Simulation based method for the analysis of energy-efficient driving algorithms using SUMO

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Abstract

The limited possibilities to evaluate the energy efficiency of driving algorithms for connected and autonomous vehicles (CAVs) make it very difficult for policymakers to decide on the potential of autonomous driving. This study is introducing a method to analyze the energy performance of a driving algorithm under various simulated traffic conditions using the microscopic traffic simulator SUMO. The method can also be used to optimize driving algorithm parameters for chosen traffic scenarios. Therefore, a tool-chain is developed that can simulate a CAV under many traffic scenarios in SUMO systematically. In those scenarios, one or more vehicles are controlled by the implemented driving algorithm. The resulting driving cycles are then analyzed by a forward-facing energy model to calculate the consumed energy. To validate the model, three measurement cycles under real urban traffic conditions were taken and the speed and state of charge (SOC) data of the test vehicle, a 2017 Tesla Model S 75D, were collected. The energy model was shown to be highly accurate and the simulated road network and traffic, which were chosen to represent the same urban traffic scenario as the measured cycles, were shown to result in similar statistics as the measurements. A simple driving algorithm that is already implemented in SUMO's Kraus car-following model was chosen to verify the model's applicability. For different values of the algorithm parameters acceleration and deceleration, a range of random driving cycles was simulated. In the simulations and the measurements, the effect of higher and lower use of auxiliary systems was also analyzed. The results show that the analyzed driving algorithm achieves similar results for the energy consumption as the human driver in the measurements with the best performing parameters. Also, the significance of auxiliary system use on the energy consumption and its effect on a driving algorithm's parameter to remain energy efficient due to the higher impact of the trip duration is pointed out.

1 Introduction

In the controversial debate about the pros and cons of CAVs, one of the most commonly used arguments to advocate for their use and their further development is their promising increase in energy efficiency. However, such an increase in energy efficiency under urban traffic conditions is very difficult to estimate. This study is introducing a simulation-based method for the analysis of the energy efficiency of a driving algorithm for a certain electric vehicle (EV).

To generate realistic traffic scenarios and analyze them down to a single vehicle, microscopic traffic simulation tools are already widely used today for various objectives. One of those simulation tools is the open-source Simulator for Urban Mobility (SUMO) of the German Aerospace Center (DLR) [11]. SUMO comes with an application programming interface called Traffic Control Interface (TraCI) ([19]) which can be used to control certain vehicles inside the simulation with an external driving algorithm.

To calculate the energy consumption of a vehicle, microscopic traffic simulators are usually based on backward-facing energy models. Those backward-facing energy models such as the

VT-CPEM proposed by Fiori et al. [3] or the one of T. Kurczveil et al. [10] implemented in SUMO can deliver instantaneous energy consumption estimations requiring only a few vehicle-specific parameters. They remain computationally efficient by calculating the consumed energy based on simple equations from the current speed "backward" to the energy source. However, forward-facing models such as ADVISOR [13] can deliver more accurate instantaneous energy consumption estimations for the cost of being computationally more complex. They also take the speed-over-time data of a driving cycle as input. This speed is then used as a reference for a driver model which controls the torque request to the engine. From this torque request, the drive train is calculated "forwards" to the wheels resulting in an actual speed of the vehicle. Since all of the vehicle aggregates and the drivetrain components can be simulated, the consumed energy to achieve the actual speed is calculated in a causal way. Therefore, forward-facing models are the better choice when it comes to a detailed analysis of a single vehicle's energy consumption.

R. Galvin analyzed the influence of different speed and acceleration values on the energy consumption over a short driving scenario without traffic in [4] for eight commonly used EVs. One of the key findings was the significant reduction of energy efficiency with modest to high acceleration. To reduce the energy consumption of CAVs different methods are proposed in the literature. They can mainly be divided into two groups: eco-routing approaches, and eco-driving approaches. Eco-routing focuses on the energy-efficient routing of one or more vehicles. For example, the traffic light control can be optimized on the energy consumption of all vehicles on the road as Luin et al. demonstrated in [12]. In their study, they used SUMO together with a backward-facing energy model to verify their results. In this case, a more accurate, forward-facing model would be unfavorable since its computational complexity would result in very long simulation times when calculating the energy consumption for a whole vehicle fleet. Eco-driving approaches focus on the optimal speed for a single-vehicle. For the evaluation of the energy performance of a driving algorithm for CAVs, J. Han et al. proposed an eco-driving control system for energy-optimal acceleration and deceleration and simulated the performance in [6]. Their simulation was based on the assumption, that the preceding vehicle stays the same and there is no other vehicle joining the gap between the controlled vehicle and its leader over a whole driving cycle. However, this assumption is usually not fulfilled in real urban traffic.

The method presented in this study is coupling SUMO with a highly accurate, forward-facing energy model implemented in Simulink [14]. This coupled model allows the implementation of a driving algorithm for one or more vehicles in the SUMO simulation and the following analyses of the energy consumption for the resulting driving cycles with the energy model. Lots of realistic traffic scenarios are generated with SUMO and the performance of different driving algorithms and parameters can be analyzed. With the forward-facing energy model also powertrain optimizations of the considered vehicle would be possible for the cycles generated with the driving algorithm.

To validate the Simulation results, this study also presents the speed and state-of-charge (SOC) data collected from a test vehicle in real urban traffic. Therefore, a 2017 Tesla Model S is driven three cycles around the test track for automated and connected driving (TAVF) in Hamburg [5]. A SUMO model of the same road network, the TAVF, is used together with route files representing realistic traffic demand on those streets. With this model, driving cycles for the test vehicle following the same route, as in the measurements are simulated. Thereby, the test vehicle is controlled by a driving algorithm and the resulting cycles are analyzed for the vehicle's energy consumption.

Figure 1: The TAVF with the starting points of Cycle 1, 2, and 3 [2]

2 Experimental Setup

2.1 Route

For the data collection, three driving cycles were measured: Cycle 1, Cycle 2, and Cycle 3. All of them had the same route. The test vehicle was driven one circle on the TAVF in Hamburg [5]. In Cycle 1 and Cycle 2, the starting- (and ending-) point was in front of the train station Hamburg Dammtor and the Cycle 3 started (and ended) at Holstenwall (next to the park Planten un Blomen). The TAVF is shown in Figure 1. Also, the starting points of the cycles are marked. In all three cycles, the big, counterclockwise round on the TAVF was driven over Stephansplatz and Dammtor. At the Elphilharmonie, a turn was performed to continue the route.

The TAVF is located in the center of Hamburg and represents real urban traffic. On the route there are 37 traffic lights, the streets have between 2 and 3 lanes and the speed limit is 50 km/h.

