Improving Range Prediction of Battery Electric Vehicles by Periodical Calculation of Driver Parameters based on Real Driving Data

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Abstract: Due to the battery's limited storage capacity, it is important to reduce energy consumption of electric vehicles. Depending on the average speed, an aggressive driving behaviour can result in an up to 40 % higher energy consumption compared to an economic one. In this work, we propose a methodology, which calculates driver parameters based on measured real drive speed and acceleration profiles as well as signposted speed limits. The presented approach compares the energy consumption and driver parameters between our past estimation and the real drive speed profile in order to continuously improve the energy demand estimation for the remaining distance. Thus, this paper provides a procedure to increase the accuracy of energy demand estimation for battery electric vehicles which helps to reduce the range anxiety. In future work, it will be used within a navigation assistance system that supports the driver in reaching his destination with a low battery charge.

1 INTRODUCTION

Electrification of vehicles plays a major role in the current change of the automotive industry. Particularly, in case of battery electric vehicles (BEV), precise prediction of the available range is essential in order to give the driver confidence in his vehicle. Furthermore, it is necessary to determine wheater the destination is reachable with the available energy or not.

In addition to the battery's limited storage capacity, the utilized range is even smaller due to the psychological factor of *range anxiety*. This is the driver's fear not be able to continue driving because the battery is out of charge. In this case, it is - different to a vehicle with combustion engine - not possible to get a BEV ready to drive again with a few liters of fuel. Due to this point and the small number of charging stations, this fear is even higher compared to vehicles with an internal combustion engine. The range anxiety can be minimized by an accurate range prediction.

One factor that can significantly increase or reduce the vehicle's range is the driving behaviour (Badin et al., 2013). In addition to environmental and traffic influences, the driving behaviour has to be taken into account, in order to make the most accurate energy demand estimation as possible. For this purpose, the current behaviour has to be recognized and included into the energy demand estimation.

These issues are addressed through the following contributions:

- An approach to describe the driver's behaviour through a specific set of parameters without the usual classification of the driver.
- A sensitivity analysis of the parameter set to investigate the influence of an individual parameter on the energy demand for a given route.
- A methodology for evaluating the differences between current and predicted driving style and a periodical adjustment of the relevant parameters to increase prediction accuracy for the remaining journey.

These points are described within the structure of this paper as followed: In Sect. 2, we summarize previous work concerning driver parameters as well as energy demand estimation and distinguish our approach from the state of the art. In Sect. 3, we explain the necessary basics for understanding our energy demand estimation model, followed by a description of the chosen driver parameter and their impact on the energy demand in Sect. 4. Our proposed methodology is descriped in Sect. 5 and subsequently, we discuss the results. In the last section, we summarise our outcomes and describe further work.

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2 RELATED WORK

In related work, driver types are usually divided into different numbers of classes. For example, into the - most commonly used - three classes *relaxed*, *normal* and *dynamic* (Wilde et al., 2008; Park et al., 2017) or into five classes *aggressive*, *sporty*, *moderate*, *anxious* and *energy efficient* (Bär et al., 2011; Araújo et al., 2012).

A driver type is primarily definied by the average acceleration. For urban areas for example, defined ranges are: calm 0.45 to $0.65\,m/s^2$, normal 0.65 to $0.80\,m/s^2$ and aggressive driver 0.85 to $1.10\,m/s^2$ (de Vlieger et al., 2000). For motorways, on the other hand, the acceleration for all three driver types is only in the range from 0.08 to $0.20\,m/s^2$ (Langari and Won, 2005). Most of the related work use fuzzy logic to classify the driver (Bär et al., 2011; Langari and Won, 2005). A further approach is to use the ratio of the standard deviation of the acceleration and the average acceleration in order to get a better comparability (Langari and Won, 2005).

In this paper, we do not separate the driver into predefined groups nor we evaluate his driving behaviour with a fuzzy set. This is one of the main differences between this work and the above-mentioned works. After the classification into driver types, the properties are no longer modified. Assuming that a driver is assigned to a specific group of drivers, but his driving style changes within the boundaries of the group, these changes are not transferred to a subsequent prediction. This would lead to an error in the energy demand estimation. This error can be avoided by evaluating driving data such as speed and acceleration during the journey rather than dividing it into individual driver types.

