A Computationally Inexpensive Battery Model for the Microscopic Simulation of Electric Vehicles

Sebastian Schellenberg, Rüdiger Berndt, David Eckhoff, and Reinhard German
Computer Networks and Communication Systems
Dept. of Computer Science, University of Erlangen, Germany
{sebastian.schellenberg,ruediger.berndt,david.eckhoff,reinhard.german}@fau.de

***Abstract*—The transition from classic combustion engine vehicles to electric vehicles is a major step to reduce worldwide CO_2 emissions. In order to correctly and efficiently investigate impacts on the electric grid and the dimensioning of charging infrastructure, or to explore new technologies for a further increase of the driving range, realistic simulation models are required. In this paper, we present an accurate yet computationally inexpensive battery and kinematic model to be used in microscopic traffic simulation to help study the performance of thousands of electric vehicles. Our model also supports recuperation and range extender modules while only relying on the vehicle's speed and a set of constant predefined parameters. It can therefore be easily coupled with current sophisticated traffic simulators. We show its applicability and correctness regarding the State of Charge and power flows using comprehensive real-life experiments.**

Keywords—Electromobility; IVC; lithium-ion battery model

I. Introduction

Due to the lack of direct CO_2 emissions, Electric Vehicles (EV) are not only believed to alleviate the global warming phenomenon but also to considerably lessen the degree of dependence on fossil fuels like petroleum and natural gasses. The trend towards an increasing number of electrified vehicles requires to take several issues into consideration: For example, the limited battery capacities and the corresponding shortened driving ranges, the development of the energy demand according to the penetration rate, the layout of the charging infrastructure, or the impacts on the electric grid in general.

Field Operational Tests (FOTs) are an adequate way to study these problems and identify potential impacts regarding the initiation of EVs into the market. Due to their cost and time-intensive nature, these tests are often accompanied by modeling and simulation efforts that can be used to validate results from FOTs and investigate further scenarios that could not be covered by real life experiments. This way, different penetration rates or the placement of charging infrastructure can be investigated in a cost-efficient manner.

The quality and meaningfulness of simulation results highly depends on the deployed simulation models. In the case of EVs the major challenges are given, on the one hand by the microsimulation of traffic and, on the other hand by the modeling of a vehicle's battery. Since state-of-the-art traffic simulators (cf. [1], [2]) are quite sophisticated, a simplified and validated battery model would allow to efficiently simulate thousands of EVs and, consequently, contribute to performance evaluations of electric vehicles. Besides, such a simulation model cannot only be used to assist the planning of charging infrastructure or vehicle fleets but also to explore the potentials of further technologies like Inter-Vehicle Communication (IVC) systems. For example to help analyzing the benefit of communicating intelligent traffic lights [3].

In this article, we introduce a computationally inexpensive battery model, which is suited for microscopic traffic simulation. The vehicle's battery State of Charge (SOC) is derived from a kinematic model based on speed and constant preset parameters, only. In addition to that, our model provides the possibility to include a range extender and recuperation module. We validate the model's behavior using real life experiments and show that it produces accurate results.

The remainder of this article is organized as follows: Section II provides an overview of related work. In Section III, we introduce our battery model including the SOC calculation, the kinematic model, and the recuperation and range extender model. In Section IV we present the validation of our model using two different real-life driving scenarios (urban and freeway). Section V concludes our work and indicates future steps.

II. Related Work

The most important and commonly final parameter in many battery models is the State of Charge (SOC) which reflects the charging level of the battery. Different calculation models with varying degrees of accuracy were proposed. Watrin et al. [4] gave an overview about the literature and clustered the approaches into three groups.

The first group includes direct measurement methods where some parameters of the battery are measured to calculate the SOC. One example is the voltage measurement method with voltage as input for the estimation function. However, since we want to calculate the SOC from traffic simulation—where the exact battery voltage is not included—this method does not fit our requirements.

The second cluster includes indirect or book-keeping methods. Approaches of this kind count the charging and discharging current and rely on constant battery parameters (e.g. *Coulomb Counting Method*). The SOC is determined by integrating over the counted current (cf. Section III-B) These approaches are widely used for battery models in traffic simulation.