2.2 External Influences

The energy consumption for a cycle on the TAVF has many external influences that do not depend on the driving behavior of the car such as traffic, traffic lights, and temperature. The traffic depends highly on the weekday and time. The experimental data of Cycle 1 and Cycle 2 were taken consecutively on the 16th of December 2020 between 14:00 and 15:00. The ambient temperature was 8 degrees Celsius. During those measurements, the cabin of the car was already well-tempered to around 18 degrees Celsius. Cycle 3 was measured on the 13th of January 2021 between 15:00 and 16:00 at an ambient temperature of 4 degrees Celsius. At the beginning of this cycle, the cabin was still cold and the air conditioning systems were used to a higher extent to warm up the cabin, as shown in the next subsection 2.3.

2.3   Auxiliary Systems

The auxiliary systems with the most significant energy consumption of the test vehicle were analyzed in a previous study [15]. Those values are also taken into account in the energy model (subsection 3.4) with a factor representing the percentage of use of each of those systems. Table 1 shows those factors for each system in the three cycles approximately.

Note, that the AC and ventilation were set to a higher power during the measurements of Cycle 3 compared to the measurements of Cycle 1 and 2.

Measurement	AC	Ventilation	Seat Heater	Headlights	Infotainment
Cycle 1	0.3	0.3	0	1.0	0.1
Cycle 2	0.3	0.3	0	1.0	0.1
Cycle 3	0.8	0.8	0	1.0	0.1

Table 1: use factor of auxiliary systems during the measurements of Cycle 1 to 3

2.4   In-Vehicle Setup

The used test vehicle is a 2017 Tesla Model S 75D [17]. The internal systems of the car communicate over a Controler Area Network (CAN) bus. On the CAN3 bus, data regarding the powertrain is shared. This CAN3 bus can be accessed over pin 18 and 19 of the Tesla Diagnostic Connector under the Touchscreen of the middle console. During the driving cycles on the TAVF, the bus messages are read and logged using the software CANalyzer Mini3 [7]. To ensure that no signals are disturbed and nothing can be sent on the bus, a certified CAN-diode, the CAN-Bus Iso-Koppler [8], is used for the connection.

All messages from the CAN3 are logged in a CSV file. The speed data is published on the bus with the identifier 0x256 with a frequency of 10Hz. The SOC-value has the identifier 0x302 and is published with a frequency of 1 Hz.

2.5   Measurement Results

The collected speed and SOC data for the three cycles are shown in Figure 2. The duration in seconds, the distance in meter, the average speed in km/h and the difference in the SOC in percent of the battery charging state over the whole cycle are given in Table 2 for each cylce respectively:

Measurement	duration (s)	distance (m)	average speed (km/h)	Δ SOC (%)
Cycle 1	1442	8491.4	21.2	2.2
Cycle 2	1406	8605.2	22.03	2.3
Cycle 3	1462	8240.0	20.29	2.7

Table 2: Key values of the measurements of three TAVF cycles with human driver

TAVF Cycle 1
1442 s, 8491.4 m, av. speed: 21.2 km/h, delta soc: 2.2 %

TAVF Cycle 2
1406 s, 8605.2 m, av. speed: 22.03 km/h, delta soc: 2.3 %

TAVF Cycle 3
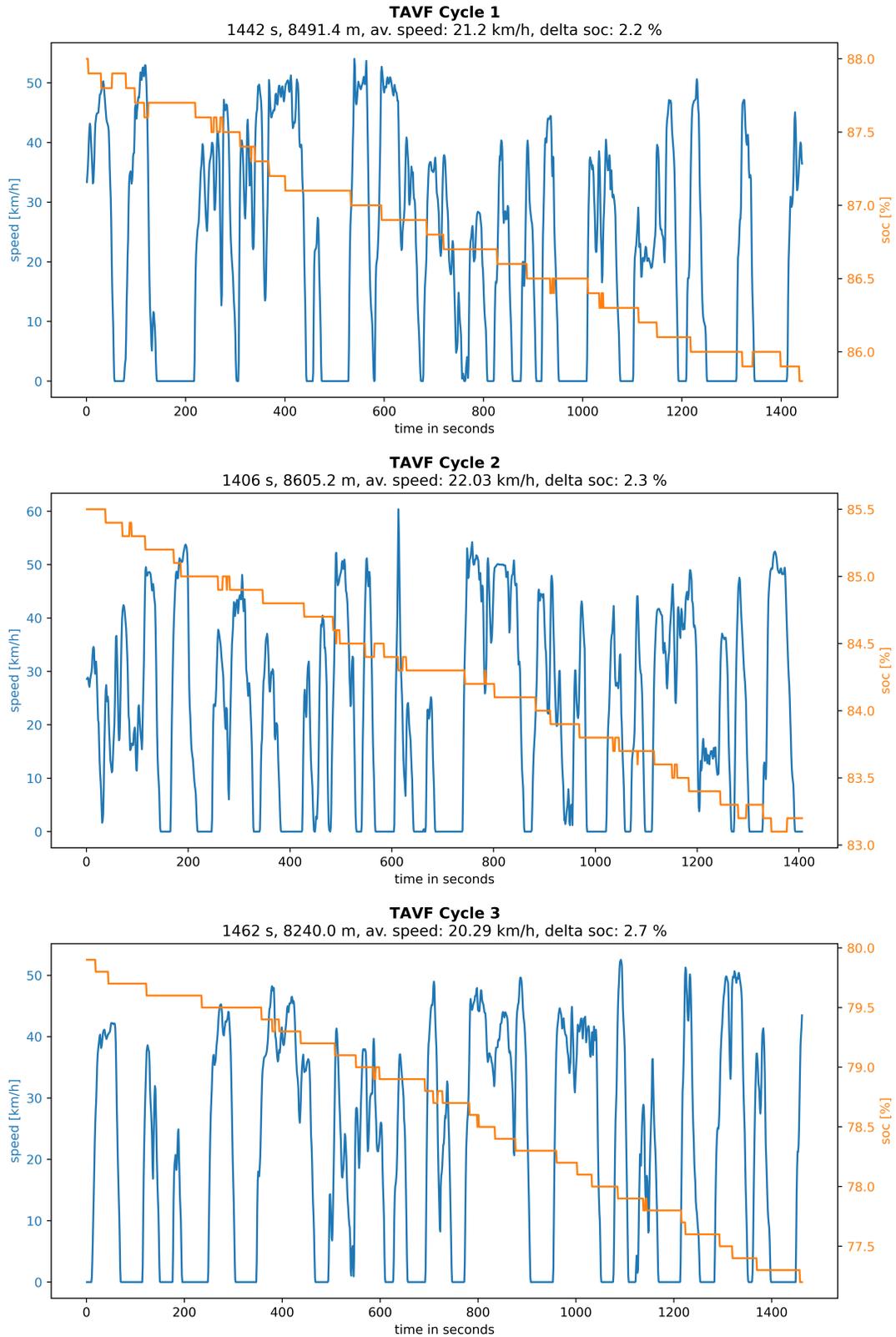1462 s, 8240.0 m, av. speed: 20.29 km/h, delta soc: 2.7 %

Figure 2: Measurement data from Cycle 1, Cycle 2 and Cycle 3

153

3   Simulation Setup

3.1   Simulation Toolchain

To test different driving algorithms for the test vehicle in a large number of driving scenarios on the TAVF, the toolchain of different simulations is realized as a python script. The script couples both simulation tools SUMO and Simulink runs a chosen number of random scenarios and saves the resulting speed over time and SOC over time data of the test vehicle. Also, the driving algorithms are implemented in python.

