A generalized component efficiency and input-data generation model for creating fleet-representative vehicle simulation cases in VECTO

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Abstract

The Vehicle Energy Consumption calculation Tool (VECTO) is used for the official calculation and reporting of CO_2 emissions of HDVs in Europe. It uses certified input data in the form of energy or torque loss maps of driveline components and engine fuel consumption maps. Such data are proprietary and are not disclosed. Any further analysis of the fleet performance and CO_2 emissions evolution using VECTO would require generic inputs or reconstructing realistic component input data. The current study attempts to address this issue by developing a process that would create VECTO input files based as much as possible on publicly available data. The core of the process is a series of models that calculate the vehicle component efficiency maps and produce the necessary VECTO input data. The process was applied to generate vehicle input files for rigid trucks and tractor-trailers of HDV Classes 4, 5, 9 and 10. Subsequently, evaluating the accuracy of the process, the simulation results were compared with reference VECTO results supplied by various vehicle manufacturers. The results showed that the difference between simulated and reference CO_2 emissions was on average -0.6% in the Long Haul cycle and 1% in the Regional Delivery. Such a process could be a powerful tool for calculating HDV CO_2 emissions for development and analysis purposes, e.g. for new vehicle prototypes or multistage vehicles, and for creating VECTO equivalent models that can be used to assess alternative operating conditions and mission profiles of existing vehicle models. The methodology was applied for creating input of various components in the US tool for HDV certification, GEM, for generic sample-vehicle models available.

Introduction

Heavy Duty Vehicles (HDV) account for 4% of the vehicle fleet, but despite their low share contribute to 30% of the overall greenhouse gas emissions of road transport [1]. The European Union has committed to reducing road CO_2 emissions [2], and for this reason, the European Commission has introduced a CO_2 emissions certification approach that is based on vehicle simulation [3] and subsequently proposed CO_2 reduction targets for the decade 2020-2030 [4]. Using simulation tools for certifying CO_2 emissions in the HDV sector was the solution of choice because HDV configurations are highly customizable and a laboratory measurement-based approach, like in the case of light-duty vehicles, would not be possible. A similar approach has also been adopted in other regions such as the United States and Japan [5]. In this context, the Vehicle Energy Consumption calculation Tool (VECTO) was developed as the official tool for calculating and reporting HDV CO_2 emissions.

VECTO was first launched in 2012 and has since then undergone various updates in order to become in 2017 the official tool to be used for the certification of HDV CO_2 emissions in the EU [6,5]. HDVs are highly customizable, but they exhibit some common characteristics based on their intended use, which enabled their classification into HDV classes VECTO is capable of simulating all HDV classes, which except for trucks also include buses and coaches, but the focus was given to the regulated HDV classes are 4, 5, 9 and 10. These classes include vehicles for freight transport and the primary interest also lies in the fact that they consist the bulk share of HDV [7]. The HDV classes are defined based on the vehicle type, axle configuration and minimum gross weight as described in Table 1. VECTO supports two modes for running simulations: Declaration and Engineering. Declaration mode in VECTO is used for official certification purposes and uses predefined settings for a series of parameters, such as payload and driving cycles, as foreseen by the corresponding EU regulation [8]. The Engineering mode is used for providing the user with more freedom for testing different vehicle configurations and boundary conditions.

Table 1: HDV Classes definition.

HDV Class	Vehicle type	Minimum gross vehicle weight (t)	Axle configuration
4	Rigid truck	16	4x2
5	Tractor	16	4x2
9	Rigid truck	-	6x2
10	Tractor	-	6x2

VECTO requires as input a series of parameters, some of which are publicly available, and others that are proprietary, such as the engine fuel consumption map, and hence are not available to the public. However, the use of VECTO for policy analysis, validation, research, or other purposes could be of interest to various users such as universities, and research organizations. As the lack of data could be a significant obstacle for using any simulation tool, the current study proposes an approach where a series of component models were deployed to produce the missing data and complemented by publicly available information reconstructing a reliable estimator of the EU HDV fleet performance.

The development of the component input-data models relied on JRC in-house data and information supplied by vehicle OEMs that was

used for identifying correlations between various input parameters, developing the structure of the methodology, and validating it. The study focused on HDV classes 4, 5, 9 and 10, which include rigid and tractor-trailer combinations. In this context, the current investigation proceeded by streamlining a process that generated all necessary vehicle input data to run VECTO by using as little data as possible. The next step was to test the capacity of these models to produce realistic results by implementing them into a process that would produce a significant number of simulation cases. VECTO simulation results were validated against manufacturer supplied simulation results that were provided to the JRC [9].

Methodology

The VECTO inputs can be classified into three main categories, Vehicle, Engine and Gearbox-Axle. The data input in each category can be separated into three types:

- Categorical data: The user chooses a parameter, usually from a drop-down menu, and VECTO applies the corresponsive internal function e.g. Manual Transmission (MT) or Automated Manual Transmission (AMT) gearbox type.
- Scalar data: The data are numerical inputs like the vehicle's payload and the drag area (CdA).
- Component maps: This is tabulated data that describe the component behaviour under various operation ranges. In most of the cases, this data corresponds to component efficiency like gearbox efficiency maps, while others set an operation range like the engine's full load curve.

The categorical and scalar data are defined based on the vehicle characteristics and the desired vehicle simulation parameters. The main vehicle characteristics are usually provided publicly by the manufacturer, e.g. gearbox type, vehicle curb weight. However, some vehicle data are considered proprietary, competitive information and are not disclosed, such as the vehicle's air drag value. Similarly, component maps are almost never disclosed or published. However, the component behaviour can be assessed with the use of distinct generic models, that can be subsequently be used as VECTO input. The current investigation focused on the development of a model for each of the required component maps and subsequently proceeded into validating the results. In this context, the component models were used for producing the required input, which was used for creating the respective vehicle models and running VECTO simulations. Accordingly, the VECTO results were compared with reference VECTO results.

The OEM vehicle input data that was publicly available was used and in cases that the required data was not included in the dataset, then it was retrieved from the respective websites. A simulation plan was formed based on the input data, which was used to generate the vehicle cases to be tested through the direct input of the scalar and categorical data. For the input data, which there was no information, like the component map data, the investigation applied the component models mentioned above. The vehicle sample comprised of 100 randomly chosen models from the top 200 sellers per HDV class. A summary of the vehicle characteristics is presented in the Appendix.