Another difference between this and related work is the use of input quantities. Other work use the brake pressure (Bär et al., 2011) or the moving average values of the gas and brake pedal during acceleration or deceleration respectively (Wilde et al., 2008). Spatial (speed limits, roundabouts, school zones, ...) and temporal (purposes, time, day of the week, ...) conditions are used by (Ellison et al., 2015). Mostly, the input quantities are referenced to special situations such as approaching towns and villages, taking sharp turns and approaching a stop sign (Bär et al., 2011) or to the driving environment (city, rural, motorway) based on signposted speed limits (Castignani et al., 2013).

A further approach is to calculate the driver parameters through speed, acceleration and rotation rate of a smartphone by processing the data from acceleration sensor, magnetic field and GPS receiver (Castignani et al., 2013; Araújo et al., 2012).

In our work, we use a combination of speed limits and the measured speed profile in order to calculate driver-specific parameters, which form the base for a new energy demand estimation. In contrast to a classified type of driver, this allows us to measure the driver characteristics depending on each speed limit range. This avoids the mentioned problem of driving style changes within the borders of a classified driver type. Thus, we want to reduce the error in our energy demand estimation.

A further distinguishing feature between this and related work is the processing of the collected data. We continuously calculate parameters which serve for the determination of cornering speed, acceleration, braking and the resulting upper speed limit. Moreover, the real and simulated energy consumption are compared in order to determine correction factors, which then influences the renewed estimation through feedback. From all above-mentioned works, only (Langari and Won, 2005) optimize the driver parameters by a direct comparison between estimation and simulation.

Other work, for example, do not aim to use the collected data for an energy demand estimation in a closed-loop, rather they score the driver between 0 and 100, to evaluate the driving behaviour in terms of accident risks and their avoidance (Ellison et al., 2015) or in terms of cost-efficiency (Castignani et al., 2013).

While recording trip data, our model distinguishes whether a vehicle in front is present or not. This distinction results in two datasets of driver parameters, with and without a vehicle in front. If the driver slows down due to a vehicle in front, signal processing is interrupted to avoid incorrect classification. This approach has been partially adopted from (Wilde et al., 2008) in this paper. The advantage of this is that, depending on the predicted traffic volume, a distinction can be made between whether the driver has nearly unrestricted driving or the traffic is largely determining his driving behaviour.

Within the framework of the presented methodology, the results of the energy demand estimation are applied as an input quantity. Other work that deals with prediction of expected energy demand and range estimation (Sehab et al., 2011; Vaz et al., 2015; Ferreira et al., 2013; Zhang et al., 2012), are not described in detail here.

3 ENERGY DEMAND MODEL

Our prediction model generates the forthcoming route including environmental and traffic parameters. Then, we calculate an estimated driving profile for this given route on the basis of vehicle and driver parameters. The individual steps are explained in the following subchapters.

3.1 Generation of Route Data

In order to generate a virtual route, serveral data are collected. Therefore, the route generating algorithm runs through five steps shown in Fig. 1.

First, waypoints - which have a distance of about 100 meters to each other - are queried between start, destination and optionally specified intermediate destinations. Using these waypoints, different APIs retrieve traffic information (Step 2), route properties (Step 3) such as speed limits, traffic lights, signs or tunnels, and weather conditions (Step 4) along the route. In the last step, the elevation data for each waypoint of the generated route is determined by the SRTM C-band dataset.

The necessary input data for the algorithm are:

- Starting point *[LAT/LON]*
- Destination *[LAT/LON]*
- Time *[DD.MM.YYYY HH:MM]*

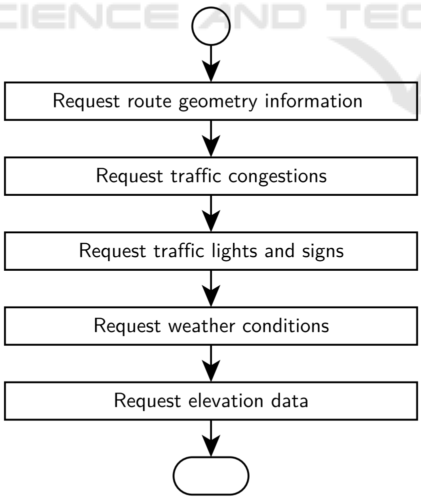

Figure 1: Flow chart of route generating algorithm. The input data are starting point, destination, time and optionally one or more waypoints (Gutenkunst et al., 2015).