At the beginning of a simulation run, the number of cycles to be simulated and the driving algorithm of the test vehicle is specified. Then, for the chosen number of cycles, SUMO is started as a server using the Traffic Control Interface (TraCI), and the simulation is executed. The time-step length of the simulation was set to 1 second for this study. Between every simulation step, a driving algorithm implemented in python can calculate the speed for the test vehicle in the simulation for the following step. Therefore, the driving algorithm can access data from the current situation of the test vehicle in the SUMO simulation. Once the test vehicle has finished its round on the TAVF, the logged speed over time data is passed to the Simulink energy model. The Simulink model is started and controlled from the python script with the Matlab engine for python.

After the model has calculated the energy consumption for the cycle, the SOC over time array is returned to the python script. The SOC and speed data for the cycle are saved as a file and as a plot figure.

The script runs until the chosen number of scenarios is generated. Each of those scenarios is different since each of the SUMO simulations is initialized with another seed value for the pseudo-random number generator.

3.2   Required Software

The top layer python script is implemented in python version 3.6.8 [18]. This is the newest version that is still compatible with the Matlab engine for python [14], which is also used. The energy model used in this study requires Simulink, the Powertrain Toolbox, and the Parallel Computing Toolbox of MathWorks from version 2020b or newer. In the python code, the cycle data is analyzed and saved using the NumPy [16] library. For the SUMO simulation the SUMO version 1.7.0. is used [11].

3.3   SUMO Simulation

SUMO is used to generate random scenarios for the route of the test vehicle. With SUMO, the chosen driving algorithm can be analyzed under a big range of different traffic models for example on highways, in urban traffic, or certain cities or districts. The only requirements are accurate network and routing files for the whished traffic situations and enough computer power and time to run the simulations. The driving algorithm can be used to control one or more vehicles in the simulation. Note that especially the analyses of the energy consumption with the forward-facing energy model is computationally expensive, which increases the run time of this toolchain significantly if the energy consumption is calculated for multiple vehicles of the same scenario. Also, the energy model has to be parameterized for the exact vehicle it is representing (see subsection 3.4).

In this study, all generated cycles are done on the same road network, which is a model of the TAVF and only one vehicle in the simulated scenarios is controlled by the driving algorithm

and analyzed with the energy model.

This vehicle is representing the test vehicle of the measurements. It virtually drives the same route on the TAVF as the real test vehicle in the measurements with the starting point at Hamburg Dammtor (as in Cycle 1 and 2 of the measurements) in every simulation scenario. Also, the other vehicles in the simulation - the traffic demand - are the same for every simulation. SUMO allows pseudo-random changes in the driving of the other vehicles and a random departure offset of every vehicle based on an integer seed value. In one simulation run, for every SUMO simulation, the seed value is increased by one. This way, many different cycles are generated with the same route files.

The used network file and route files of the TAVF were provided from the German Aerospace Center (DLR). The route files are based on induction loop count data of the streets of the TAVF from the authorities of the state of Hamburg. Cars and trucks were generated from this data using a GEH statistic so that they represent weekday traffic between 15:00 and 16:00 with an accuracy between 95 and 99 %. The cars and trucks have a sigma value of 0.5, which means their driving behavior includes random deviations from a perfect one with a factor of 0.5. Additionally, buses are considered in the route files. The bus routes are based on the schedules from the Hamburger Verkehrsverbund (HVV, the public transport provider in Hamburg) from autumn 2019.

With the network file also the traffic lights are defined. In the provided network file of the TAVF, three of the 37 traffic lights of the TAVF are implemented based on the real phases of their counterparts, namely LSA 34, 560, and 94. The rest of the traffic lights were generated automatically by SUMO and partly optimized to guarantee realistic traffic flow during the simulations.

The different cycles simulated with SUMO from the python script all have the same configuration file except for the seed value, which is increased with every simulation by one. Therefore, the simulated scenarios are repeatable, but the behavior of the cars and their starting time varies randomly in every single scenario. The seed value for the random number generator (RNG) of SUMO is influencing the random behavior of other vehicles and the random depart offset of each vehicle, which is set in the simulation configuration to a maximum of 30 s. Therefore, every vehicle departs with a random offset between 0 and 30 s to their programmed departure time in every simulation.

3.4   Energy Simulation

The used energy model is based on the Electric Vehicle Reference Application from MathWorks [14] which was parameterized for the 2017 Tesla Model S and extended for the most energy-consuming auxiliary systems of the Tesla in a previous study [15].

The model takes a driving cycle in the form of a two-dimensional vector as an input. In the first column, the time in seconds is passed and the second column contains the corresponding speed in km/h. This driving cycle with one speed value per second is seen as the target speed cycle. The car model calculates a torque request based on the actual speed and the target speed. From this torque request, the whole drive train is calculated in a forward and causal way, resulting in an actual speed of the vehicle.

Besides the driving cycle input, the extended model also takes the percentage of use of the auxiliary systems over time as an input. Those percentages result in factors that are multiplied with the maximum current measured for the respective system in the test vehicle.

In [15] the maximum current of the air-conditioning (AC), the ventilation, the seat heater, the headlights, and the infotainment (speaker, radio) of the 2017 Tesla Model S was measured.

The AC and the ventilation are supplied from a 400V system meanwhile the rest of the considered systems run with a 12V power supply. The maximum current of the systems was measured to be for the AC 6A, the ventilation 2A, the seat heating 0.6A, the headlights 0.4A and the infotainment systems 0.2A.

For simplification, the use factors for each of those systems were not changed over time in this study. Therefore, they were assumed to stay unchanged for the whole cycle. Also, the atmospheric temperature is considered by the model and taken as an input.

Since the model calculates the whole drive train from the motor to the wheels, the performance of all internal systems can be accessed at any time point of the cycle. For this study, the SOC data in % of the battery is used to compare the energy consumption of different cycles. This data is outputted as a vector of the same length as the input drive cycle containing the SOC value in % of the battery for every second over the cycle time.