In the third cluster, hybrid or adaptive approaches combining direct and indirect methods are included, e.g. Artificial Neural Networks.

Tielert et al. [5] used a modified passenger car and heavy duty emission model (PHEM) to study the impact on the energy consumption of cars considering communicating traffic lights and vehicles. The SOC calculation is based upon an electric circuit model and the battery characteristics are described by analytical functions. Unfortunately, these functions are not comprehensively described within the article. Furthermore, the validation reflects the New European Driving Cycle (NEDC) only and does not include a comparison with real world data.

Maia et al. [6] presented a model based on the mechanical and electrical traction. While most subsystems of the vehicle—c.f. auxiliary consumers—were abstracted, the mechanical traction is derived from several forces, e.g. the force induced by rolling resistance. Having combined this model with the traffic simulator SUMO (Simulation of Urban Mobility) allowed to conduct energy consumption studies. However, this article does not cover an accurate recuperation model and the authors did not consider a range extender module. Besides, the model was not evaluated with real reference data.

Various battery models were proposed using electrochemical [7], mathematical [8], or electrical [9] modeling. Focusing on studies of battery behavior and electrical efficiency these models provide a high level of accuracy due to a lower abstraction level and many input parameters. Considering traffic simulations and the effects of Inter Vehicular Communication (IVC) on the power consumption, such an accuracy level is not necessary and too expensive to be combined with simulation tools like SUMO.

In the next section, we present our lightweight battery model where speed and, if enabled, the recuperation stage are the only dynamic parameters.

III. Battery Model

To allow our battery and kinematic model to work with today's well established microscopic traffic simulators [1], [2], we focused on a simple and computationally inexpensive design that uses as few parameters as possible.

A. Preliminaries

In this work we do not consider battery charge cycles since microscopic traffic simulations usually cover a simulated time span of some minutes or hours, only. We believe that battery aging does not play an important role in such short time periods, and therefore can be neglected. Aged batteries could be simulated by adapting the relevant parameters [10], e.g. by reducing the maximum capacity.

Furthermore, although auxiliary systems such as air conditioning or headlights consume energy we did not model them in detail. For the sake of simplicity and computational speed we approximate their impact on the SOC using constant values.

Moreover, we neglect temperature effects considering the charge and discharge process and assume a constant temperature. We acknowledge that temperature dependence is an important feature of lithium ion batteries, however, we lack the required data to fully validate a temperature dependent battery model. This will be the scope of future work.

B. State of Charge calculation

The outcome of a battery model, among others, is the State of Charge which is usually measured in percent—100 % represents a fully loaded and 0 % a fully discharged battery. In the state of the art, the SOC can be calculated in several ways (cf. Section II). We chose the Coulomb counting method, which is a book-keeping method, where the charging or discharging current is measured to estimate the SOC. Equation 1 shows the general computation, where $I_{\text{Bat}}(t)$ is the battery current flow and Q_n the nominal capacity of the battery in Ampere Seconds [As].

$$SOC(t_n) := \int_{t_0}^{t_n} \frac{I_{\text{Bat}}(t)}{Q_n(t)} dt \tag{1}$$

To be able to calculate the SOC in the context of a discrete event simulator, we need to transform Equation 1 to account for the fixed time step length Δt and $n := \frac{t_n - t_0}{\Delta t}$

$$SOC(t_n) := \sum_{i=0}^{n} \frac{I_{\text{Bat}}(t_i)}{Q_n(t_i)} \Delta t. \tag{2}$$

The current State of Charge $SOC(t_n)$ can be calculated as using the last level $SOC(t_{n-1})$ and the observed current flow $\frac{I_{\text{Bat}}(t_n)}{Q_n(t_n)} \Delta t$.

Since $I_{\text{Bat}}(t) = \frac{P_{\text{Bat}}(t)}{U(t)}$ and $Q_n(t) = \frac{Q_{\text{Bat}}}{U(t)}$, where Q_{Bat} is a given battery capacity in kilowatt hours [kWh $\hat{=}$ VAs], we can eliminate the voltage and get a voltage-free equation that only depends on the changing power flow within one fixed period Δt and the fixed battery capacity

$$SOC(t_n) := SOC(t_{n-1}) - P_{\text{Bat}}(t_n) \cdot \frac{\Delta t}{Q_{\text{Bat}}} \tag{3}$$

By doing so we only need to calculate the power flow $P_{\text{Bat}}(t)$ to derive the SOC of the battery. For this, we have developed a kinematic model, which takes only one non-constant input parameter into account: the vehicle's speed.

