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Integration of Real Driving Data into the Electric Powertrain Design Process for Heavy-duty Trucks

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Abstract

While the share of electric vehicles in the passenger car sector is steadily increasing, electrification in the commercial vehicle sector is progressing much slower. The reasons include lower production figures and an even stronger focus on efficiency and costs. When developing new powertrain systems, it is crucial to consider individual user and application requirements. Real driving data representing the demands of different application scenarios can be integrated into the development process and combined with a modular and holistic concept design approach for drive modules to accelerate and automate powertrain development. This process is being developed at the Institute for Automotive Engineering (ika) of RWTH Aachen University. In this paper, the application potential for real driving data within the concept design of drive modules for heavy trucks is analysed and current research projects at ika in the field of heavy-duty vehicle powertrain development are presented.

Content

1 Introduction and Motivation

The reduction of CO_2 emissions is one of the most important tasks of the current era. At 8.8 Gt CO_2 in 2022, global mobility-related emissions represent a significant share of the 36.8 Gt total CO_2 emissions [1]. Road freight transport in particular has a major share in this. Road freight transport in particular has a major share in this. The substantially lower quantity of trucks is overcompensated by the high mileage. In 2022, transport performance in Germany was 504.8 billion ton kilometres [2].

The electrification of vehicles represents a promising opportunity to reduce both local and global CO_2 emissions. At the same time, it presents one of the greatest challenges for vehicle manufacturers, suppliers and the customers. Aspects such as range, charging speed, reliability and durability are even more important in the commercial vehicle segment than for passenger cars for economic operation. In order to design and optimise new electric vehicles to their specific requirements, new methods are required as well. Currently, the design of electric powertrains is mainly based on reference data and load collectives available internally to the vehicle manufacturers, but less real driving data, which is publicly available or can be easily generated. For application-specific design of powertrains however, representative driving profiles are essential. These can be derived from measured real driving data, improving the development process for electric powertrains in heavy-duty vehicles.

2 General Methodology

In order to assist the process of powertrain electrification for heavy-duty trucks, a methodology of holistic powertrain concept design has been developed at the Institute for Automotive Engineering (ika). This method is extended by the integration of real driving data to derive application-specific design requirements within the research project “BEV Goes eHighway – BEE”. The general methodology is shown in Fig. 1.

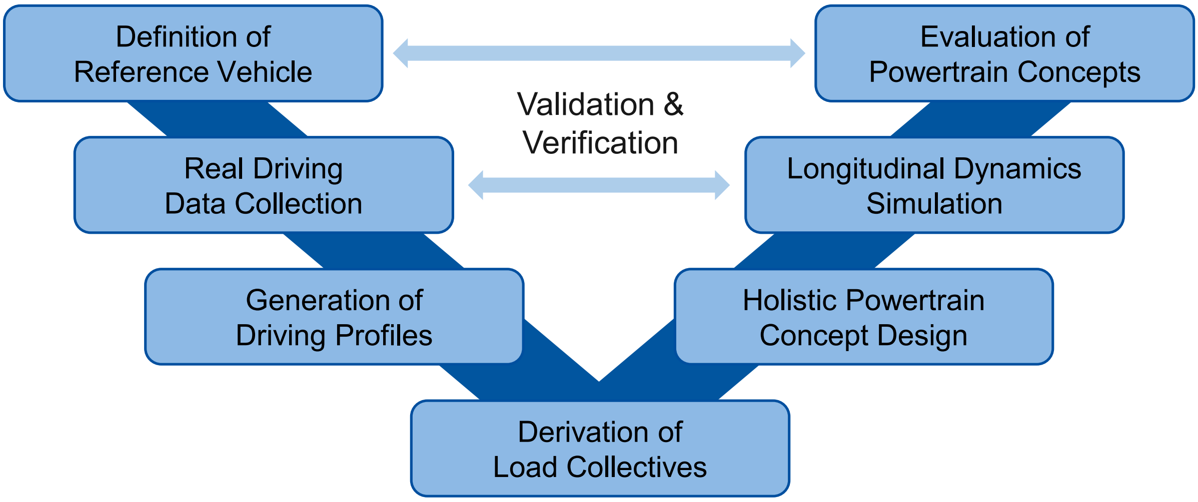

Fig. 1 V-model: Methodology of extended powertrain design at ika

The methodology of real driving data-based holistic powertrain design begins with the definition of a conventional diesel-powered reference vehicle, which is to be electrified or substituted by a requirement-appropriate electric vehicle. From the reference vehicle, static base and application-dependent requirements such as maximum velocity and gross vehicle mass (GVM) are derived and requirements specific for the vehicle type and segment such as legal or market requirements are defined.