3.5   Driving Algorithms

With the method presented in this study, any longitudinal driving algorithm that is based on input data available in the SUMO simulation can be implemented in the python script to control the speed of one or multiple vehicles in the simulation. The performance of an implemented algorithm can then be tested over lots of random scenarios and under different traffic conditions. Furthermore, with the method presented in this study, the algorithm can be analyzed in its energy consumption for a certain vehicle and its parameters can be optimized for the chosen traffic conditions.

Over the Traffic Control Interface (TraCI) of SUMO, the algorithm can access data of the vehicle's surroundings from the SUMO simulation in between each simulation step. A selection of the information that can be accessed with TraCI is given below.

- The current speed of the vehicle

- The current lateral speed of the vehicle

- The current position of the vehicle

- A list of traffic lights on the vehicle's route with their current state and distance

- The leading vehicle of the car and its distance

- The current speed of any vehicle in the simulation

Based on this input data, the algorithm can control the vehicle's speed over the whole simulation. The route of the controlled vehicle can be programmed before in the route file so that the algorithm has to take care only of the longitudinal movement. The vehicle can be controlled by the algorithm by setting either its speed or its position for the next simulation step. It is also possible to consider lane changes in the driving algorithm. In that case, it can be implemented as a car-following model in SUMO.

To show the applicability of the presented method, the energy efficiency of the driving algorithm of the Kraus car-following model [9] is analyzed. This algorithm is already implemented in SUMO and calculates the speed of a vehicle for the next simulation step based on the parameters of its acceleration, deceleration, emergency deceleration, the minimal gap it should have to a leading vehicle, a value sigma representing the imperfection in the driving behavior and a value tau representing the reaction time a driver needs to react on changing conditions. The values sigma and tau are implemented to simulate non-perfect, human driving behavior

in SUMO. Since in this study, the algorithm is used to simulate an autonomous vehicle, sigma is chosen to be 0 (no random variation in speed) and tau to the shortest possible value of the simulation step length, which is set to one second for the simulations in this study.

The algorithm decelerates the vehicle with a deceleration corresponding to the deceleration parameter value d to stop if a red or yellow traffic light is coming up or to respect the minimal gap to any leading vehicle. Otherwise, the vehicle is accelerated depending on the acceleration parameter a.

4 Model Validation

4.1 Energy Model Validation

The energy model was run for each measurement cycle with the required inputs: atmospheric temperature, the percentage of use of the considered auxiliary systems, and the speed cycle. Those values for the Cycles 1 to 3 are shown in section 2.

In Figure 4 the resulting SOC calculations for Cycle 1, 2, and 3 are plotted in red on top of the corresponding measurements.

One can see that the SOC values calculated with the energy model are ruffly following the measured ones. Note that the measured SOC was logged with a precision of 0.1 and the calculated values were rounded to a precision of 0.001. For Cycle 1, the delta SOC, so the difference of SOC at the beginning of the cycle to the end of the cycle, is measured to be 2.2 % and calculated to be 2.219 %.

The absolute and relative differences between measured and calculated Δ SOC % consumed by each cycle are listed in Figure 3.

TAVF Cycle	measured [%]	calculated [%]	difference abs. [%]	difference rel.
Cycle 1	2.2	2.219	0.019	0.86 %
Cycle 2	2.3	2.291	-0.009	-0.39 %
Cycle 3	2.7	2.673	-0.027	-1.00 %

Table 3: Δ SOC [%] measured and calculated for each TAVF cycle

Cycle 3 shows the biggest gap with an absolute difference of 0.027 % SOC. In all three Cycles, the energy model comes to a Δ SOC with a relative deviation of 1 % or less.

In Figure 3 the difference in the SOC value in % from the energy model (calculated) to the measured one is shown over the whole cycle for TAVF Cycle 1, 2, and 3. In the plots, the highest resolution of the measurement values of 0.1 is marked in yellow.

One sees that even though the calculated SOC value is quite close to the measured one at the end of the cycles, during the cycles the difference is significantly higher. It can also be seen that this difference follows a bit of a pattern, where it is slightly increasing over more or less the whole cycle and then at some point dropping at a comparably high rate. In Cycle 1 and Cycle 2, this drop happens at about the same period of around 500 to 700 and 600 to 800 seconds meanwhile in Cycle 3 the drop can be seen between 150 and 350 seconds approximately.

This phenomenon can be explained by the road grade of the route. The TAVF is comparably flat over most of its length but has a higher negative road grade between U St. Pauli and U Landungsbrücken. Since the road grade is not considered in the energy model, in this part of the cycle the test vehicle consumes less energy than calculated. This results in higher calculated energy consumption over that period than measured, and consequently the difference between
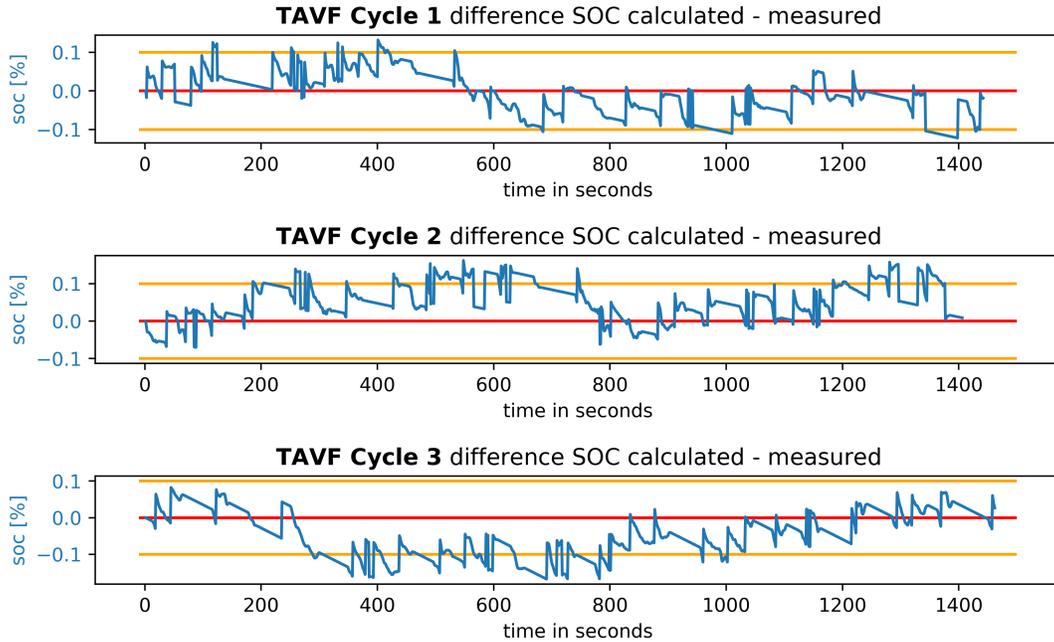
Figure 3: Difference from calculated SOC to measured SOC

calculated and measured SOC is decreasing. This explaination also agrees with the results of the study of S.C. Yang et al. [20], in which the influences of different road grades on an EVs energy consumption was analyzed.