The simulations were run in VECTO Declaration-mode and focused on reference payload over Regional Delivery and Long-haul cycles. The respective driving cycle speed profiles are presented in Figure 1.
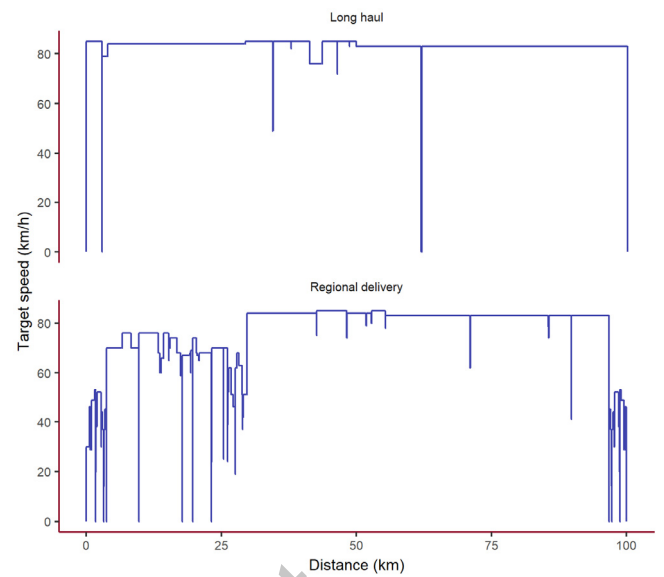
Figure 1: Driving profile of Long haul and Regional Delivery cycles [11].

The vehicle manufacturers' VECTO output was from version 3.2.0.940 and for consistency, this study used the same version.

Component models

The main approach followed to generate the component input data models was to correlate existing available data to specific, publicly available vehicle parameters. The majority of the component maps contain the following data: input rotational speed, input torque, and torque or power losses. In this sense, the input speed and torque are known parameters as they depend on characteristic vehicle values like the engine torque output. The torque losses are the parameter to be calculated and for this reason, it would be referred to as "unknown" parameter, that was linked to known parameters. The model development process summary is shown in Figure 2.

In Step 1, the normalization process that was used throughout the investigation is shown in the Eq.(1). The component map values were normalized based on a characteristic value, expected to be publicly available, such as the maximum engine torque.

$$V_{norm} = \frac{V}{V_{char}} \qquad (1)$$

V_{norm}: Normalized value

V: Value to be normalized, e.g. torque

V_{char}: A characteristic value to normalize the results, must be in the same units as V
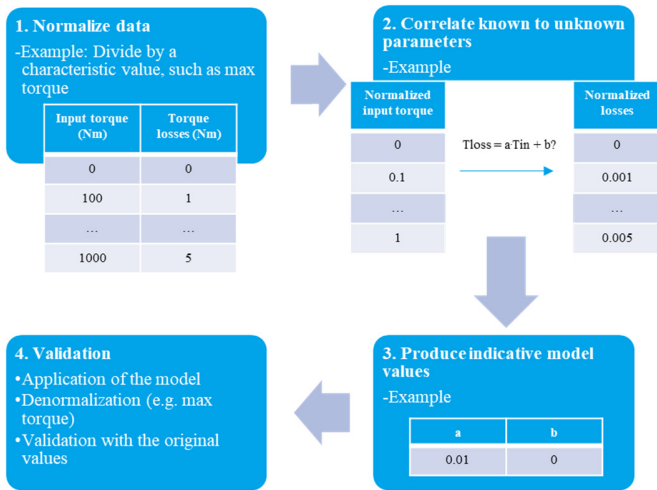
Figure 2: Model development process.

In the next Step 2, the known parameters (e.g. normalized RPMs, normalized Torque/Power) were correlated to calculate the unknown normalized parameters. The result of the process was a series of coefficients for each component input-dataset. Subsequently, in Step 3, indicative coefficients were calculated in order to provide a single input-data function/set of coefficients to be used globally for the generation of the corresponding input data throughout the vehicle class. Finally, Step 4 describes the procedure to create the respective component maps. This step involves a series of normalized values of the known parameters and the respective normalized unknown parameters, which have been calculated based on the model. Finally, all values are denormalized based on known vehicle characteristics and the VECTO component input map is created.

Figure 3 presents an example of the denormalization process. The normalized input torque is a series which ranges from 0 to 1 and the normalized losses were calculated through the use of a model. Subsequently, both series are denormalized based on the maximum input torque to produce the respective map, which is ready for input in VECTO. It should be noted that normalized values do not have units.
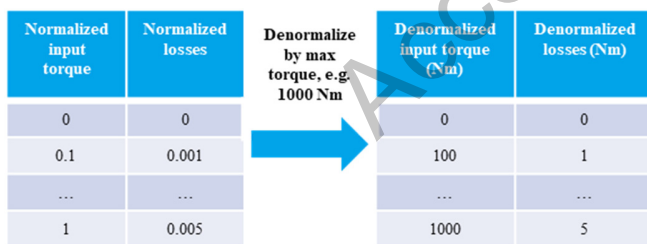

Figure 3: Example of the denormalization process. The values are indicative.

In addition to the known and unknown parameters, the various models present also the series of indicative coefficients, which have in most cases been derived from a regression analysis. The application of the models for generic use involves a series of normalized parameters and a denormalization value. The following paragraphs describe in detail the various component models and their application in VECTO.

Engine

The engine component contains technical data of both scalar and tabular types. The first describes the engine technical characteristics such as engine rated power and maximum torque. The tabular data refer to the engine fuel map and full load curve. For this reason, two models were developed: a fuel map model to calculated fuel consumption by engine operating points and a full load curve model for defining the engine operating conditions range.

Fuel map

The adopted engine fuel map model was based on a modified Willan-lines approach where Brake Mean Effective Pressure (BMEP) is linearly associated to Fuel Mean Effective Pressure (FuMEP) [9], as shown in Eq. (2).

$$FuMEP = m \cdot BMEP + q \qquad (2)$$

FuMEP: Fuel Mean Effective Pressure (bar)

BMEP: Brake mean effective pressure (bar)

The m (slope) and q (intercept) values are characteristic for each engine. In order to create representative "families" of engines, all engines characteristics and factors m and q were statistically analyzed. A Principal Component Analysis (PCA) was performed to identify possible correlations and create engine clusters. The PCA receives as input a series of parameters that are considered to be correlated and calculates a series of smaller number of variables called Principal Components. The first Principal Component is considered to account as much as possible of the dataset variability, while each following principal component accounts for less [10]. The following parameters were considered in the PCA:

- Engine rated power [kW]
- Engine idle speed [rpm]
- Engine displacement [ccm]
- Stroke [mm]
- Bore [mm]
- Compression ratio [-]
- Max torque [Nm]
- Max torque RPM [RPM]
- Cylinders [No]
- q [bar]
- m [-]

Figure 4 presents the scatter plot of Components 1 and 2 that led to the definition of seven different engine clusters (See vertical lines). The clusters are defined based on engine displacement and maximum torque and for each cluster, representative slope and intercept values can be calculated. The formula that describes the correlation of engine displacement and maximum torque is derived from the PCA as presented in Eq. (3).

$$C_i = 0.976 \cdot ec + 0.209 \cdot T_{eng\_max} \qquad (3)$$

C_i: Cluster i

ec: Engine capacity (ccm)

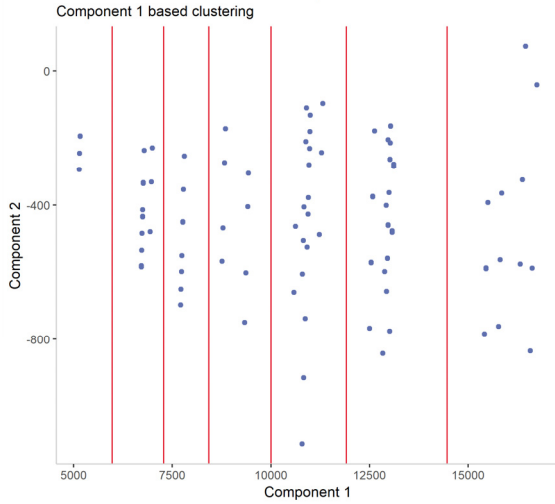T_{eng_max}: Engine maximum torque (Nm)

Figure 4: Engine clustering by Principal Component 1.

The analysis produced indicated offset and slope values by cluster, as presented in Table 2. The process to identify in which cluster an engine belongs to, requires the calculation of the Component 1, with the Eq.(3).

Table 2: Offset and slope values by engine cluster.

Cluster	Cluster range	Offset	Slope
1	[0 - 5977)	1.411	2.246
2	[5977 - 7280)	2.656	2.261
3	[7280 - 8429)	2.142	2.222
4	[8429 - 10005)	2.691	2.155
5	[10005 - 11909)	2.393	2.11
6	[11909 - 14465)	1.896	2.146
7	[14465 -)	2.283	2.149

Having the corresponding offset – slope values from Table 2 the engine fuel map to be used in VECTO can be calculated as follows. An engine power-speed grid is created that covers the whole operation range of the engine. For each one of these points, the BMEP value was calculated based on Eq.(4)

$$BMEP = \frac{2 \cdot ep}{ec \cdot RPS \cdot 10^{-6}} \cdot 10^{-5} \tag{4}$$

ep: Engine power (W)

RPS: Engine speed (Hz)

For each one of the operation points, the FuMEP is calculated according to Eq.(2) with the offset and slope values that were retrieved from Table 2. Finally, fuel consumption is calculated based on Eq.(5).

$$FC = \frac{FuMEP \cdot ec \cdot RPS}{2 \cdot LHV} \cdot 3.6 \cdot 10^4 \tag{5}$$

FC: Fuel consumption (g/h)

LHV: Fuel's Lower Heating Value (J/g)

Full load curve

The full load curve model made use of the observation that full load curves resemble a trapezoid shape with vertices that correspond to specific operation points. Taking this into consideration the full load curve model makes use of a normalized curve with 5 operation points, as shown in Figure 5.
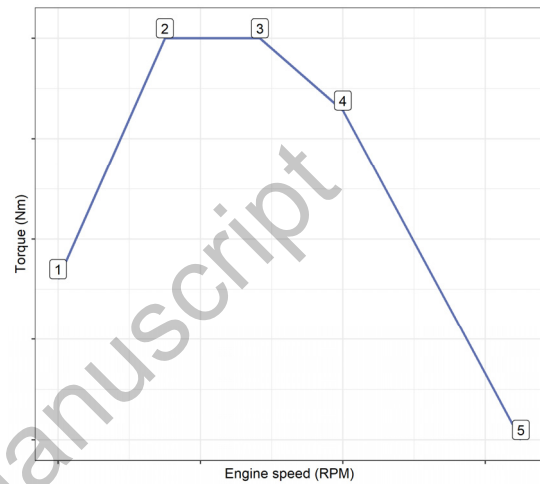

Figure 5: Normalized generic full load curve and operation points.

Each one of the 5 points represents the following operation points:

- Point 1 is the idling point
- Point 2 is the point with the minimum engine speed that maximum torque is achieved
- Point 3 is the point with the maximum engine speed that maximum torque is achieved
- Point 4 is the point of the engine's rated power and rated speed
- Point 5 is the maximum engine speed where torque reaches zero

The 5 points of the normalized generic full load curve have representative cluster values that are derived from the PCA. The normalized engine speed and torque values are presented in Table 3 and Table 4, and the cluster is chosen again by calculating Component 1, with the use of Eq.(3).

Point 4 torque value of the generic curve is replaced by normalizing the modeled engine's rated power. The engine's power is converted to torque and then it is normalized based on Eq.(1) with engine's maximum torque and V_{char}.

Table 3: Normalized engine speed values by cluster.

Cluster	Cluster range	Point 1	Point 2	Point 3	Point 4	Point 5
1	[0 - 5977)	0	0.38	0.66	1	1.39
2	[5977 - 7280)	0	0.32	0.71	1	1.24
3	[7280 - 8429)	0	0.37	0.65	1	1.38
4	[8429 - 10005)	0	0.36	0.61	1	1.34
5	[10005 - 11909)	0	0.31	0.73	1	1.57
6	[11909 - 14465)	0	0.31	0.67	1	1.55
7	[14465 -)	0	0.32	0.66	1	1.58

Table 4: Normalized engine torque values by cluster.