The second step in the design process consists of real driving data collection of the reference vehicle during its normal operation. The data sets consists of vehicle and driving parameters as well as environmental information, which are measured with an in-house developed data logger.

From the measured real driving data, representative driving profiles are generated for the reference vehicle. These driving profiles consist of the relevant parameters describing the vehicle’s longitudinal behaviour, such as velocity, acceleration and road gradient. Additionally, influences on the profiles outside of driving such as changing cargo mass during loading and unloading as well as auxiliary consumers are taken into account.

The generated driving profiles of the defined reference vehicle serve as basis to derive load collectives for designing the powertrain components electric motor, inverter, transmission and battery. In combination with a pre-selected powertrain topology, load collectives are derived for the individual components to determine efficiency and lifetime during the powertrain design process.

Within the holistic powertrain design process, concepts of electric powertrains for heavy-duty trucks are designed and evaluated. Based on the defined static requirements as well as the derived load collectives, the individual powertrain components are designed and valid variants are selected. Subsequently, the component variants are combined to full powertrain concepts and evaluated on vehicle level utilising a developed digital twin with the powertrain concept parameters.

3 Measurement of Real Driving Data

In order to model the driving behaviour of heavy-duty trucks realistically, necessary parameters and characteristics must be identified first. Since the powertrain concept design focuses on longitudinal dynamic driving behaviour, the first important parameters to be measured can be derived from the equation of longitudinal motion and driving resistances, which is given in Eq. 1.

$$\ddot{x} = \frac{1}{(e_i \cdot m_{veh} + m_{cargo})} \cdot \left[\frac{T_{wheel}}{r_{dyn}} - (F_r + F_{cl} + F_{air})\right] \quad \text{Eq. 1}$$

The given equation represents the relation between acceleration $\ddot{x}$, drive torque at the wheel T_{wheel} and driving resistances. Here, m_{veh} is the static vehicle mass, m_{cargo} is the cargo mass, e_i the mass factor, an equivalent of the rotational masses of the powertrain, r_{dyn} is the dynamic wheel radius and F_r, F_{cl}, F_{air} are rolling resistance, climbing resistance and aerodynamic drag. The equations of the stationary driving resistance forces are given in Eq. 2 to Eq. 4 respectively.

$$F_r = c_r \cdot (m_{veh} + m_{cargo}) \cdot g \cdot cos\,(\alpha) \quad \text{Eq. 2}$$

$$F_{cl} = (m_{veh} + m_{cargo}) \cdot g \cdot sin\,(\alpha) \quad \text{Eq. 3}$$

$$F_{air} = 0.5 \cdot c_d \cdot A_{front} \cdot (\dot{x} + v_{wind})^2 \quad \text{Eq. 4}$$

Here, c_r is the tyre friction coefficient, g the gravitational acceleration constant ($g = 9.81\ ms^{-2}$), α the road gradient, c_d the aerodynamic drag coefficient, A_{front} the vehicle's frontal area, $\dot{x}$ the vehicle velocity and v_{wind} the wind speed.

While some of the longitudinally relevant parameters are constant and need to be taken from the reference vehicle, others need to be measured during vehicle operation. An overview of the parameters and their origin is given in Tab. 1.

Tab. 1 Longitudinally relevant parameters and their origin

Origin	Parameter	Unit
measured/estimated	$\ddot{x}$	$\mathrm{m/s^2}$
	α	deg
	$\dot{x}$	$\mathrm{m/s}$
	m_{cargo}	kg
concept design	e_i	–
	m_{veh}	kg
	r_{dyn}	m
	c_r	–
	c_d	–
	A_{front}	$\mathrm{m^2}$
load collective	T_{wheel}	Nm

neglected	v_{wind}	$\mathrm{m/s}$

Except the wind speed, all relevant parameters are derived from the reference vehicle, can be measured or are simulated later in the concept design stage. For the measurement parameters, available options for logging in vehicle applications are identified and evaluated: While vehicle velocity can be received e.g. from the wheel speed or from *Global Navigation Satellite Systems* (GNSS) such as the *Global Positioning System* (GPS), the road gradient cannot be measured directly from the vehicle.

Apart from the longitudinally relevant parameters, which describe the current vehicle state during operation, additional driving state parameters are required for the generation of representative driving profile, such as the actual engine torque and driver demand torque. These parameters are made available by the SAE J1939 standard for networking and communication within commercial vehicles [3].