C. Kinematic model

In each time step t_i of the traffic simulation, the power flow $P_{\text{Bat}}(t_i)$ is computed as a function of the vehicle's speed $v(t_i)$, its acceleration $a(t_i)$, and the angular speed of the wheels $w_R(t_i)$.

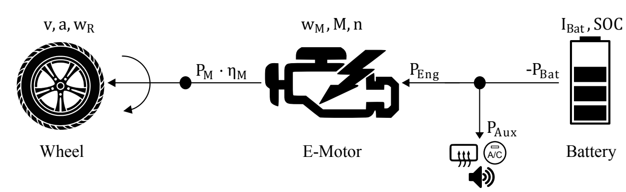

Figure 1. State of Charge (SOC) in relation to the vehicle speed

Given only v, the acceleration a can be computed as the rate of change of the speed

$$a(t_i) = \frac{v(t_i) - v(t_{i-1})}{\Delta t}. \tag{4}$$

Furthermore, the angular speed of the wheels $w_R(t_i)$ can be derived using $w_R(t_i) = \frac{v(t_i)}{r}$, where r is the radius of the car's wheel.

Consequently, the engine's angular speed w_M is given by $w_M := R \cdot w_R$, where R is the gear transmission ratio. The angular speed is used to calculate the rotational speed n, used in Equation 7.

All involved parameters are either constants, given by the constructor of the vehicle, or can be derived from the vehicle's speed. This allows us to calculate the power flow between battery and engine as follows

$$-P_{\text{Bat}} := P_{\text{Aux}} + P_{\text{Eng}}, \tag{5}$$

where P_{Aux} is the accumulated power of all auxiliary systems and

$$P_{\text{Eng}} := \frac{P_{\text{Acc}} + P_{\text{HC}} + P_{\text{Roll}} + P_{\text{Air}}}{\eta_M}, \tag{6}$$

where η_M is the engine's constant efficiency factor, P_{Acc} the power to accelerate the car, η_M is the engine's constant efficiency factor, P_{Acc} the power to accelerate the car, P_{HC} the hill climbing power, P_{Air} the power needed to overcome the air resistance, and P_{Roll} the power required to overcome the roll resistance.

The following equation yields the power which is required to accelerate the car

$$P_{\text{Acc}} = 2 \cdot \pi \cdot n \cdot M, \tag{7}$$

where n is the rotational speed of the engine and M is the torque. For each time step t_i the torque is calculated as follows

$$M(t_i) = \frac{a(t_i)}{a_{\text{max}}} \cdot M_{\text{max}}, \tag{8}$$

where a_{max} is the vehicle's maximum possible acceleration. The energy consumption for acceleration and constant drive varies with the slope of the street.

The hill climbing power is given by

$$P_{\text{HC}} = m \cdot g \cdot \sin\alpha \cdot v, \tag{9}$$

where m is the vehicle's mass, g is the gravitational acceleration, α is the elevation of the street, and v the vehicle's speed. If the car is driving on a plain street, the value of P_{HC} equals zero.

Furthermore, the engine consumes energy to overcome the air and the roll resistance of the vehicle. The power induced by rolling resistance is given by

$$P_{\text{Roll}} = c_r \cdot m \cdot g \cdot v, \tag{10}$$

where c_r is the rolling resistance coefficient and v the car's speed. The power to overcome the air resistance is calculated with

$$P_{\text{Air}} = \frac{1}{2} \cdot c_d \cdot A \cdot \rho \cdot v^3, \tag{11}$$

where c_d is the drag coefficient, A is the car's cross sectional area, ρ is the air density for the temperature of 20 °C, and v is the vehicle's speed.

If the car drives with constant speed or decelerates, P_{Acc} becomes zero and the battery discharging process only depends on P_{Roll}, P_{Air} and P_{HC}.