Cluster	Cluster range	Point 1	Point 2	Point 3	Point 4	Point 5
1	[0 - 5977)	0.27	1	1		0
2	[5977 - 7280)	0.23	1	1		0
3	[7280 - 8429)	0.35	1	1	Point of rated power and speed	0
4	[8429 - 10005)	0.39	1	1		0
5	[10005 - 11909)	0.49	1	1		0
6	[11909 - 14465)	0.38	1	1		0
7	[14465 -)	0.34	1	1		0

Once the cluster is identified according to Eq.(3) and the corresponding normalized points are retrieved from Table 3 and Table 4, the full load torque points can be denormalized according to Eq.(6). Linear interpolations between the points can be used to fill in a higher-resolution matrix of the full load curve.

$$\text{T} = T_{norm} \cdot T_{eng\_max}$$

$$RPM = RPM_{norm} \cdot (RPM_{rated} - RPM_{idle}) + RPM_{idle}$$

(6)

T: Torque (Nm)

T_{norm}: Normalized point torque (-)

RPM: Engine speed (RPM)

RPM_{norm}: Normalized engine point speed (-)

RPM_{rated}: Engine rated speed (RPM)

RPM_{idle}: Engine idle speed (RPM)

Driveline

The driveline component contains the axle, gearbox, and torque converter components. As the axle and the gearbox have similar behavior, these two components were examined together, and a common model was developed. The torque converter is employed at vehicles with automatic transmission, but due to the low market share

of these vehicles (~3% of the rigid trucks) [9], this component was not investigated in the present study.

Axle and gearbox models

The axle and gearbox models were derived from a series of maps that contained the input speed, input torque, and torque losses. Accordingly, the normalization process for each of the datasets was realized based on Eq.(1), with V_{char} as presented in Table 5. The values are multiplied by 1.3 as a safety margin to ensure that all operation conditions are covered.

Table 5: Axle and gearbox normalization V_{char}.

Component	Input speed V_{char}	Input torque V_{char}	Torque losses V_{char}
Gearbox	Gearbox max speed x 1.3	Gearbox max torque x 1.3	Gearbox max torque x 1.3
Axle	Axle max speed x 1.3	Gearbox max torque x Gear 1 ratio x 1.3	Gearbox max torque x Gear 1 ratio x 1.3

Subsequently, the model that it was developed for the axle and gearbox components that correlated torque losses to the input speed and torque, which is presented in Eq.(7).

$$T_{loss} = A + B \cdot A_{in} + C \cdot |T_{in}|$$

(7)

A_{in}: Input speed (RPM)

T_{in}: Input torque (Nm)

The application of the model requires normalized series of the ranges as shown in Table 6.

Table 6: Normalized torque and speed range for gearbox and axle.

Component	Normalized torque range	Normalized speed range
Gearbox	From -3.5 to 3.5	From 0 to 2
Axle	From -3.5 to 3.5	From 0 to 2

The torque and speed are denormalized as in Eq. (8).

$$A_{in} = A_{norm} \cdot A_{in\_max}$$

$$T_{in} = T_{norm} \cdot T_{in\_max}$$

(8)

$$T_{loss} = (a + b \cdot A_{in} + c \cdot |T_{in}|) \cdot T_{in\_max}$$

T_{in}: Input torque (Nm)

T_{norm}: Normalized torque (-)

a, b, c: coefficients of the loss model

Table 7 presents a series of indicative axle and gearbox coefficients that can be used in the respective model. It was found that gearbox direct gears (gear ratio = 1) have a different set of coefficients than

the indirect gears (gear ratio ≠1). For this reason, two sets of coefficients are provided.

Component		a	b	c
Gearbox	Indirect	0.001	0.27	0.05
	Direct	0.001	0.27	0.01
Axle		0.0005	0.02	0.04

Retarder

There are several retarder types that are supported by VECTO, depending on the component placement within the vehicle. In some cases, the retarder is integrated within other components, such as in the gearbox. The current model describes stand-alone components and it can be applied regardless of the component's position in the vehicle.

The retarder model was derived from JRC retarder data that contained the retarder speed and the torque losses. The normalization was done according to Eq.(1) and made use of the maximum input speed and torque as V_{char} values. Following, the normalized torque losses were correlated with the normalized retarder speed with second-order polynomial regression and the average polynomial coefficients were calculated.

The application of the model requires a normalized series of the input retarder speed with a range of 0 to 1, which is denormalized based on the retarder's maximum input speed. Subsequently, the calculation of the torque losses for any given retarder is realized through a denormalization process as in Eq.(9)

$$T_{loss} = (a \cdot A_{norm}^2 + b \cdot A_{norm} + c) \cdot T_{in\_max}$$

$$A_{ret} = A_{norm} \cdot A_{in\_max}$$

(9)

T_{loss}: Torque losses (Nm)

T_{in_max}: Maximum input torque (Nm)

A_{norm}: Normalized speed (-)

A_{in_max}: Maximum input speed (RPM)

A_{ret}: Retarder speed (RPM)

a, b, c: Coefficients of the loss model

Table 8 presents a series of indicative coefficients for the retarder model.

a	b	c
2.342×10^{-2}	0	4.684×10^{-3}

Application in GEM

The described models were designed based on European data for use in VECTO, but their use could be considered in any simulation tool operating under the same modeling principles, and different types of vehicle models after a recalibration of the main input-data generation models. The Environment Protection Agency (EPA) in the United States (US) uses the Greenhouse Gas Emissions Model (GEM) for simulating HDV CO_2 emissions for regulatory purposes. The present investigation considered the sample vehicles, that are included in the public GEM distribution, and attempted to apply the component efficiency models for creating the necessary input to run GEM. Due to the limited data availability, it was only possible to apply the engine fuel map and the gearbox models. Table 9 presents the vehicle IDs of the GEM sample models, along with the simulated components and the engine technical characteristics that were used for generating the component maps. Most of the vehicles were US truck class 8, which corresponds to gross vehicle weight of over 14,969 kg, while a single truck was US truck class 7 that corresponds to a gross vehicle weight of 11,794 – 14,969 kg.

Vehicle ID	US truck class	Simulated component	Engine capacity (ccm)	Max torque (Nm)	Axle configuration	CdA (m²)
1	8	Engine	15000	2100	6x4	5.4
2	7	Engine	11000	1590	4x2	5.1
3	8	Engine	15000	2800	6x4	NA
4	8	Engine	15000	2800	6x4	5.07
5	8	Engine	15000	2100	6x4	5.35
6	8	Engine	15000	2100	6x4	5.18
7	8	Engine, gearbox	15000	2100	6x4	4.88

The GEM output was converted from g CO_2/ton-mile to g/tkm for comparability purposes.

Results and Discussion

The abovementioned methodology was used to create the necessary input for running VECTO and at a later step GEM. The results of the VECTO simulations are compared below to those received initially from the vehicle OEMs, focusing on the overall "fleet-wide" performance and accuracy rather than the vehicle-to-vehicle one. Finally, an energy audit is presented focusing on individual component for the two types of data (JRC and OEM simulated). The section concludes with the presentation of the GEM simulation results.