The road grade of the rest of the TAVF does not have such significance at any other part of its length. Evidently, it does have a positive road grade at other parts to come back to the same height after a full round. Therefore, since the measured cycles were all going over a full round on the TAVF, during the rest of the cycle this effect is canceled out by the model calculating a lower energy consumption at the positive road grade parts.

The time period of the drop in the difference of calculated and measured SOC also meets the assumptions for the three cycles. Cycle 1 and 2 both have the same starting point at Dammtor. And they both show the drop event in about the same time period between 500 to 800 seconds from the cycle start.

Cycle 3 on the other hand started at Holstenwall, which is closer to the negative road grade part. Therefore, this cycle also shows the drop event earlier.
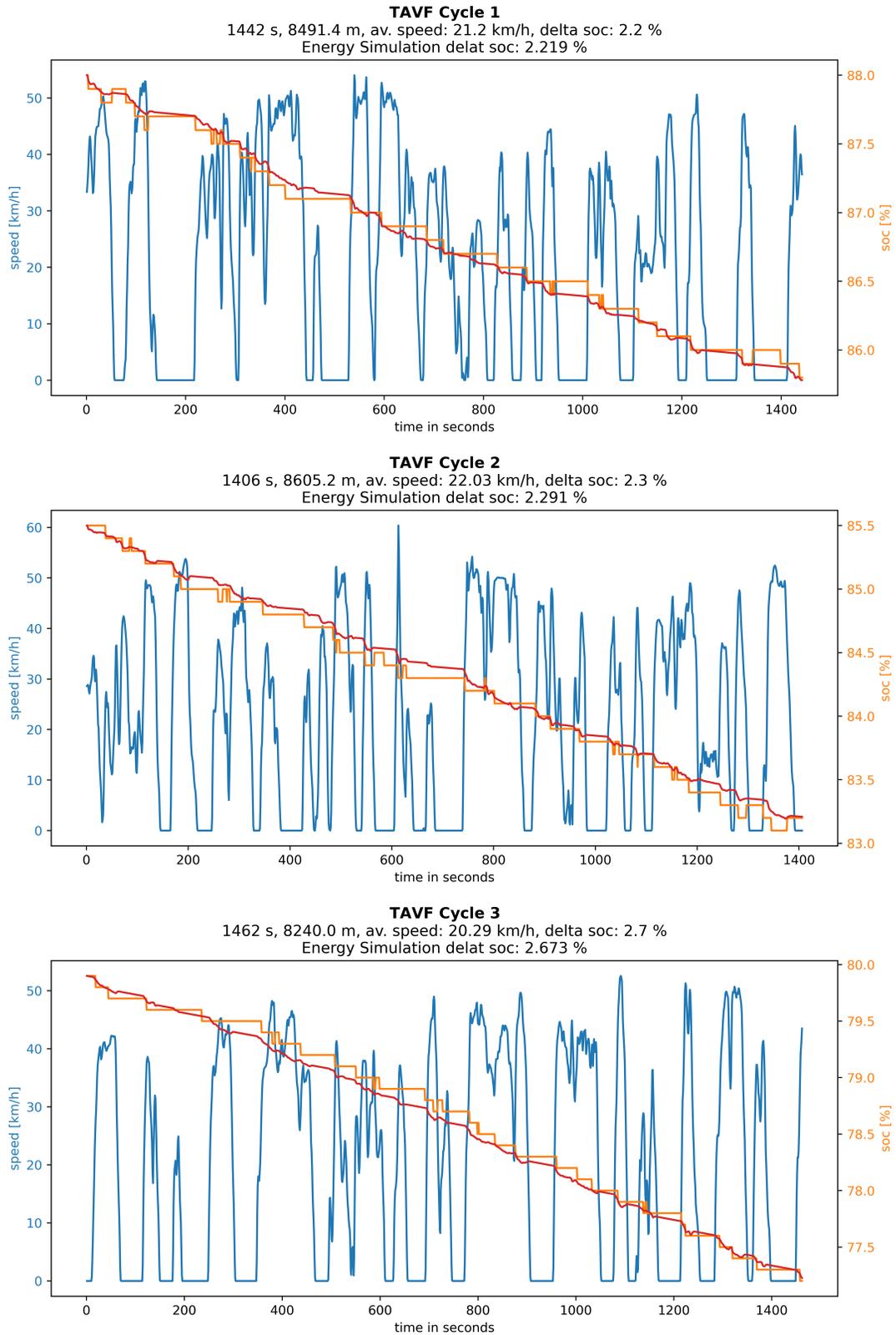
TAVF Cycle 1
1442 s, 8491.4 m, av. speed: 21.2 km/h, delta soc: 2.2 %
Energy Simulation delat soc: 2.219 %

TAVF Cycle 2
1406 s, 8605.2 m, av. speed: 22.03 km/h, delta soc: 2.3 %
Energy Simulation delat soc: 2.291 %

TAVF Cycle 3
1462 s, 8240.0 m, av. speed: 20.29 km/h, delta soc: 2.7 %
Energy Simulation delat soc: 2.673 %

Figure 4: Cycle 1, Cycle 2 and Cycle 3 measurements and the SOC of the energy model (red)

4.2 TAVF Driving Cycle Generation with SUMO Model

For the method presented in this study, SUMO is used to generate realistic driving scenarios for a vehicle under fixed traffic conditions. With the used SUMO model for the TAVF and the traffic presented in subsection 3.3, the resulting driving cycles of the test vehicle of 100 pseudo-random simulations were analyzed and compared to the measured driving cycles of the TAVF.
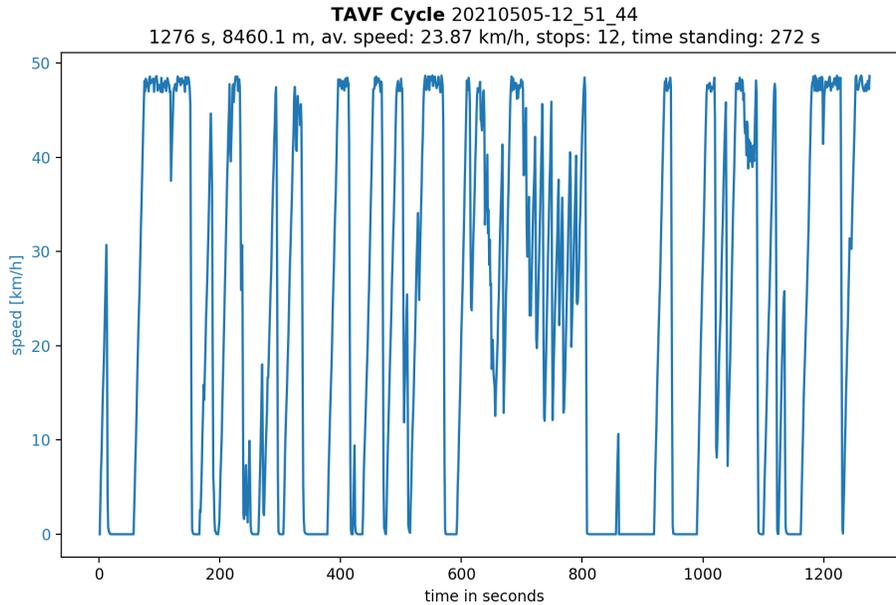