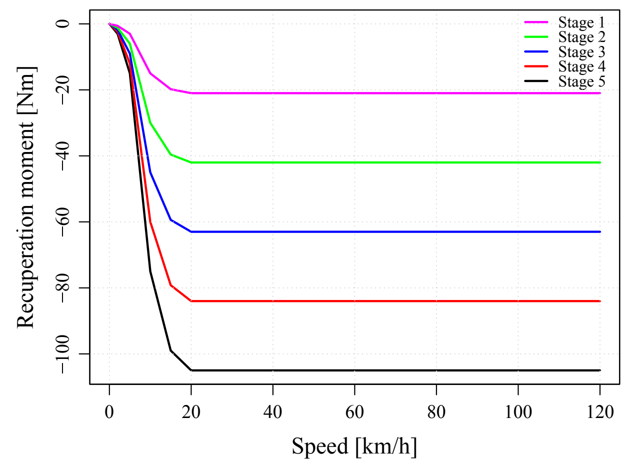

Figure 2. Speed-dependent recuperation moment M_{Recu} for each recuperation stage

Table I. LOAD LEVELS OF RANGE EXTENDER

Load Level	Generated power [kW]	Speed [km/h]
1	6	0-15
2	9	15-35
3	12	35-60
4	15	>60

D. Recuperation and range extender

So far, we derived the power consumption of the engine from our kinematic model. However, today's EVs often incorporate technology to increase the driving range by feeding back power to the battery. The most prominent among such systems are the recuperation module and the range extender.

Recuperation is a method to recover energy by converting kinetic to electric energy, during breaking and coasting. The amount of recovered energy depends on the used recuperation stage: if a higher stage is chosen, the car decelerates faster during coasting but is able to recover more energy. Accordingly, if a lower stage is chosen, the car coasts longer but recovers less energy. The stage of recuperation is usually chosen by the driver, however, some of the newer vehicles support the driver by automatically choosing the most efficient stage.

Our model includes five recuperation stages and a no-recuperation stage, as it can be found in a typical today's mid-size car. The recovered energy is calculated based on the engine's rotational speed n and the recuperation moment M_{Recu}

$$P_{\text{Recu}} = 2 \cdot \pi \cdot n \cdot M_{\text{Recu}}(v) \tag{12}$$

The speed-dependent recuperation moment $M_{\text{Recu}}(v)$ is calculated based on the determined recuperation stage. Figure 2 shows the recuperation moment curves according to the speed of the car (as specified by the manufacturer).

Usually, a range extender is a small combustion engine to generate power for the battery if the SOC is too low to reach a given destination.

The range extender delivers a constant power depending on the corresponding load level. In our model, we assume a Wankel engine with four load levels as shown in Table I. These