For measuring both physical parameters as well as vehicle communication simultaneously, a dedicated data logger is being developed at ika. The first prototype is based on a Raspberry Pi 4 and combines the following sensors:

- Air pressure sensor (STMicro LPS25HB),
- Humidity temperature sensor (STMicro HTS22)
- Inertia measurement unit (IMU) (STMicro LSM9DS1),
- GPS receiver (DFRobot USB GPS Receiver UBX-G7020-KT).

The data logger allows simultaneous recording of vehicle communication via the OBD II interface while measuring the sensor data. Communication requests are sent and evaluated at a rate of 30 Hz while the sensors, apart from the GPS receiver, operate at 30 Hz. The GPS receiver on the other hand measures at 1 Hz. The combination of sensors and vehicle communication allows for a detailed representation of driving and vehicle behaviour during operation.

4 Generation of Driving Profiles

The basic principle of driving profile generation according to [4] consists of the following steps: 1) Recording driving data during normal real-world operation, 2) analysing the recorded data to describe or characterise the driving conditions, 3) develop representative driving cycles for the recorded conditions. Representative driving profiles for heavy-duty trucks require basic vehicle operation info such as velocity profile over time or distance as well external data such as road gradient over the driven distance.

For the estimation of road gradient over the driven profile, several methods and measurement parameters are available. One common approach is the derivation of road gradient from elevation data, which is received from digital elevation models, such as the *Shuttle Radar Topography Mission* (SRTM) (cf. [5]). Here, only the vehicle position needs to be tracked during operation. Another method is to determine the elevation using the international elevation formula, which is given in Eq. 5.

$$h = \frac{288.15\,K}{0.0065\,\frac{K}{m}} \cdot \left(1 - \left(\frac{p(h)}{1013.25\,hPa}\right)^{\frac{1}{5.255}}\right) \qquad \text{Eq. 5}$$

Here, h is the calculated elevation and $p(h)$ is the elevation dependent air pressure. The air pressure can be measured by a pressure sensor, which can be found in modern smartphones, allowing for small measurement errors as described in [6]. In both cases, the road gradient can be derived from the elevation profile over driven distance s, as given in Eq. 6.

$$\tan(\alpha) = \frac{dh}{ds} \qquad \text{Eq. 6}$$

Another method using a three-axis accelerometer available from an IMU is depicted in Fig. 2.

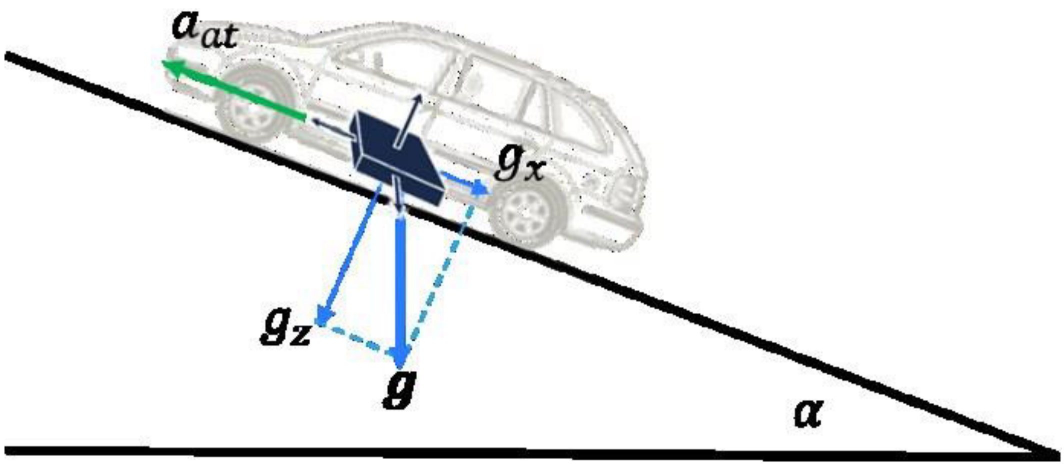

Fig. 2 Three-axis accelerometer mounted in vehicle (cf. [7])

Here, the road gradient α can be calculated from the gravity acceleration component of the measured acceleration g_x in the x-axis as given in Eq. 7.

$$\alpha = \tan^{-1}(g_x) \qquad \text{Eq. 7}$$

As the IMU cannot measure the gravity acceleration component directly, the vehicle acceleration $\ddot{x}$, which is derived from the vehicle velocity over time, is required together with the measured raw acceleration in x-axis α_x as given in Eq. 8.

$$\alpha_x = g_x + \ddot{x} \qquad \text{Eq. 8}$$

Additional methods for road gradient estimation such as gyroscopes (cf. [8]) or power target simulation (cf. [9], [10]) are also being considered. However, these require further adjustments and validation for the present use case and are therefore not yet considered. For a comparison of the so far implemented methods of height estimation, a short test drive is conducted, which is given in Fig. 3.