Subsequently, three postprocessing steps of the collected data are executed:

- Transformation of coordinates $[X,Y,Z]$
- Calculation of slope [$^\circ$ and α]
- Calculation of curve radius $[m]$

After completing the route generation and postprocessing steps, a virtual route is available for further use. Detailed information about the route generating algorithm and the subsequent postprocessing are described in (Gutenkunst et al., 2015) and (Kruppok et al., 2017), respectively.

3.2 Calculation of Vehicle Motion

The calculation of the vehicle's motion profile is based on the generated route data, descriped in the previous subchapter. The five steps are shown in Fig. 2.

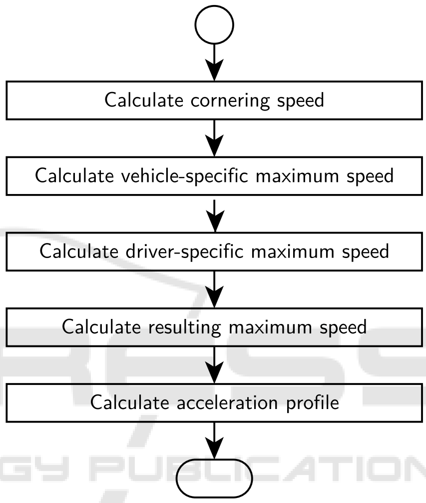

Figure 2: Determination of vehicle motion profile based on algorithm described in (Kruppok et al., 2017).

At first, the maximum lateral acceleration is used to calculate the maximum cornering speed. Subsequently, the course of the resulting maximum speed v_{max} (lidcurve) is generated, which is the minimum of the driver-specific maximum cornering speed, the driver- and vehicle-specific maximum longitudinal speed, the signposted speed limits and the deviation to speed limits caused by driver's behaviour. In the last step, the driver parameters are used to calculate the acceleration profile. The finally used acceleration value for every single acceleration phase is determined randomly within a normal distribution. The average longitudinal acceleration is assumed to be the expected value of the Gaussian function (Kruppok et al., 2017).

3.3 Calculation of Energy Consumption

Based on the estimated driving profile and vehicle parameters, the driving resistance equations (Eq. 2) which include air F_{drag}, rolling F_{roll}, gradient F_{grad} and acceleration resistance F_{acc} are used to calculate energy demand estimation E_{Drive}, see Eq. 1.

$$E_{Drive} = (F_{roll} + F_{drag} + F_{grad} + F_{acc}) \cdot s \qquad (1)$$

with

$$\begin{aligned} F_{drag} &= \frac{c_d \cdot A \cdot \rho \cdot v^2}{2} \\ F_{roll} &= m \cdot g \cdot \cos\alpha_{grad} \cdot f_R \\ F_{grad} &= m \cdot g \cdot \sin\alpha_{grad} \\ F_{acc} &= m \cdot a_F \end{aligned} \qquad (2)$$

4 DRIVER PARAMETERS

This section describes the driver parameters used in the energy demand estimation model and shows a sensitivity analysis to investigate their impact on the energy consumption. The analysis reveals the most influential parameters which are then used within the presented methodology.