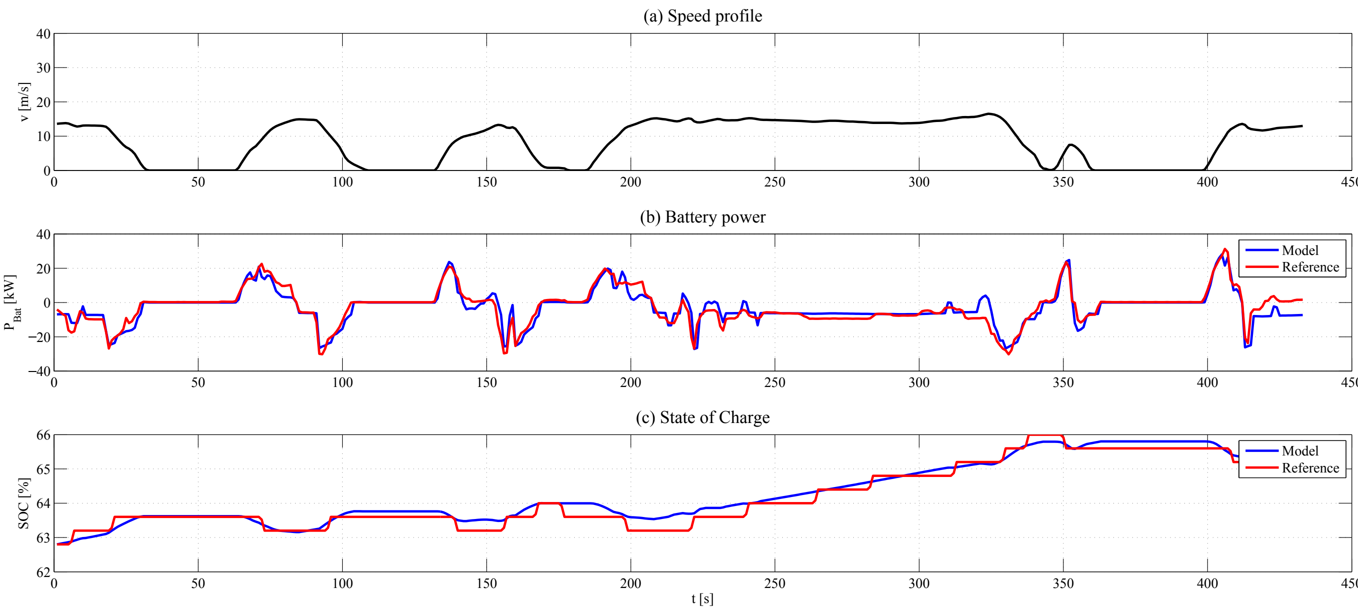

Figure 3. Validation results of the urban test drive

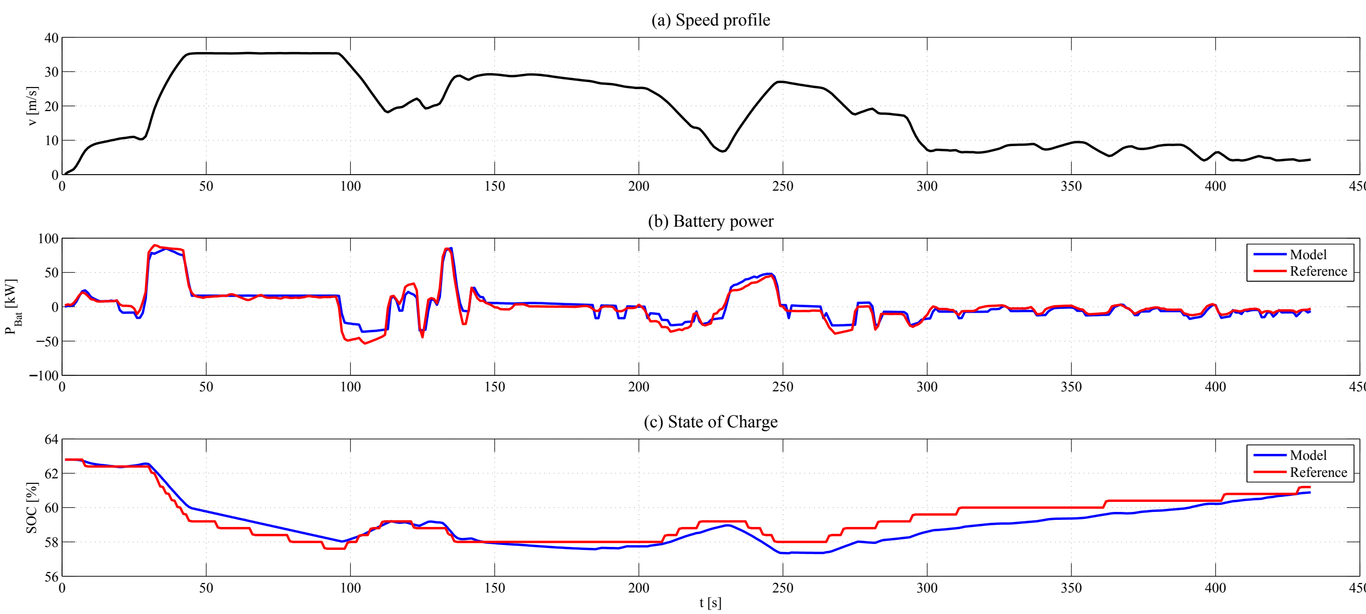

Figure 4. Validation results of freeway test drive

levels are automatically set with respect to pre-defined speed thresholds.

