko Pihlatie. “System-Level Validation of an Electric Bus Fleet Simulator.” 2019. https://doi.org/10.1109/VPPC46532.2019.8952293.

European Environment Agency. “Monitoring of CO2 Emissions from Heavy-Duty Vehicles - Regulation (EU) 2018/956.” 2024. https://www.eea.europa.eu/en/datahub/datahubitem-view/c52f7b51-c1cf-43e5-9a66-3eea19f6385a.

Le Corguillé, Juliette, Florian Hacker, Katharina Göckeler, Moritz Mottschall, and Theresa Dolinga. *Real-World Data Analysis of Energy Consumption, Activity and Charging Patterns of Battery Electric Trucks Operating in Germany*. Öko-Institut, 2025. https://www.oeko.de/fileadmin/oekodoc/Real-world-data-analysis-of-battery-electric-trucks.pdf.

Lopez-Ibarra, Jon Ander, Haizea Gaztannaga, Joel Anttila, Pekka Rahkola, Mikaela Ranta, and Mikko Pihlatie. “Electric Bus Forward and Backward Models Validation Methodology Based on Dynamometer Tests Measurements.” *2020 IEEE Vehicle Power and Propulsion Conference, VPPC 2020 - Proceedings*, November 1, 2020. https://doi.org/10.1109/VPPC49601.2020.9330924.

Ragon Pierre-Louis. *Real-World Use Cases for Zero-Emission Trucks*. ICCT, 2025. www.theicct.org.

Ranta, Mikaela, and Joel Anttila. “Simulated Energy Consumption of Electric Vehicles.” n.d. https://doi.org/10.5281/zenodo.18431851.

Speth, Daniel, Verena Sauter, Patrick Plötz, and Tim Signer. “Synthetic European Road Freight Transport Flow Data.” *Data in Brief* 40 (February 2022): 107786. https://doi.org/10.1016/j.dib.2021.107786.

Vehviläinen, Milla, Pekka Rahkola, Janne Keränen, et al. “Simulation-Based Comparative Assessment of a Multi-Speed Transmission for an E-Retrofitted Heavy-Duty Truck.” *Energies* 15, no. 7 (2022). https://doi.org/10.3390/en15072407.