Figure 5: One of 100 random TAVF cycles generated with SUMO

For the 100 cycles, the test vehicle was simulated with the Kraus car-following model in SUMO. Its acceleration was set to 1.0 m/s², the deceleration to 5 m/s² and the value for sigma - which represents a driving imperfection in SUMO - was chosen to be 0.5. In Figure 5 one of those 100 cycles is shown. When compared to the measured driving cycles from Figure 4, one can see in the example plot that the driving behavior simulated in SUMO does not match the real human driving behavior from those cycles very closely. Nevertheless, the generated cycles do deliver some clues about the suitability of the TAVF model in SUMO. Therefore, the values of duration, distance, average speed, the total time standing, and the number of stops are observed for the generated cycles and compared to the measured cycles.

All of these values are approaching a normal distribution over the 100 random cycles. Their average, maximum, minimum, and standard deviation for the 100 simulations are shown in Table 4 together with the data of the measurements. The time standing is the number of seconds where the vehicle had a speed of 0 km/h and for the number of stops, the occurrences of standing situations (consecutive speed of 0 km/h) are counted where short movements of less than 5 seconds (up to four consecutive seconds with a speed other than 0 in between two standing situations) are respected as one single stop. This prevents a stop at a single traffic light where the vehicle moves forward again after stopping to close the gap to the leading vehicle

TAVF Cycle	duration	distance	average speed	stops	time standing
Cycle 1	1442 s	8491.4 m	21.20 km/h	15	428 s
Cycle 2	1406 s	8605.2 m	22.03 km/h	16	340 s
Cycle 3	1462 s	8240.0 m	20.29 km/h	15	489 s
100 generated cycles:					
average	1394 s	8464.2 m	22.08 km/h	15.95	384 s
max	1772 s	8472.1 m	28.57 km/h	23	662 s
min	1067 s	8450.8 m	17.19 km/h	9	127 s
std. dev.	137.11 s	4.35 m	2.22 km/h	3,1	98,47 s

Table 4: key values of random SUMO cycle generation compared with measurements

in the same red phase to be counted as two stops.

The statistics of the simulated cycles show that the model matches the values from the measured Cycle 1, 2, and 3 in the chosen categories. The values for duration, average speed, and stops of all three measured Cycles are inside one standard deviation from the mean value over the 100 simulated cycles. For the standing time, only Cycle 3 is outside this boundary with 489 seconds, being 1.35 % higher than the one standard deviation over the mean. Also, this Cycle is well below the maximum standing time of all 100 generated cycles which is 662 seconds. The only category in which the value range of the simulated cycles does not cover the values of the measurements is the distance of the cycle. Here, the standard deviation over the values of 100 simulated cycles is very little with 4.35 m. The difference in the distance of the simulated cycles is, therefore, a lot smaller than the difference between the distance of the measured cycles, which have a maximum difference of 365.3 m. This could partly be caused by the driving behavior of the vehicle in the simulation. Here, the test vehicle performs only the necessary lane changes for its route, which is the same in every simulation. In the measured cycles, the human driver also performed some lane changes that were not necessary to complete the route. This effect explains a greater difference in distance between the measured cycles compared to the simulation. It can also explain a higher total distance in the measured cycles because of more (unnecessary) lane changes as one sees in Cycle 1 (27.2 m more than the average of the simulated cycles) and Cycle 2 (141,0 m more). What it can not explain is a measured distance that is lower than the lowest simulated one, like the one of Cycle 3 with 210,8 m less. One can therefore assume that the route of the used TAVF model in SUMO is at least about this distance longer than the real route on the TAVF (that would be 2,56 %).

Overall, the randomly generated cycles show that the TAVF model used in this study matches the expectations of the three measured cycles of the real TAVF. Excepts for the distance where the lowest simulated one is 2.56 % larger than the lowest measured one, the values of the 100 simulated cycles are all distributed over a range that contains the measured ones. If one assumes that the used model was representing the TAVF perfectly, the measured values of Cycle 1 to 3 for the duration, average speed, stops, and standing time do not only represent possible but also very probable quantities when compared to the distribution of the values from the simulations. Vice versa, the presented results can be seen as evidence that the network and routing files used in the simulation are an accurate model of the real TAVF with realistic traffic.

5 Simulation Results

In this section, the simulation results for the energy consumption of the driving algorithm of the Kraus car-following model are presented. With the method described in section 3, the test vehicle is simulated to drive always the same route on the TAVF. During the simulation, its speed is controlled from the algorithm of the Kraus car-following model described in subsection 3.5 with different parameters for acceleration and deceleration. Then, the performance of the algorithm is analyzed for the energy consumption, duration, stop time and the number of stops.

The acceleration parameter a was set to 0.5, 1.5, 2.5, 3.5 and 4.5 m/s^2 and the decelartion parameter d to 1.5, 2.5, 3.5, 4.5, 5.5 and 6.5 m/s^2. For each possible combination of a and d in the driving algorithm, the test vehicle was simulated over 20 random cycles and its energy consumption has been calculated.
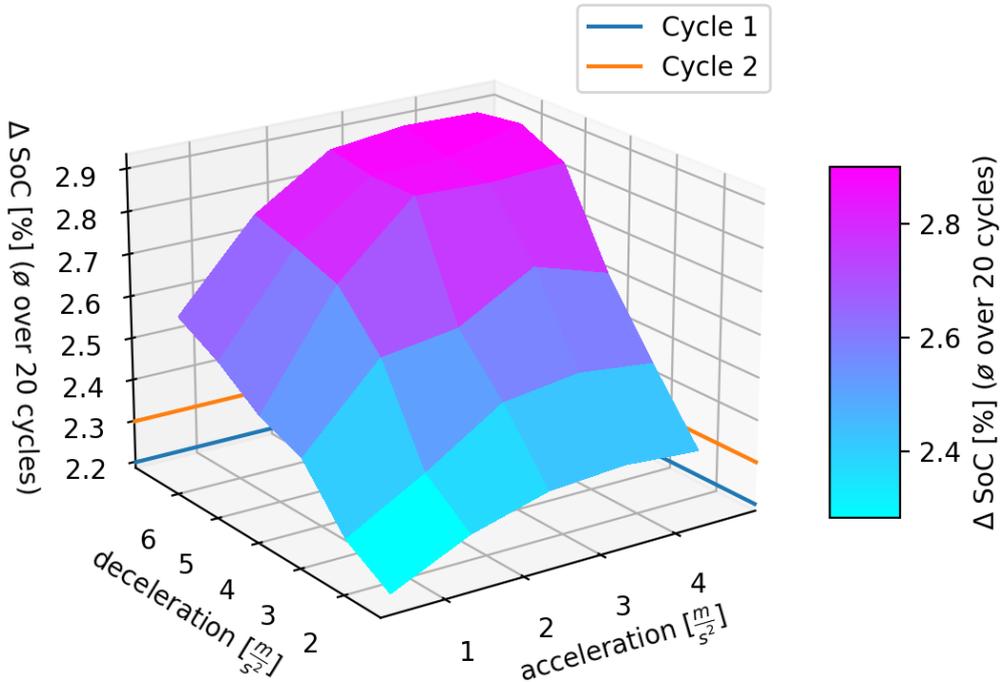