Validation

The first step was to calculate the relative CO_2 emissions difference between the simulation results calculated by VECTO using input data created as per the methodology described, and the OEM provided reference values. As a second step a brief statistical analysis is introduced in order to identify trends and skews in the results. Figure 6 presents a distribution of the CO_2 emissions relative difference by cycle and HDV class.
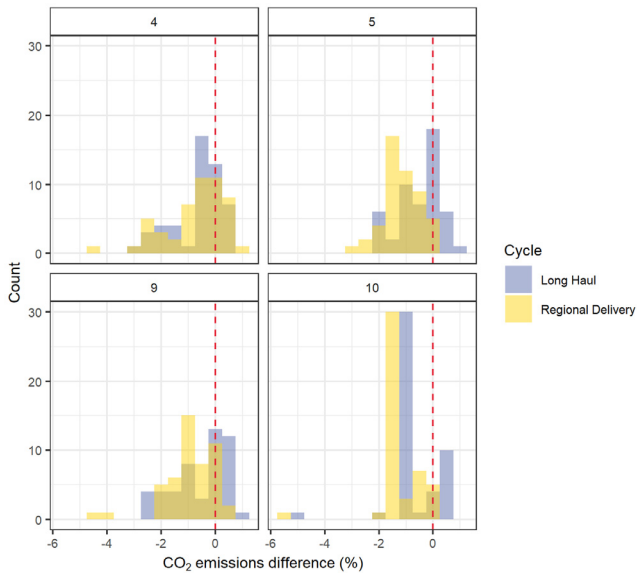

Figure 6: Histogram of CO_2 emissions relative difference (methodology/reference-1 [%]) by HDV Class and mission profile

The errors introduced by the methodology remain in most cases within a limited range not exceeding ±2%. This is a very positive finding which demonstrates that the methodology could be applied for fleet wide estimates introducing a limited bias in the final results. The distributions appeared to be skewed to the left, suggesting a trend of the proposed methodology to underestimate emissions. A more detailed view of this trend can be found in Table 10.

Table 10: Statistical analysis of CO_2 relative difference (as per Figure 6)

Cycle	HDV class	Mean	Median	Min	Max	Standard deviation
Long Haul	4	-0.6%	-0.4%	-2.8%	0.4%	0.9%
	5	-0.5%	-0.2%	-2.2%	1.0%	0.8%
	9	-0.5%	0.0%	-2.6%	1.2%	1.0%
	10	-0.7%	-0.9%	-5.0%	0.6%	0.9%
Regional Delivery	4	-0.7%	-0.6%	-4.7%	0.8%	1.1%
	5	-1.2%	-1.2%	-2.9%	0.1%	0.7%
	9	-1.0%	-0.8%	-4.3%	0.5%	0.9%
	10	-1.3%	-1.4%	-5.4%	0.0%	0.8%

The mean relative difference is lower in the Long Haul than in the Regional Delivery cycle, which could be attributed to the fact that the

Long Haul cycle has higher mean target speed making the air drag losses more prominent [12] than other loss factors. At lower speeds, such as in the Regional Delivery, the vehicle internal losses have higher contribution than the drag area. In this case, the mean relative difference was about -1%, while for the Long Haul was -0.6%. However, it is interesting that the mean standard deviation was the same ~0.9% for both cycles. The apparent skew towards lower estimates is in-line with the findings of a JRC study, which examined OEM data and proceeded into a normalization of the results [9].
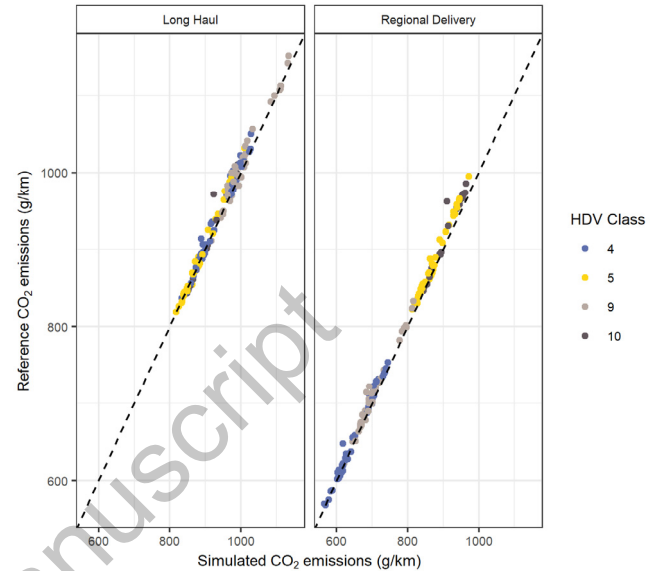

Figure 7: Comparison of reference and simulated CO_2 emissions.

Figure 7 presents a comparison by driving cycle between the simulated CO_2 values and the respective reference values for all vehicles. The simulated CO_2 emission values showed a good convergence with the validated values and in order to quantify the accuracy of the models, Table 11 presents the Root Mean Squared Error (RMSE) by HDV class and driving cycle.

Table 11: RMSE by HDV class and driving cycle.

HDV class	Long Haul	Regional Delivery
4	10.34	9.21
5	8.97	12.24
9	11.58	9.66
10	11.02	14.61

The CO_2 emission range is ~900 – 1000 g/km in the Long Haul and between 650 and 930 g/km in the Regional Delivery and in this sense the RMSE could be considered low.

As a next step, the performance at component level was assessed, comparing the simulated and reference values per each component. The assessment was based on VECTO energy output values and calculated the relative difference between simulated and reference values. Figure 8 presents the comparison, with the error bars corresponding to one standard deviation. The gearbox losses were examined separately as they showed higher divergences.
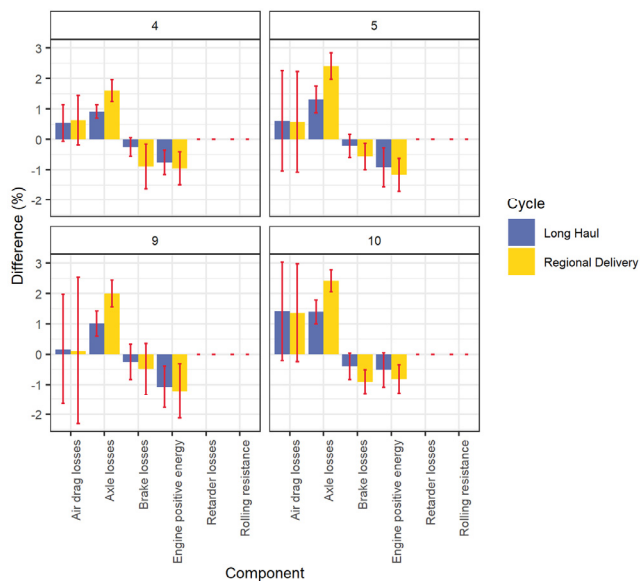
Figure 8: Error in energy loss estimation by component or resistance source