The resulting battery power flow P_{Bat} is then calculated as follows

$$P_{\text{Bat}} := -P_{\text{Aux}} - P_{\text{Eng}} + P_{\text{Recu}} + P_{\text{RE}}, \tag{13}$$

where P_{Eng} as calculated in Equation 5, P_{Aux} is the power consumed by auxiliary systems, P_{Recu} is the recovered recuperation power, and P_{RE} is the power generated by the range extender. If the engine does not consume power, e.g. while freewheeling, the SOC of the battery increases if recuperation or range extender are in use and produce more power than the auxiliary systems consume.

Table II shows all relevant car-independent and car-specific parameters used in our model.

IV. Validation

For the validation of our model, we implemented it in MATLAB and conducted real-life test drives using an AUDI A1 e-tron as a reference car. We recorded all necessary variables and used the car's speed as input for our model to compare the computed SOC against the recorded one.

A. *Urban test drive*

In a first experiment, we took the test vehicle to a German city and conducted a 7min test drive. The speed profile of

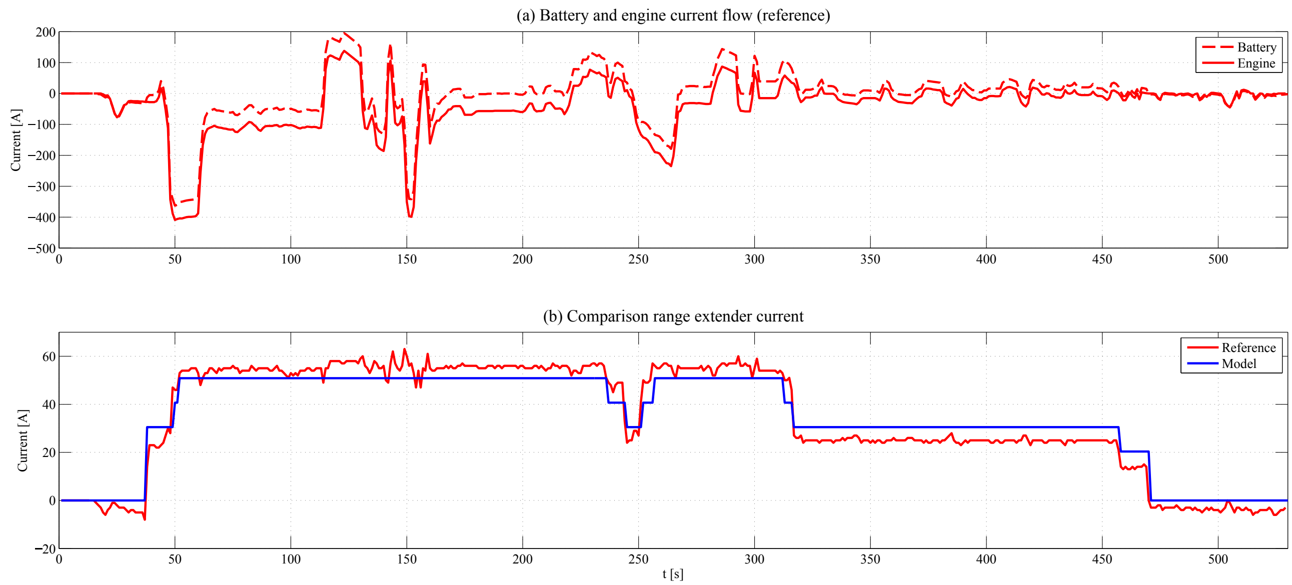

Figure 5. Validation results of range extender module

Table II. PARAMETERS AND THEIR TYPICAL VALUES USED IN THE BATTERY AND KINEMATIC MODEL

Parameter	Common symbol	Typical Value
Maximum power	P_{max}	75 kW
Maximum torque	M_{max}	300 Nm
Maximum rotational speed (engine)	n_{max}	6490 rot/min
Maximum acceleration	a_{max}	2.7 m/s^2
Car's empty weight	m	1400 kg
Battery capacity	C_N	12 kWh
Car's cross sectional area	A	2 m^2
Drag coefficient	c_d	0.32
Rolling resistance coefficient	c_r	0.015
Air density at 20 °C	ρ	1.2041 kg/m^3
Radius of the car's wheels	r	0.302 m
Engine's efficiency factor	η_M	0.9

this experiment is shown in Figure 3a. We observe the typical inner-city start-and-stop behavior with short periods of non-driving during red traffic light phases followed by acceleration to 14 m/s (50 km/h), which is the inner-city speed limit in Germany.