Figure 6: Average Δ SOC over random 20 TAVF cycles for different acceleration and decelaration parameters with low auxiliary system use

In Figure 6 the average difference in SOC per cycle over 20 cycles is plotted for different combinations of the driving algorithm parameters of a and d. The energy model was set to the lower auxiliary system use of Cycle 1 and 2 of the measurements (see subsection 2.3). One can see a trend for higher energy consumption if the algorithm is set to higher a and d values.

Figure 7 shows the average duration and average speed per TAVF cycle over 20 cycles for the same a and d values. Since the average cycle distance does not vary more than 10 m between the simulated parameters (the minimum is 8457 and the maximum 8466 m), duration and average
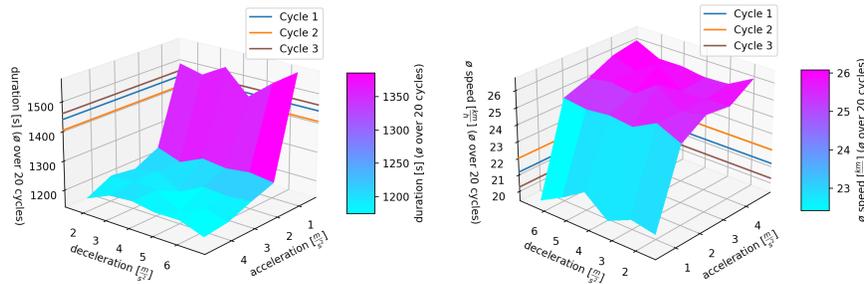
Figure 7: Average duration (left) and average speed (right) over random 20 TAVF cycles for different acceleration and decelaration parameters

speed data show the same trend. One can see that for a values of 1.5 m/s² and higher the average cycle duration remains very similar around 1200 seconds. For those parameters, the maximum duration is 1237 s (at $a = 1.5$ m/s² and $d = 3.5$ m/s²).

Meanwhile a values above 1.5 m/s² do not result in significant changes in the cycle duration, the simulation results show significantly higher values for a lower a of 0.5 m/s². Here, the duration is between 1444 and 1568 s, which is between 16,7 % and 26,8 % higher, than the highest result for other parameters (1237 s). The parameter d does not influence the cycle duration considerably over the whole range of simulated values.

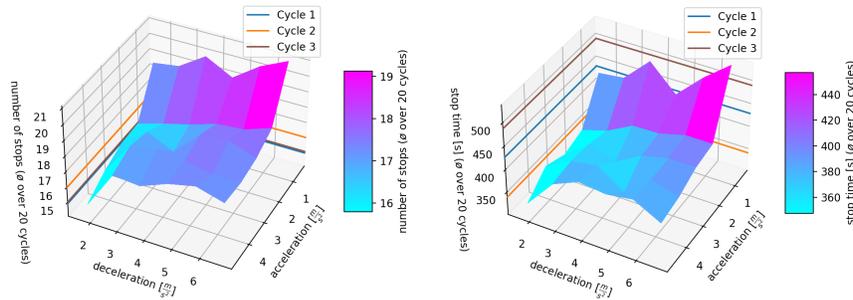

Figure 8: Average number of stops (left) and average stoping time (right) per cycle over random 20 TAVF cycles for different acceleration and decelaration parameters

The average number of stops and the average stopping time per cycle are shown in Figure 8. The plots indicate that generally for the simulated scenarios and over all the acceleration and deceleration parameters, more stops lead to longer stopping time. Also, they show that for a low a of 0.5 m/s² the stopping time is significantly higher than for a values of 1.5 m/s² and above. This can explain the longer cycle duration for those simulations and the lower average speed. The results for the average number of stops and stopping time in the simulated TAVF cycles for different acceleration and deceleration parameters of the driving algorithm also show a light trend of lower values for a lower d meanwhile the average cycle speed does not show this trend. Therefore, for the lower deceleration values, lower stopping time and fewer stops do not result in a higher average speed or lower cycle duration.

Regarding the average energy consumption per cycle for lower auxiliary system use in Figure 6, the cycles with an a value of 0.5 m/s², which have a longer cycle duration, still show a

lower energy consumption than the cycles with higher a values that have shorter trip duration.
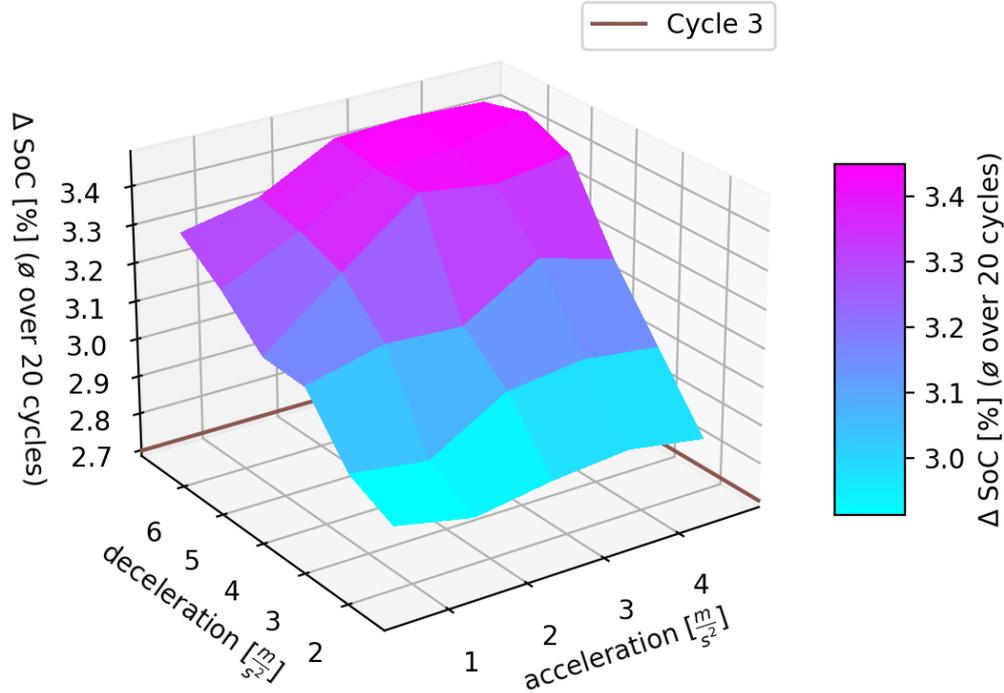