4.1 Applied Driver Parameters

Contrary to previous work, the driver is described by the following six characteristics which influence the energy demand estimation. The first three factors affect the calculated upper speed limit (lidcurve). The last three factors determine the acceleration and deceleration of the estimated speed profile:

- **Maximum Lateral Acceleration** (a_x) is used to calculate the maximum cornering speed.
- **Global Speed Limit** ($v_{drivermax}$) represents the driver's desire of an upper speed limit. Usually, it only has an effect on road sections without signposted speed limits.
- **Speed Limit Compliance** ($compliance_v$) is a measure of the driver's compliance with signposted speed limits and has a major impact on all groups of speed limits.
- **Acceleration Behavior** ($scaling_a$) is greater than 1, if the driver accelerates or brakes rather strongly, and less than one, if he accelerates or brakes with restraint.
- **Maximum Longitudinal Acceleration** (a_x) represents how dynamic the driving behaviour in curves is.
- **Maximum Longitudinal Deceleration** (a_{brake}) describes the intensity of the driver's braking procedures. The minimum value and the default value can be identical, if the vehicle determines the deceleration due to the recuperation mode, which is active when the accelerator pedal is pressed slightly or not at all.

4.2 Sensitivity Analysis

In order to investigate the influence of driver parameters on the energy consumption, a sensitivity analysis with the six parameters mentioned above is carried out. In each case, the same route with the same vehicle and environmental conditions is simulated, so that only the driver parameters are varied. The total energy consumption and the share caused by air resistance are calculated from the varied driving profiles.

The analysis is based on recorded GPS tracks of a BMW i3, but is equally applicable for other BEVs. The way from Bruchsal to Karlsruhe and back is used for the analysis and has a overall distance of $49.481\,km$, see Fig. 3. The outward route runs along the motorway (A5) with a length of $27.511\,km$, while the return route is $21.970\,km$ long and follows a federal highway (B3).

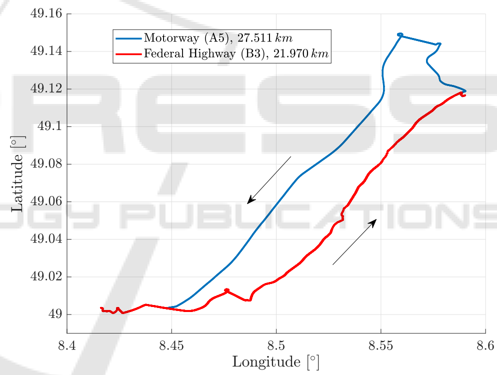

Figure 3: Route with color-separated outward and return path used for sensitivity analysis and algorithm validation.

Each parameter set is simulated several times, since the acceleration within the energy demand estimation model is determined by a random Gaussian distribution. From these simulations, the mean value is calculated to minimize the random error and to make the results more comparable. By simulating with different parameter sets, the effect of a single factor on energy consumption is shown. Therefore, adjustments can be implemented more effectively. Initial values, step size and range of variiation are shown in Table 1.

The results of the analysis in Table 2 show that $compliance_v$ and $scaling_a$ have the largest impact on the total energy demand.

Table 1: Overview of the six driver parameters and their initial value, step size and their range of variiation within the sensitivity analysis procedure. The step size has been selected to obtain arround 10 values for each parameter.

Parameter	Initial	Range	Step
$a_x[m/s^2]$	3	3 to 7	0.5
$a_{brake}[m/s^2]$	-1.6	-2 to -1	0.1
$a_y[m/s^2]$	5	0.5 to 5.5	0.5
$v_{drivermax}[km/h]$	130	125 to 150	2.5
$compliance_v[-]$	1	0.6 to 1.6	0.1
$scaling_a[-]$	1	0.6 to 1.6	0.1

Table 2: Results of the sensitivity analysis sorted in descending order according to the largest energy difference: Necessary maximum and minimum energy $[kWh]$ to overcome the air resistance and the overall driving resistances depending on the varied six driver parameters.

Resistance	Air		Total		
	Max	Min	Max	Min	Δ
$compliance_v$	4.41	3.53	9.13	7.76	1.37
$scaling_a$	4.18	3.90	8.99	8.19	0.80
$v_{drivermax}$	4.51	3.91	9.16	8.43	0.73
a_y	4.08	3.73	8.65	8.15	0.50
a_{brake}	4.10	3.99	8.71	8.41	0.30
a_x	4.08	4.00	8.61	8.45	0.16

Thus, the following methodology uses these parameters for the periodical estimation of the energy demand in order to adapt it to the real consumption. The variation of these two factors between 0.6 and 1.6 as well as the resulting energy demand are shown in Fig. 4.