Figure 3b shows the comparison of the recorded test drive power flow and the power flow of the battery computed by our model. A positive level means, that power is consumed, while a negative level indicates that power was fed back into the battery. Hence, whenever the vehicle decelerates there is a noticeable power inflow generated by the recuperation module. Our model and the real life data are quite similar and in agreement for almost the entire test drive. The small deviations are mainly caused by the vehicle going down- or uphill and the fact that we did not have exact elevation data for the test drive.

In Figure 3(c) we compare the resulting SOC of the vehicle's battery. Again, the model and the recorded reference data are almost identical (note the small range of the y-axis), showing the correctness of our approach. In this test drive, the SOC actually increases over time as the range extender was continuously running and recharging the battery. The steps in the recorded data are caused by limitations of our measurement hardware.

The results show that our model is able to model the SOC of an electric vehicle in an urban environment very well.

B. Freeway test drive

The second experiment was conducted on a German freeway, where we recorded a maximum speed of 35 m/s (125 km/h). The results are summarized in Figure 4.

The speed profile (Figure 4a) shows an uninterrupted drive and higher overall speed levels than in the urban experiment with fewer acceleration/deceleration cycles. Figure 4b shows that our model is able to accurately reproduce the measured battery power levels. Please note that effects such as trucks in front of the test car reducing the air resistance and hence the required power are not considered in our model and can therefore lead to small deviations.

When comparing the SOC obtained by our model with the real life measurements (Figure 4c), we observe that the overall accuracy of our model is quite good. Driving at high speed at the beginning of our test drive drained the battery more than the range extender could charge it. When we arrived in a more congested section of the freeway the range extender could recharge the battery due to the lower speed. Our model slightly underestimated the SOC in this part of the experiment, however, the gap between model and measurements disappeared only a few seconds later, showing the applicability of the presented battery model in both urban and extra-urban scenarios.

C. Range extender validation

To validate the correctness, we compared the current generated by the range extender module in our freeway test drive with the values obtain from the simulation model. The current flow of the battery and the engine are shown in Figure 5a.

For the sake of simplicity we inverted the engine curve in this graph because a positive incoming flow here corresponds to a negative one in the battery. The difference between the dashed and the solid line is the current flow generated by the range extender. As the load level is set based on the current speed, the lines are further apart when the vehicle is driving faster due to the then higher amount of power generated by the range extender.

Figure 5b shows that our model is able to reproduce this current flow well and that it can therefore be used to accurately capture the effects of range extender modules on the driving range of EVs. The small deviations in the plot are caused by measurement errors and smaller side-effects that cannot be considered to keep the model computational inexpensive. Our overall results show that the level of abstraction is sufficient to simulate the realistic behavior of a today's lithium-ion battery in an electric vehicle while still maintaining low complexity.

V. Conclusion and Future Work

In this paper, we presented a lightweight and computationally inexpensive battery model. Using a kinematic model, we showed how to calculate the SOC based only on the vehicle's speed and fixed predefined parameters. Additionally, our model is able to include recuperation and range extender modules. We validated the model by comparing its output with data collected from comprehensive test drives. The results show that our model could reproduce the car's power consumption and battery level with high accuracy and therefore allows for realistic representation of electrical vehicles in microscopic traffic simulation.

Future work will concentrate on the simulation of realistic city-wide traffic based on empiric data to evaluate the impact of the substitution of common combustion engine vehicles with their electric counterparts. Based on these steps, we will investigate possible benefits of Inter-Vehicular Communication (IVC) on battery management. Furthermore, we will focus on extending our model to also account for the influence of temperature on the battery parameters.

VI. Acknowledgment

This work is founded by the German national program *Schaufenster Elektromobilität*, e-NUE. We would like to thank AUDI AG and N-ERGIE Aktiengesellschaft for providing the necessary data to conduct this research. Furthermore, we would like to thank Ekaterina Masalkina for her valuable input.

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