Range prediction of electric vehicles

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Abstract – Due to environmental and energy goals to protect the environment and climate, the attractiveness of electric vehicles have risen sharply, because local emissions from sources such as the combustion engine are reduced. Therefore, especially in urban centers electro mobility experiences a political accord. However, even technical framework conditions must be created in order to increase the acceptance of electric vehicles. There are extraordinary challenges in building of infrastructure and the inherent disadvantages of the energy storage technologies. In this context drivers of EV's are unsettled by inaccurate prediction of residual range. Within the project "Intelligent Electric Vehicle" (IEV), a methodology was developed that allows a more precise forecasting and optimization of the residual range of electric vehicles.

Keywords – prediction, electric vehicle, EV, driver model, driver behavior, driver assistance, DoE

1. Introduction

For the reason that electric vehicles emit very low local emissions (both acoustical and particle emissions) and because their upper speed is limited, they are ideal for use in urban areas with high environmental restrictions. Therefore the popularity and attractiveness of EV's is raised. However, even technical framework conditions must be created in order to increase the acceptance of electric vehicles. There are extraordinary challenges in building of infrastructure and the inherent disadvantages of the energy storage technologies. In this context drivers of EV's are unsettled by inaccurate prediction of residual range. The mentioned reasons cause a big confusion among users and reduce the desirability. Nevertheless forecasts say that the demand for electric mobility continues [1]. Hence it is required to predict the remaining range with a high precision to advance toward a better state of art and a more durable market presence.

For older generations of battery electric vehicles, the range was predicted with very simple and static algorithms – like moving average methods. Out of this problem statement the range prediction was not accurate enough and furthermore detailed methods were established who deals with this topic. In [2] it is described how to emulate dynamical effects with an enhanced HVAC system model, particularly for EV's. Especially the thermal effects of the battery were modelled and implemented in the prediction. Also the heating system and from user preferred thermal comfort was respected. The work in [3] describes a model-based approach for range prediction of battery electric vehicle. The physical model is based on system parameters such as vehicle speed, vehicle mass, vehicle frontal area, drivetrain efficiency, motor efficiency, electrical system efficiency, drag coefficient, rolling resistance, air density, gravitational acceleration, state-of-charge, battery cell temperature and estimated energy in battery. In addition an energy und state-of-charge models are implemented which calculates the consumption gradient. Compared with, the authors of [4] presented a framework for an application of neural network to predict the energy flow. Furthermore, it facilitates different transport deployment scenarios for vehicle-fleet operators that may use EVs within a specific environment, such as inner-city public transport or the use of urban delivery vehicles. The publication [5] approaches an analytical model on the Federal-Test-Procedure urban cycle. The authors of [5] are focused on a battery, motor and inverter model. The authors of [6] presented a model-based approach for predicting the residual range in combination with statistic methods as the kernel density estimation and unscented Kalman filter (UKF). In a first step the Bayesian tracking algorithm (UKF) estimates the SOC level as a starting condition for further propagation. In a second step multiple driving profiles are predicted by stochastic approach based on Markov chains. The residual range is finally approximate as a probability density function. For developing especially synthetic driving cycles like UDDS, ARTEMIS Rural and HWFET are simulate. But the potential as an explicit error validation for a real or random driving cycle of this approach is not discussed. Anyway, the efficiency of the algorithm largely depends on the number of evaluated driving profiles. Further publications, e.g. [7] or [8], are concentrated on the battery behavior to forecast the energy consumption.

Furthermore it is shown that additional and more significant influences have to be modeled and consider. In particular the driver style impacts a great influence on the energy consumption. More factors are also discussed.

2. Research

This chapter presents a short overview of the research results from preliminary studies and experiments. That was necessary to investigate the manner of the energy flow. Therefore the statistic method Design-Of-Experiments (DOE) for information-gathering was used. This allows a very effective and comprehensive analysis of complex relationships.

2.1 Driving cycle

Explicitly for energy studies a real driving cycle "Ilmenau Driving Cycle” (IDC) was defined, which reflects the urban rural regions. It is approximately divided into three sections: motorway, city and suburban area. Also, the height profile is special for the environment around Ilmenau – exclusively the extensive slopes. As part of the research about 10.000 km were driven.