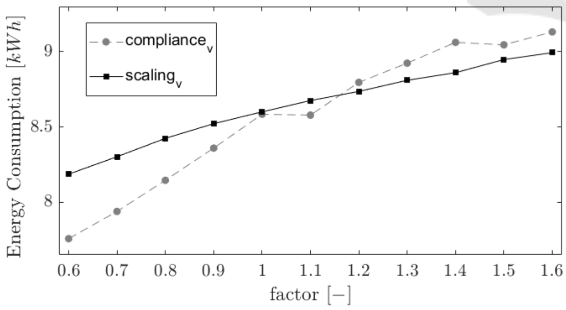

Figure 4: Energy consumption for the variation of the driver parameters $scaling_a$ and $compliance_v$ between 0.6 and 1.6 with a step size of 0.1.

The influence of v_{Max} grows with the number of sections without speed limitation along the route. In addition, the lower v_{Max} is defined, the more sections are affected and the greater is the impact of this parameter. A change in longitudinal and lateral acceleration has hardly any effect on energy consumption.

Only when the lateral acceleration falls below $1.5\,m/s^2$, it becomes relevant, due to the fact that the resulting cornering speed is often lower than the signposted speed limits. This results in a reduction of the speed level and thus also of the necessary energy demand. The lower the maximum longitudinal acceleration, the more often the applied acceleration of the driver model, which is based on a Gaussian distribution, is limited by this threshold value and the lower is the energy demand.

5 METHODOLOGY

The data used for the investigation are based on a prediction model on the one hand and on a real test drive

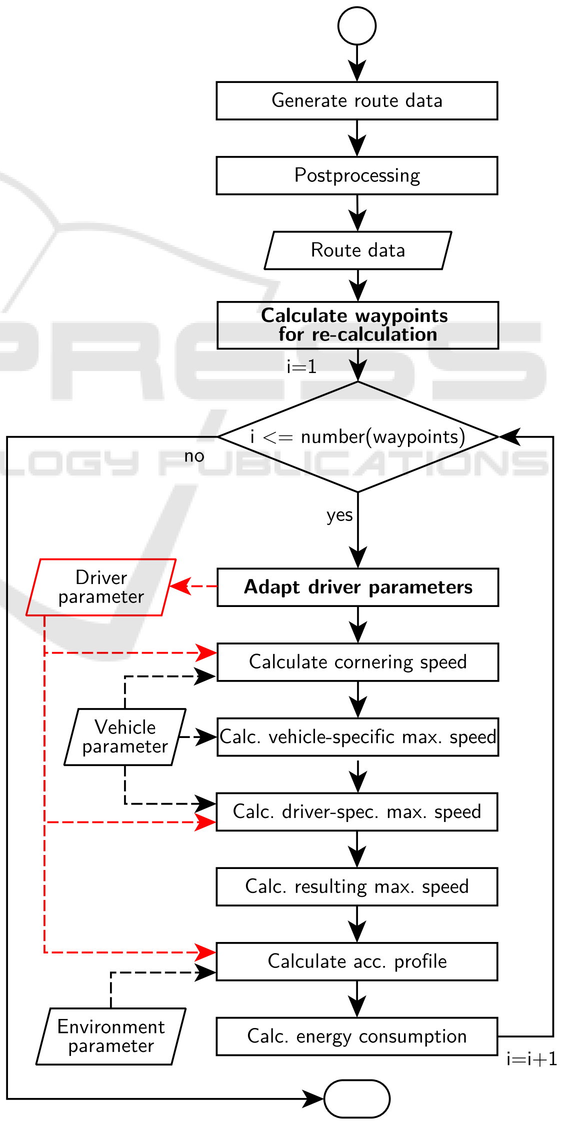

Figure 5: Flowchart of the main algorithm. The red arrow indicates the usage of driver parameters. Bold text indicates a new functions within the framework of our methodology.

on the other. Based on the parameter influences and the existing speed profile calculation, the concept was designed, see Fig. 5.