Overall, the energy losses in the various components and resistances were simulated quite accurately remaining in all cases within a ±3% of the reference values. Air drag losses showed high standard deviation, that could be attributed to the drag area determination. The vehicle cab dimensions, that were used for calculating the frontal area, were publicly available [12,9] and occasionally due to lack of information some vehicles could have been associated to the wrong or inaccurate cab dimensions. There is also a wide uncertainty regarding the aerodynamic drag coefficient of individual vehicles. The remaining components presented an average divergence of up to 2.5%, except for the gearbox which discussed separately (Figure 9).
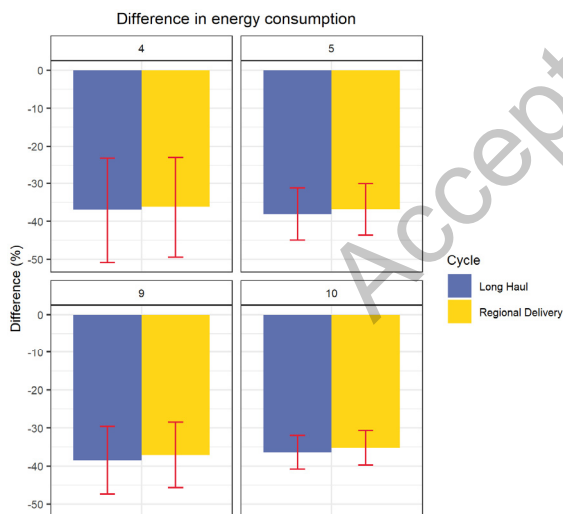

Figure 9: Error in energy loss estimation at the gearbox

The error in the gearbox energy losses extends down to almost -40%, suggesting a consistent underestimation across all HDV classes and cycles. This observation could partly explain the bias of the simulated values towards lower CO_2 emissions. There are different possible explanations for such a behavior. The sample gearbox loss maps used for calibrating the torque loss model at the gearbox correspond to more efficient and recent gearboxes. In addition it has been suggested

that for reducing certification costs, the gearbox manufacturers do not measure torque loss maps over all gears, but only for the most relevant ones (eg last 3 gears). The rest of the VECTO input is supplemented by generic values which tend to overestimate energy loss in an effort to incentivize the use of test-derived loss values. One should consider that the axle losses were calculated using a similar physical model regarding the energy losses introduced at a geared connection that performed quite accurately, so it is unlikely that the physical model does not function in the case of individual gears. Further investigation and calibration data are necessary in order to address this issue.
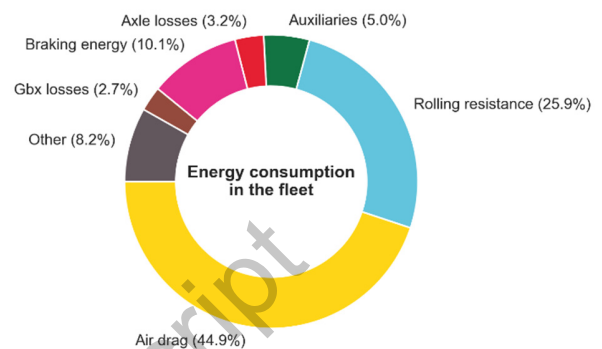

Figure 10: HDV fleet energy losses breakdown [13]

According to [13], the gearbox losses comprise a low share of the overall vehicle losses, as shown in Figure 10. Gearbox losses comprise 2.7% of the overall vehicle losses, which explains the low impact on CO_2 emissions. Further improvement could reduce the divergence and produce a more reliable model.

In addition, Figure 10 highlights the importance of also using accurate scalar values, e.g. CdA and rolling resistance coefficient. Proxies for these values will be available from official sources in Europe, as for example RRC can be obtained by the tire energy class and the vehicle aerodynamic drag class will be published in the future.

Fleet-wide analysis

The following figures provide an overview of the CO_2 emissions of the JRC simulated vehicles (in g/km and g/tkm) for all 4 vehicle classes. Figure 11 presents the distribution of CO_2 g/km emissions by HDV class and cycle. Table 17 in the Appendix presents detailed statistical data of the CO_2 emissions with the g/km metric by HDV class for each cycle.

Figure 11: Distribution of CO$_2$ emissions (g/km) by HDV class.

The distribution shows that CO$_2$ emissions are significantly higher in the Long Haul cycle than in the Regional Delivery for the rigid trucks. The explanation for this lies in the fact that rigid trucks are considered to be towing a trailer in the Long Haul cycle, which significantly increases the vehicle's curb weight by 5.4 t. A more suitable metric to capture the transport efficiency would be to present the CO$_2$ emissions per tonne-kilometer (g/tkm), as shown in Figure 12. The metric refers to the tonne of payload transferred and not to the total vehicle weight. Table 18 in the Appendix presents more detailed statistical data of the g/tkm metric for CO$_2$ emissions by HDV class and driving cycle.

This analysis could be used as a proxy of the average vehicle emissions and should not be mistaken with average fleet emissions, as the results do not reflect weighted average emissions. However, it could be a starting point for assessing overall CO$_2$ emissions from the freight transport section in future research.
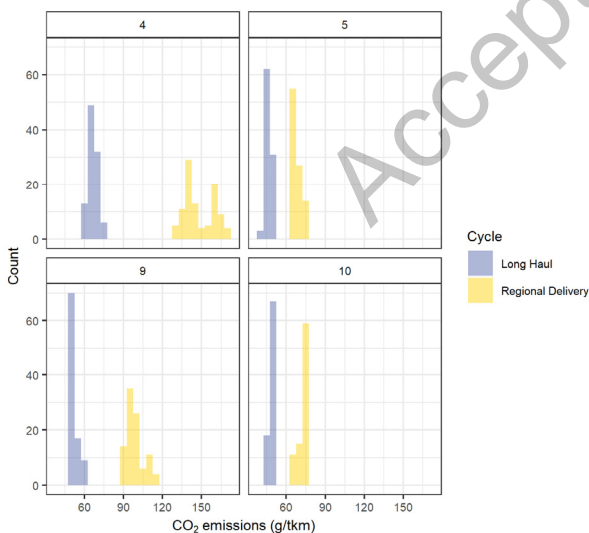
Figure 12: Distribution of CO$_2$ emissions (g/tkm) by HDV class.