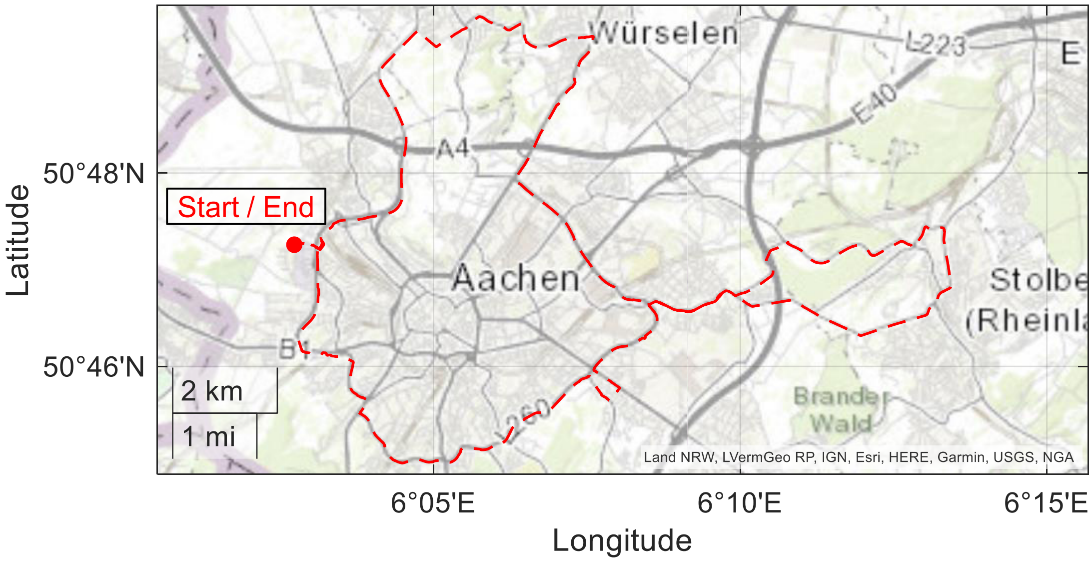

Fig. 3 Round course around Aachen used for height estimation

The test drive represents a round course within the city of Aachen and the surrounding area. The course begins and ends on the premises of ika. This serves as a validation point, as the relative change of height over the round course is expected to be zero. The test vehicle is equipped with the data logger described in chapter 3. The results of the different methods of height estimation for the round course are shown in Fig. 4.