Figure 9: Average Δ SOC over random 20 TAVF cycles for different acceleration and deceleration parameters with high auxiliary system use

In Figure 9, the energy consumption for the same cycles is shown with higher auxiliary system use. Therefore, the energy model is set to the parameters for auxiliary systems and atmospheric temperature of the measurements Cycle 3. One can see that with this auxiliary system use, the energy consumed in all cycles is higher. The average Δ SOC per cycle over all the cycles is here 3.196 %. For the energy calculations with lower use of auxiliaries in Figure 6, the average over all the cycles is 2.610 %. Therefore, the energy consumption per TAVF cycle increased by 22,4 % on average when changing from a low auxiliary system use as in measurement Cycles 1 and 2 (AC and Ventilation to 30 %) to a higher one as in the measurements of Cycle 3 (AC and Ventilation to 80 %, see subsection 2.3).

One can also see when comparing Figure 6 and Figure 9, that the longer cycle duration for simulations with an a value of 0.5 m/s² leads to a larger increase in energy consumption for the high auxiliary system use than for other a values, that correspond to lower cycle durations. In the cases for $d = 1.5$ m/s² and $d = 2.5$ m/s², one can see that with the high auxiliary system use, the energy consumption is even larger for an a of 0.5 m/s² than for one of 1.5 m/s², due to the longer duration of those cycles. In fact, in the simulations with $d = 1.5$ m/s², the average Δ SOC value over 20 cycles for different acceleration was even the second highest for an accelarion of 0.5 m/s²with 2.905 % (only with $a = 3.5$ m/s²the resulting energy consumption was slightly higher with a Δ SOC of 2.912 %).

The lowest average energy consumption per cycle achived by the algorithm is 2.862 % SOC

for high auxiliary system use with the parameters $a = 1.5$ m/s^2 and $d = 1.5$ m/s^2. For the simulation with low auxiliary system use (Figure 6), the best value of 2.204 % is achived with the lowest simulated parameter values of $a = 0.5$ m/s^2 and $d = 1.5$ m/s^2.

6   Conclusion

A method to evaluate the energy consumption of an EV controlled by a driving algorithm in realistic urban traffic was developed in this paper. The simulation model couples the microscopic traffic simulator SUMO with a forward-facing energy model in Simulink. The energy model was validated with speed and SOC data collected under real urban traffic on the TAVF in Hamburg, Germany with a 2017 Tesla Model S 75D. The energy model with the parametrization of [15] was shown to calculate an energy consumption with a difference of 0.86 %, -0.39 % and -1.00 % to the measured one for the three measured TAVF cycles, respectively.

The used network and route files of the TAVF in SUMO were shown to deliver realistic cycle statistics when simulating driving cycles with the same virtual route on the TAVF in SUMO, that was driven for the measurements.

With the introduced method, a driving algorithm for a vehicle can be analyzed on the vehicle's energy consumption and also on other statistics such as trip duration, trip distance, average speed, number of stops, and stopping time. The compatibility for algorithms is so far limited to input variables available in SUMO and the vehicle can not be controlled by a torque request, but by setting its speed directly. However, in this direction, the model can possibly be extended (see section 7).

To demonstrate the applicability of the simulation model, the driving algorithm of the Kraus car-following model was analyzed. Therefore, multiple, random scenarios for different values of the acceleration and deceleration algorithm parameters were simulated. In each of the simulations, the driving algorithm controlled the speed of the test vehicle during one cycle on the TAVF. It was shown that the introduced simulation model can serve as an energy consumption analysis and optimization tool for a driving algorithm. With the model, a driving algorithm can be used to control one or multiple cars in any traffic scenario implemented in SUMO. The energy consumption for a simulated driving cycle can be calculated for any given vehicle, that the energy model is parameterized for.

The simulation results show that, for the Kraus driving algorithm on the TAVF with low use of auxiliary systems, the cycles with the lowest values for the acceleration and deceleration parameters of 0.5 m/s^2 and 1.5 m/s^2 respectively have the lowest energy consumption with a Δ SOC of 2.204 %. This is very close to the energy consumption of the measured, human-driven cycles with the same auxiliary system use, namely Cycle 1 and Cycle 2. Here, the consumed energy was measured to be 2.2 % and 2.3 %, respectively. It was also shown that the trip duration for one cycle on the TAVF does not depend on the deceleration parameter of the driving algorithm. For the acceleration parameter a, the cycles simulated with a value of 0.5 m/s^2 had durations up to 26.8 % higher than the one simulated with higher values for a. Meanwhile, the duration of cycles simulated with $a = 1.5$ m/s^2 did not vary from the ones simulated with higher a values by more than 6.68 %.

Furthermore, the energy simulations with higher use of the auxiliary systems AC and ventilation show that, for the same cycles, higher steady energy use results in a larger reduction of energy efficiency for cycles with a higher duration. Therefore, in this simulation with the higher auxiliary system use, the parameters deceleration = 1.5 m/s^2 and acceleration = 1.5 m/s^2 resulted in the lowest average energy consumption due to their lower cycle duration. With these parameters, the driving algorithm achieved an average Δ SOC of 2.862 % for a TAVF cycle.

This is relatively 6 % more than the measured Δ SOC of 2.7 % of Cycle 3 with a human driver, which had the same, higher auxiliary system use.

The energy simulations demonstrate the significant effect of auxiliary systems on a vehicle's energy consumption. Over all the 600 TAVF cycle simulations, the consumed energy per cycle increased by 22.4 % when changing the use factor for the AC and ventilation from 30 % to 80 %. This finding also overlaps with the results of [3].

7   Future Work

The authors intend to extend the model presented and couple it with the open-source robot simulator Webots [1]. This software can generate a 3D simulation environment corresponding to the street network of the SUMO Model including all vehicles from the SUMO simulation. In Webots, real sensors like lidar and camera sensors can be simulated for the test vehicle. It is planned to implement a driving algorithm that controls the car based on simulated vehicle cameras in Webots. Therefore, the driving algorithm in the simulation could use the same input data to control the car as the real 2017 Tesla Model S is using for automated driving.

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