Energy audit

In order to better understand the performance of the developed methodology in depth, the simulation results are studied at component level together with the energy dissipation. In the context of an energy audit, the analysis investigated component energy values, along with the air drag, rolling resistance and brake losses. The values were initially expressed in kWh and they were normalized through conversion to a percentage of the engine positive work. Figure 13 presents the overall energy consumption by component.
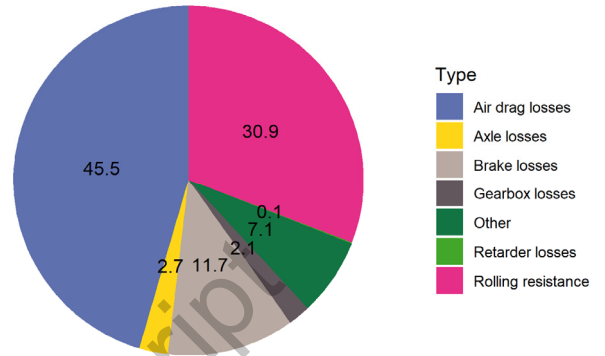

Figure 13: Overall energy consumption breakdown

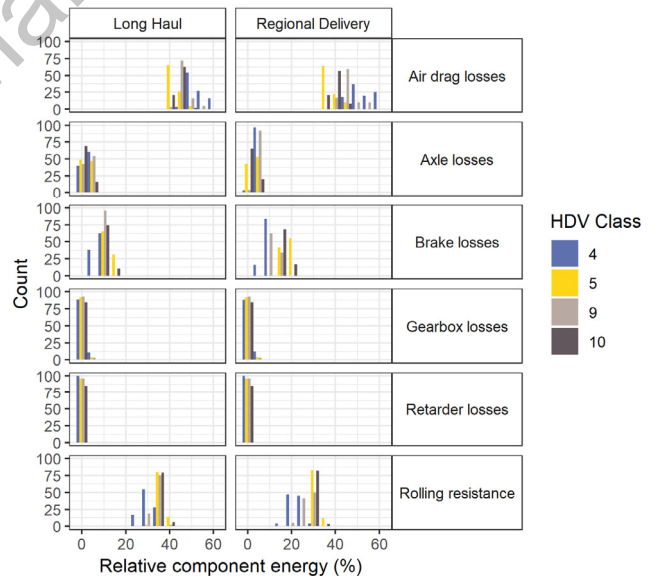The distribution of the various energy losses are presented in detail in Figure 14

Figure 14: Distribution of relative component energy.

The values present a uniform distribution in the case of gearbox and retarder losses, while there is a tendency to normal distribution in the other cases. In the next step, a comparison of the relative component energy between the simulated and the reference values could provide a proxy of the accuracy of the method. Figure 15 presents a comparison of the energy audit between the simulated and the reference values.
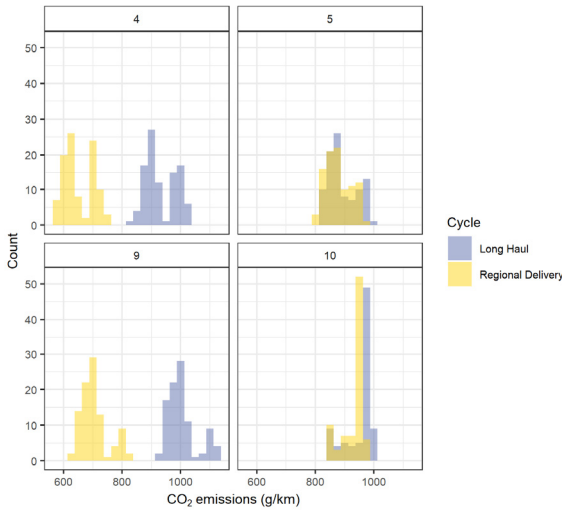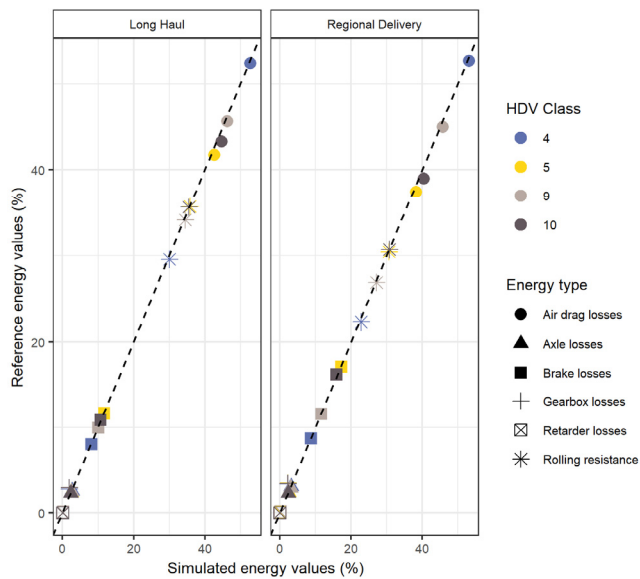
Figure 15: Comparison of energy consumption between simulated and reference values.

The comparison shows a convergence between the validated and simulated values. The average difference between the simulated and validated gearbox values was -1% for the Long Haul and -1.2% for the Regional Delivery, while the respective axle values were 0.04% and 0.08%. The retarder losses average difference was almost zero as these losses attribute to a small percentage of the overall vehicle losses. In general, the energy values expressed as a percentage of the engine output work showed good convergence with the reference values and it could be considered that the various component models sufficiently capture the component behavior within the simulation scenario.