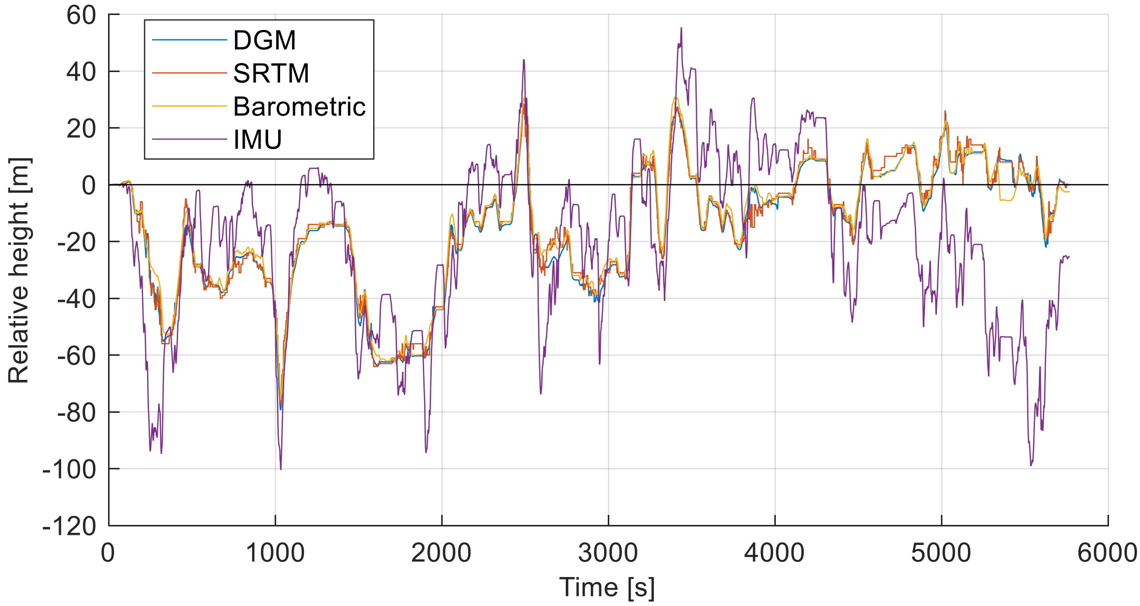

Fig. 4 Relative height profile of implemented methods for test drive

The evaluated methods of height estimation are GPS map matching based on the data sets of the German Elevation Model (DGM, blue) and SRTM (orange), international or barometric elevation calculation (yellow) and derivation of acceleration of the IMU (purple). For the given exemplary round course, the height estimation results based on map matching show the most promising results with a final deviation of 0.11 m and 1 m for DGM and SRTM respectively. The resulting height from the barometric elevation calculation ends with a deviation of 2.47 m and the IMU based method shows the largest deviation of 25.25 m.

The minor deviations from the GPS map matching results can be attributed to the high accuracy of the GPS receiver and the high level of detail for the available map data. The SRTM data set provides a step size of 30 m and a height detail degree of 1 m while the DGM data set offers a step size of 10 m and an accuracy of approx. 0.01 m. As the test drive poses a round course, the GPS map matching method is proving advantageous. The results from the barometric elevation calculation only compare the beginning and final state as well. Here, changes in temperature and humidity have influence on the accuracy of the results, but the deviation appears small. The method based on the acceleration data of the IMU has a disadvantage compared to the other methods due to the integration of the gradient. Here, the absolute difference at the end of the trip coincides with the accumulated deviations during the measurement, which causes the method to have a larger final error if the measurement lasts longer. However, the absolute height is only of minor interest for the methodology, with the focus lying on the measured or calculated gradient. Improvements are ongoing regarding the increase of robustness for the shown methods, but for now, the results of GPS map matching with the DGM data set are used for the further process steps.

With the estimated road gradient and measured vehicle and operation data, driving profiles are generated. The current approach uses a Markov chain-Monte Carlo (MCMC) technique based on the methodology presented in [11]. Here, a 2-D Markov chain is considered for $\dot{x}(t)$ and $\alpha(t)$. Therefore, every state combines a synthesised velocity class and a road gradient class with a probability for the state in the next time step. The synthesis of velocity and gradient through two-dimensional Markov chains incorporates their interdependencies, allowing unrealistic driving behaviour, for example increasing velocity with simultaneously increasing gradient, to be eliminated in advance. The Monte Carlo sampling method is based on a Poisson distribution, which is built from the measured driving data. This MCMC method enables the generation of driving cycles for the representative representation of the measured real driving behaviour. Fig. 5 shows three generated drive cycles in comparison to the measured driving cycle on which the results are based on.