Subsequent to the RouteGeneration and Postprocessing steps, mentioned in Sect. 3, the number of waypoints at which the driver parameters are to be recalculated is determined. Since the driver parameters have no influence on the previous calculations for determining the slope, curve radius and route geometry, they will not be updated periodically but rather assumed to be static during the initial calculation. This minimizes additional computing time. The waypoints required for the simulation, at which the recalculation of the parameters takes place, are time-dependent and therefore not equidistant due to different route courses. The period of time between waypoints can be variably selected in the model and is limited only by the calculation time of the program sequence.

The measured data are not used to classify the driver. Instead, the above-mentioned parameters are calculated from the data and these are directly included in the simulation. In addition, a comparison is made between the real and simulated energy consumption, in order to adjust the simulation by means of the correction factors $scaling_a$ and $compliance_v$. The model derives driver parameters from the recorded measurement data at several waypoints along the route. A simulation is carried out periodicly at each individual waypoint.

5.1 Adaptation of Driver Parameters

The driver parameters are determined step by step from the measured data. The program's simplified flow chart is shown in Fig. 6.

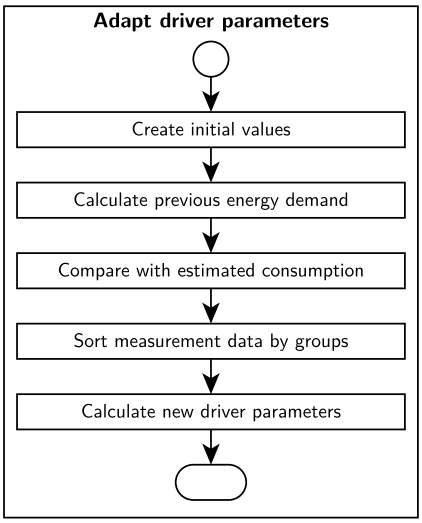

Figure 6: Algorithm for adapting the driver parameters.

For the first prediction, the program uses initial driver parameters. These are initially independent of the current driver and his driving style, as there is no data available on his upcoming driving behaviour. A parameter set from past journeys, which can be assigned to a certain driver, for example by the identification with a unique key (of the vehicle or a car-sharing ID) or by the selection of a certain seat position from the memory are conceivable, but do not matter in the context of this paper.

Within the second iteration, which means the first new prediction, measurement data have already been collected and sorted according to various criteria. A distinction is made between speed limits and whether the test vehicle was preceded by a vehicle in front. For sorting the speed limits, two approaches were compared: a division of the measurement data into twelve speed limit groups, from $30\,km/h$ to $130\,km/h$ in increments of $10\,km/h$ including a group for sections without speed limits, as well as a division into three speed limit groups. In the latter case, they are set to *slower than* $60\,km/h$, $60\,km/h$ *to* $100\,km/h$ and *faster than* $100\,km/h$. Accordingly, the last group contains the sections without speed limit.

In addition to sorting measured data, the energy consumption for the travelled distance so far is also calculated, which then is used for a comparison with the simulated energy consumption. Afterwards, the sorted measurement data according to the driving situation are evaluated and, if possible, the correction factors are determined. The factor $scaling_a$, which should correct the accelerations, is calculated by comparing the acceleration resistance energies. The correction factor $compliance_v$, which represents the deviation to speed limits caused by driver's behaviour, results from a comparison of the air resistance energy.

6 RESULTS

The validation of our methodology is based on simulations with twelve and with three groups of speed ranges, but it is conducted on the same route with the same measurement data. Comparing the results of the simulations with the real drive shows that both estimated energy consumptions are too low, see Table 3.

The estimated energy consumption with twelve and three speed range groups is 15 % and 12 % lower, respectivly, than the real energy consumption. The differences of the energy of rolling resistance, gradient resistance and air resistance between simulation and real driving are very small. A negligible difference in rolling resistance is due to inaccuracies in our model for energy demand estimation compared to re-

Table 3: Energy demand between simulation with twelve and three speed groups compared to the real drive. All values given in the table are expressed relativ to the real drive energy consumption.