Use in GEM

The investigation focused on seven GEM sample vehicle models producing their engine fuel maps, while for one vehicle it was also possible to produce the gearbox efficiency map. At this point the main assumption made was that these components exhibit more or less the same behavior both in Europe and the US. Figure 16 presents a comparison between the values of the reference GEM model results and the simulations run using input data generated based on the proposed method. The divergence ranged from 0.67% to 6.82% and the highest divergence was observed at the model where the gearbox efficiency map was also simulated. However, it should be taken into consideration that all the generated component models have been calibrated based on European truck and component data, which could explain the divergence on the application on US trucks. In this sense, the Vehicle 2, which had the lowest divergence, had an engine capacity of 11000 ccm and an axle configuration 4x2, which is close to the 11120 ccm of a similar European vehicle of Class 5 [9]. All the other GEM models had an axle configuration of 6x4, which has not been investigated, and engine capacities of 15000 ccm that is significantly higher than the overall average engine capacity of 12740 ccm in Europe [9]. The use of component efficiency models shows a potential use for vehicles outside Europe, provided that model parameters are calibrated according to the characteristics and particularities of the components in each market. Future research could focus in calibrating and validating these models for GEM in the

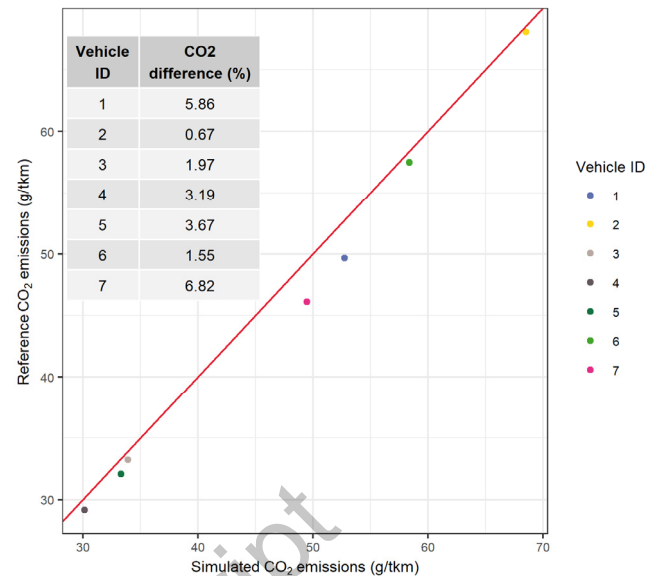United States or in other regions provided that the necessary data are available.

Figure 16: Comparison of GEM results between original efficiency maps and modelled component maps.

Conclusions

The current study introduced a method to reliably produce VECTO input data when certified input data regarding specific component are not available. A series of simulation cases were generated by applying the method and making use of publicly available data for a series of reference cases. Initially, the method was validated by comparing simulated and reference CO_2 emissions and subsequently on component level through comparison of the respective energy values. The approach resulted in low errors for CO_2 emissions with a mean difference compared to the reference emissions of -0.6% in the Long Haul cycle and -1% for the Regional Delivery cycle. In the energy losses comparison, most of the components were found on average up to 2.5% divergence with the reference values, with the exception of the gearbox, which presented high losses and should be further improved. The described methodology showed to be reliable in generating the vehicle cases and simulating CO_2 emissions. The methodology could be deployed to generate simulation data for a single vehicle case or for generating multiple cases that could cover the vehicle fleet. In addition, the process could be expanded by improving further the models and also including technologies that have not been investigated, such as torque converter and automatic transmission. Having a complete such process could be a powerful tool for calculating HDV CO_2 emissions for development and analysis purposes, such as in the case of prototypes, multistage vehicles or for creating VECTO equivalent models for assessing alternative operating conditions and mission profiles. Additionally, the methodology showed a potential for use in simulation tools other than VECTO, such as GEM.

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Disclaimer

The views expressed in this paper are purely those of the authors and shall by no means considered as an official position of the European Commission

Definitions/Abbreviations

ACEA	Association des Constructeurs Européens d'Automobiles (European Automobile Manufacturers' Association)
AMT	Automated Manual Transmission
BMEP	Brake Mean Effective Pressure
CdA	Drag area (m^2)
EPA	Environment Protection Agency
FuMEP	Fuel Mean Effective Pressure
GEM	Greenhouse Gas Emissions Model
HDV	Heavy Duty Vehicle
JRC	Joint Research Centre
LHV	Lower Heating Value
MT	Manual Transmission
OEM	Original Equipment Manufacturer
PCA	Principal Component Analysis
RMSE	Root Mean Squared Error
RPM	Revolutions per Minute
RPS	Revolutions per Second
RRC	Rolling Resistance Coefficient (-)
VECTO	Vehicle Energy Consumption calculation Tool

Appendix

Table 12: Vehicles' engine rated power statistics. Units = kW

HDV Class	mean	median	min	max
4	287.5	294	228	375
5	334.9	338	265	375
9	318.0	320	228	420
10	332.5	330	290	420

Table 13: Vehicles' engine rated speed statistics. Units = RPM

HDV Class	mean	median	min	max
4	1964	1900	1700	2200
5	1834	1800	1700	1900
9	1877	1800	1700	2200
10	1817	1800	1750	1900

Table 14: Vehicles' engine displacement statistics. Units = ccm

HDV Class	mean	median	min	max
4	10440	10677	8710	12880
5	11790	11120	10677	12880
9	11465	11120	8710	12880
10	12316	12809	10677	12880

Table 15: Vehicles' drag area statistics. Units = m^2

HDV Class	mean	median	min	max
4	6.66	6.20	4.95	8.41
5	6.46	5.89	5.49	8.71
9	6.31	5.88	5.04	8.52
10	7.42	7.87	5.50	8.60

Table 16: Vehicle's rolling resistance coefficient. Units = dimensionless

HDV Class	mean	median	min	max
4	0.0060	0.0060	0.0047	0.0074
5	0.0058	0.0057	0.0049	0.0065
9	0.0061	0.0061	0.0050	0.0070
10	0.0060	0.0060	0.0053	0.0066

Table 17: Statistical analysis of CO_2 emissions (g/km).

Cycle	HDV class	Mean	Median	Min	Max	Standard deviation
Long Haul	4	931.5	913.2	833.9	1029.5	54.2
	5	892.4	881.4	813	1010.4	50.1
	9	1004.8	997	916.8	1133.9	52.6
	10	951.8	973.1	847.4	1006.1	45.2
Regional Delivery	4	651.8	632.2	566.2	744.8	50.4
	5	876.9	868.4	806.6	971.6	42.2
	9	703.8	691.4	622	816.4	47.2
	10	930.7	947.6	839.8	974.7	37.6

Table 18: Statistical analysis of CO_2 emissions (g/tkm).

Cycle	HDV class	Mean	Median	Min	Max	Standard deviation
Long Haul	4	66.5	65.2	59.6	73.5	3.9
	5	46.2	45.7	42.1	52.4	2.6
	9	52.1	51.7	47.5	58.8	2.7
	10	49.3	50.4	43.9	52.1	2.3
Regional Delivery	4	148.1	143.7	128.7	169.3	11.5
	5	68	67.3	62.5	75.3	3.3
	9	99.1	97.4	87.6	115	6.6
	10	72.1	73.5	65.1	75.6	2.9