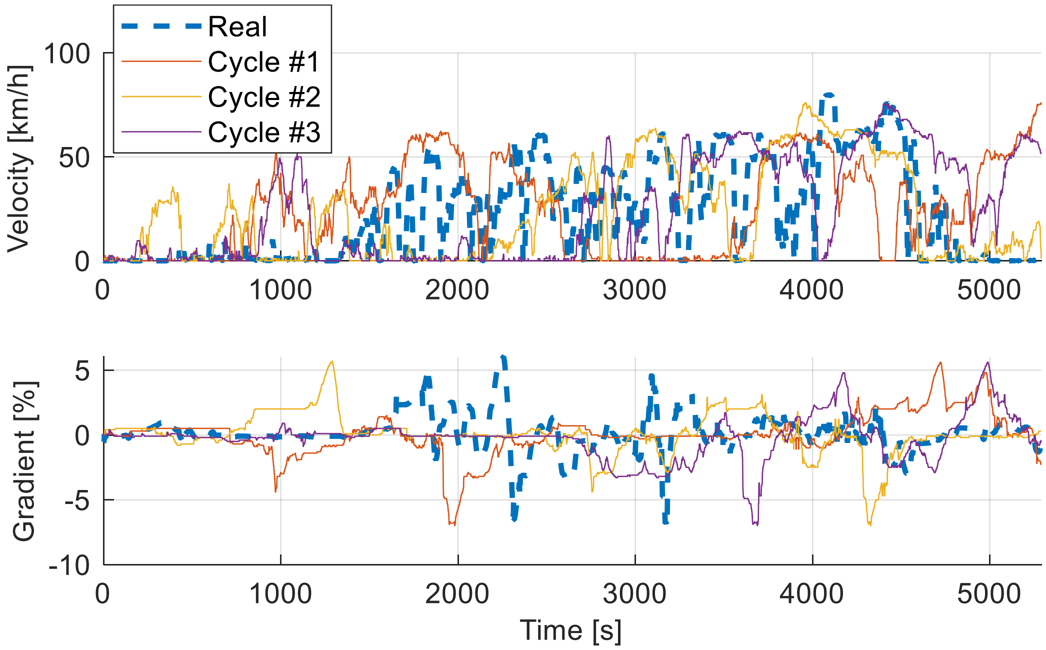

Fig. 5 Exemplary generated cycles in comparison to the logged test drive

The validity of the generated cycles to represent the measured driving behaviour is given by passing the following deviation criteria:

- Deviation of mean velocity $\sigma_{v,mean,tar} \leq 10$ %
- Deviation of standard deviation of velocity $\sigma_{v,std,tar} \leq 10$ %
- Deviation of maximum velocity $\sigma_{v,max,tar} \leq 10$ %
- Deviation of mean gradient (absolute) $\sigma_{\alpha,mean,tar} \leq 15$ %
- Deviation of standard deviation of gradient $\sigma_{\alpha,std,tar} \leq 15$ %
- Deviation of minimum gradient $\sigma_{\alpha,min,tar} \leq 15$ %
- Deviation of maximum gradient $\sigma_{\alpha,max,tar} \leq 15$ %

As the cycles are generated time-based, deviations in distance travelled and cumulative height result accordingly. The exemplary results are depicted in Fig. 6.

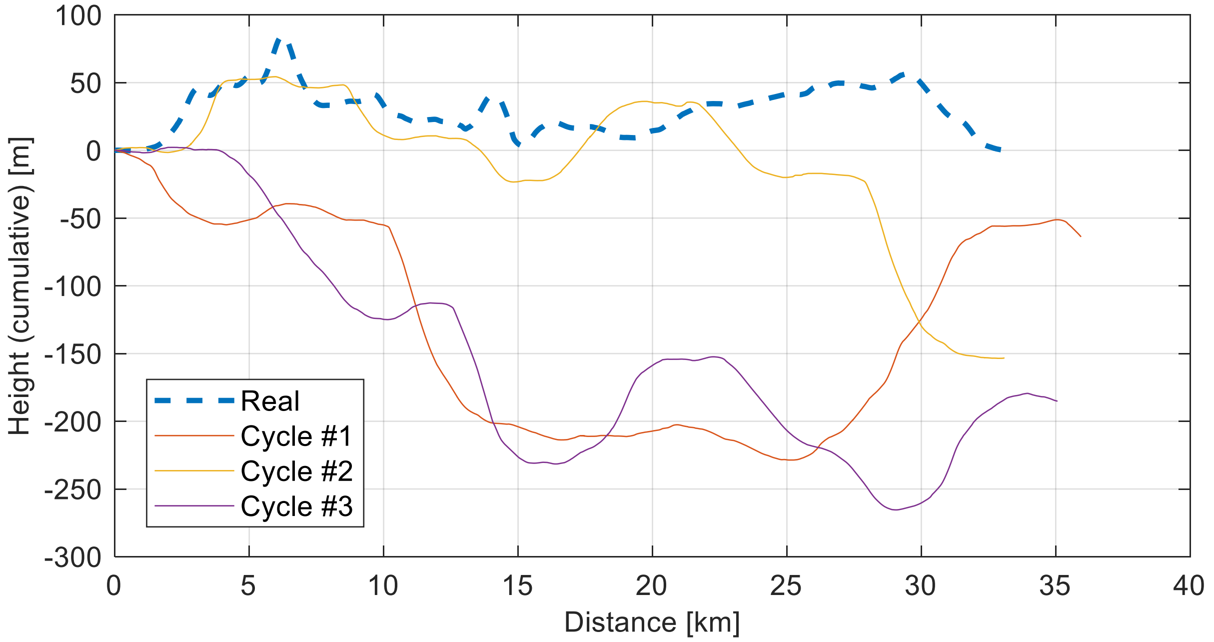

Fig. 6 Cumulative height and distance of generated cycles in comparison to the logged test drive

As the total driven distance and the cumulative height are a function of the velocity and gradient criteria respectively, their validity is given implicitly. The results therefore prove the selected method to function for representing the given use case under the accepted deviations from the measured data. For the subsequent powertrain concept design, the selected method is applied onto a more extensive data set and a representative cycle is generated for a simulation duration of 2500 seconds. Several valid cycles are generated from the data set and compared based on a cost and weighting function given in Eq. 9, resulting in a weighting coefficient W.

$$W = \frac{1}{n_{crit}} \sum_{i=1}^{n_{crit}} \frac{\sigma_i}{\sigma_{i,tar}} \qquad \text{Eq. 9}$$

Here, n_{crit} is the number of deviation criteria, σ_i is the resulting deviation per criterion and $\sigma_{i,tar}$ is the allowed target deviation per criterion. The generated cycle with the lowest weighting coefficient W and therefore smallest deviation from the measured data set is chosen from the generation results. The resulting cycle for the exemplary application in this paper is given in Fig. 7.