# of groups	twelve	three
E_{drag}	3.5 %	5.3 %
E_{roll}	0.9 %	0.9 %
E_{acc}	−44.2 %	−40.3 %
E_{grad}	0.0 %	0.0 %
E_{total}	−14.9 %	−12.0 %

ality.

The decisive difference is caused by the acceleration resistance. The deviation of our estimation compared to the real drive values can partly be explained by significant differences in the speed profile, see Fig. 7. These represent a journey from Bruchsal to Karlsruhe via the A5 motorway, whose course is already presented in Fig. 3.

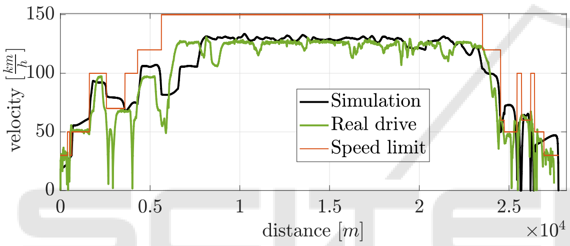

Figure 7: Speed limitation and speed profiles from simulation and real drive.

Due to red traffic lights at the beginning of the real journey, the vehicle slowed down three times from around $70km/h$ - twice even to a complete standstill - and accelerated back to the initial speed. These deceleration and acceleration phases do not take place in the simulation, as the status of the traffic lights has been randomly determined. In addition, the speed fluctuations on the section without speed limit are more pronounced in reality than in simulation, which also contribute a small part to the energy difference. For this reason, it can be seen that from the next waypoint after the 10km mark, there is a significant increase in accuracy regarding the estimation of the total energy demand, see Fig. 8

7 CONCLUSIONS

This paper presented a methodology to adapt driver paramters based on a measured speed profile in order to improve the accuracy of the energy demand estimation for the upcoming route. At the beginning of this paper, our model for energy demand estimation was presented and a sensitivity analysis with the

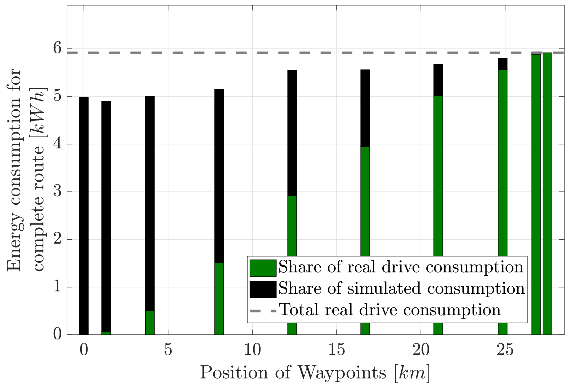

Figure 8: Comparison of predictively determined and real energy consumption. At each waypoint, energy consumption for the entire route is calculated from previous real drive and remaining energy demand estimation.

driver-specific parameters was carried out. The effect of individual driver parameters on the result of the estimation was determined and it was found that large deviations can be caused by the scaling of the overall acceleration behaviour and the non-observance of speed limits.

Subsequently, a function was introduced which determines these driver parameters on the basis of measured real drive data. The route was divided into several waypoints. On each point, the previous measurement data since the start of the journey are used to derive the driver's characteristics. This data is used on every single waypoint for a new energy demand estimation. The results have shown that a significant deviation occurs due to route-dependent circumstances. Grouping the driver parameter on the basis of different speed ranges revealed that 12 groups do not offer an advantage compared to 3 groups.

Further work will cover real driving data including the information about a vehicle in front. It is planned to use the traffic volume as a distinguishing feature instead of the division between with/without a vehicle in front, e. g. in the gradation *none*, *light*, *medium* and *heavy*. In addition, the classification of speed classes into groups of different sizes is also investigated in order to achieve an optimum between the number of data points per group and the accuracy of the driving behaviour. Further investigations will show which distances between the periodical predictions are necessary and whether the consideration of the route profile brings added value to the determination of these distances. Furthermore, we will investigate whether time-weighted pedal signals, as they are also used by (Wilde et al., 2008), result in a more precise estimation, i. e. whether newer signals have a higher influence than older ones.

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