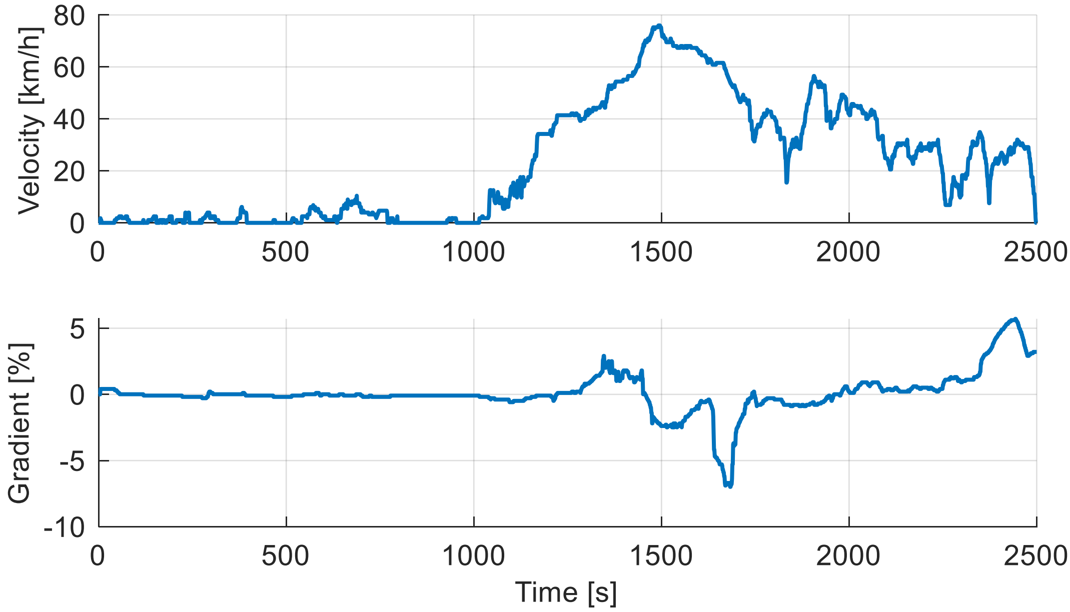

Fig. 7 Selected generated cycle from measured data set

The weighting coefficient W of the selected cycle is 0.3678 and the driven distance over 2500 seconds of simulation time equals 16.25 km. From the selected cycle and the known parameters from the given reference vehicle, load collectives representing real driving behaviour are derived in the next step.

5 Holistic Powertrain Concept Design Process

Based on the generated driving profiles and the available reference vehicle parameters, potential electric powertrain systems are conceptualised. For this task, a modular holistic concept design methodology for electric powertrains has been developed at ika, as presented in [12], [13], [14] and [15]. This concept design method comprises the requirement derivation, the individual concept design of the components electric machine, inverter and transmission and concludes with prototype validation on test rigs. Since the method is tailored for designing electric powertrains, its modularity allows not only systematic development from scratch but also targeted component optimisation.

From use case definition, a load spectrum for further powertrain development is derived based on the distribution of load points. Fig. 8 shows the distribution of the generated drive cycle's load points.

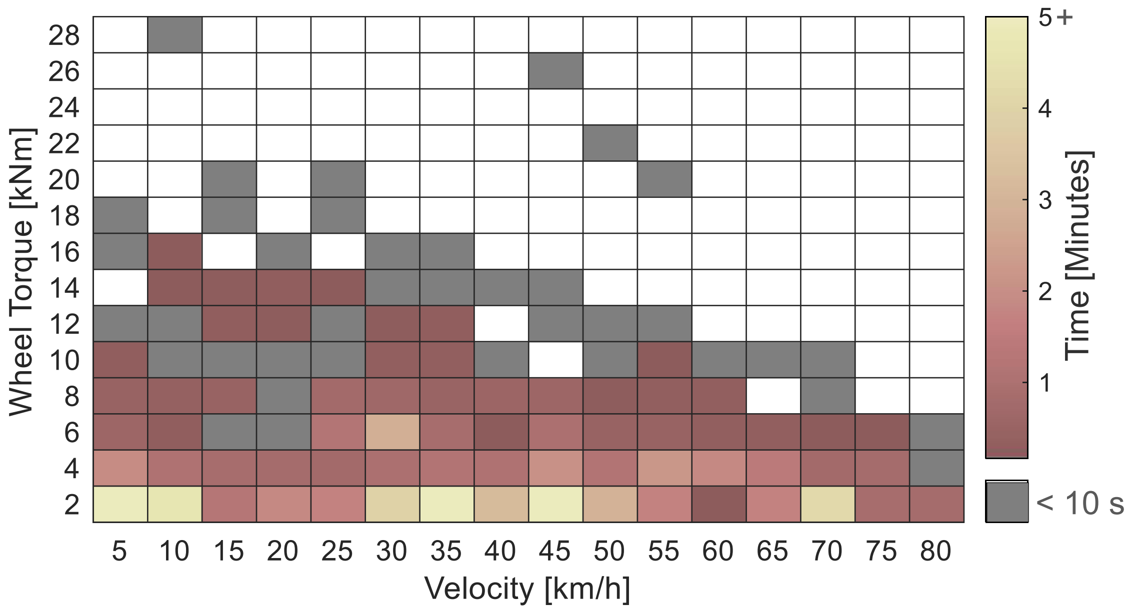

Fig. 8 Distribution of load points on wheel level derived from generated drive cycle

As can be seen from Fig. 8, in most cases wheel torques between 4 and 6 kNm are required over the whole velocity range (city and highway). From these wheel based load points, requirements for the powertrain component concept design are derived in accordance with the reference vehicle specific data. Together with topology-specific boundary conditions, a first rough sizing of the components electric machine, inverter and transmission is conducted. After selecting a powertrain topology (e.g. high speed electric motor, dual-speed transmission), the automated concept design of the components is run, followed by a holistic evaluation regarding factors such as feasibility, lifetime, efficiency, costs etc. The concept design process with focus on the transmission synthesis is described in detail in [16].

6 Application of Methodology in Current Research Projects

The presented methodology is being improved and applied in multiple research projects at ika. Within the BEE project, the initial concept of application-specific powertrain design is developed. Here, a diesel-powered DAF XD FAN is available for initial data logging. Additionally, a battery-electric DAF XD FAN with identical body and vehicle options is used for validation of the presented methodology. The battery-electric vehicles will be equipped with a pantograph system to operate as overhead line trucks, which will be used for test drives on dedicated test routes and in real operations of logistics companies. In addition to the validation, this will also serve to increase the existing database for the development of the methodology. [17]

As a further source for data for the presented methodology, it is planned to acquire data of conventional trucks in field operation within the project eTestHiL. For this purpose, a logging hardware setup is chosen which is easily adaptable and minimal invasive. Logged data is sent to a server hosted by ika, which interprets the CAN data to physical values. This data is then processed according to the aforementioned methodology. [15]

Within the EU-funded project *Powering EU Net Zero Future by Escalating Zero Emission HDVs and Logistic Intelligence* (ESCALATE), highly efficient zero emission heavy-duty vehicles are developed and demonstrators are built. For the powertrain concept design of the demonstrators, the presented methodology will assist the requirement definition and derivation of load collectives. [18]

7 Summary and Outlook

Within this paper, a method for the integration of real driving data into the concept design of drive modules for heavy trucks was demonstrated. The process of measuring real driving data from a reference vehicle with a prototypic data logger was shown. Based on exemplary measured data, the current approach of driving cycle generation and load collective derivation was introduced. At last, the holistic powertrain concept design process at ika was presented and an overview of the current research projects in the field of heavy-duty vehicle powertrain development, where the methodology is or will be applied, was given.

With the selected methodology for driving profile generation, representative velocity and road gradient profiles can be synthesised. However, the current approach neglects both the variable payload mass of the vehicle and possible undermotorisation during driving, both important factors within the operation of heavy-duty trucks. In addition, the method operates based on statistical distribution only, wherefore no dependencies (e.g. change of payload during standstill) are considered yet. These points are addressed in the ongoing refinement of the algorithms. Additionally, the data logger prototype is being optimised for operation in vehicle fleets instead of individual vehicles only. For this purpose, automation and robustness are improved according to the field of application and an online evaluation of the measured driving data is added.

8 Acknowledgement

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