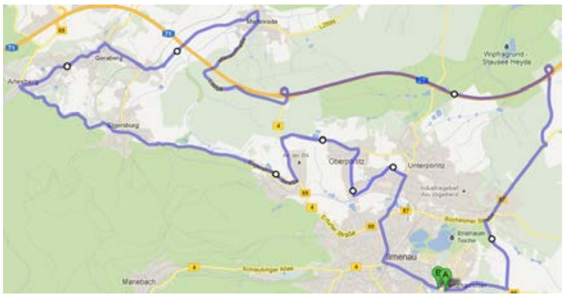

Figure 2.1: Ilmenau Driving Cycle

In addition to the real driving tests synthetic driving cycles (NEDC, 10-15 Mode, etc.) also were performed under reproducible laboratory conditions in cooperation with “TÜV Thuringia”.

2.2 Test vehicle

To investigate the energy flow and driving dynamics the vehicle was fitted with numerous measuring instruments and data loggers. They were focused on essential energy consumers as powertrain, air conditioning and further aggregates. Moreover CAN signals were recorded to indicate directly vehicle states. Powertrain analysis of the test vehicle shows a simple rule-based operating strategy, constitute in Figure 2.3. As specify, the permanent-magnet synchronous machine have a typical characteristic. Thus, initially the motor power increases linear up to a maximum, which is limited by cooling respectively heat up and inverter power [9], [10], [11]. If the motor speed exceeds a specified level, the maximal power is decrease.

Figure 2.2: EV on a dyno test bench

Furthermore, in Figure 2.3 the special features of electrical machines are shown, as the possibility to recuperate energy while run out or braking. Note, the recuperation by braking is a static characteristic between recuperation power, vehicle speed and brake pedal position. Compared with that, is the recuperation characteristic for a run out a static relationship between vehicle speed and recuperation power. Whereas, the energy recovering gradient during a run out is optional adjustable in three stages by the driver. However, Figure 2.3 shows only one stage. For specified speed thresholds is no recuperation scheduled.

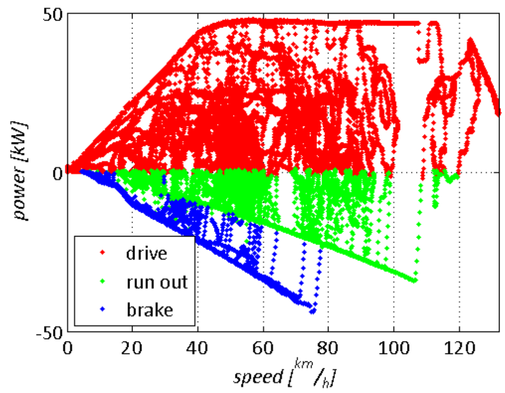

Figure 2.3: Powertrain power characteristics

2.3 Influences on energy consumption

An important role played the statistical method for planning and evaluation of exercises – the so-called "Design of Experiments" (DoE). Based on a combinatorial design which deals with the experimental parameters driving style, recuperation, initial SOC and the secondary consumers, a universal energy flow model could be implemented, which can be adapted to other vehicle types. To generate more information the DOE-interpretation was separated into a consideration of the influential strength on energy consumption in Figure 2.4 and energy recovering in Figure 2.5. The gradient of these figures represents the influence strength of each DOE parameter variation.

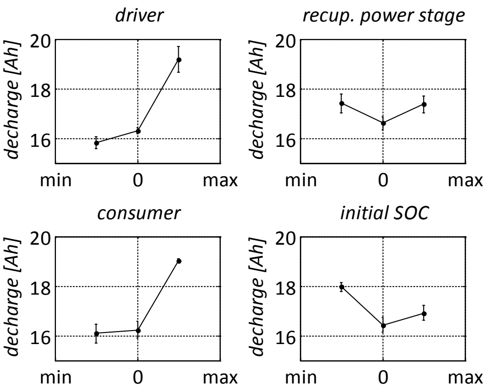

Figure 2.4: DOE parameter Influence on energy consumption

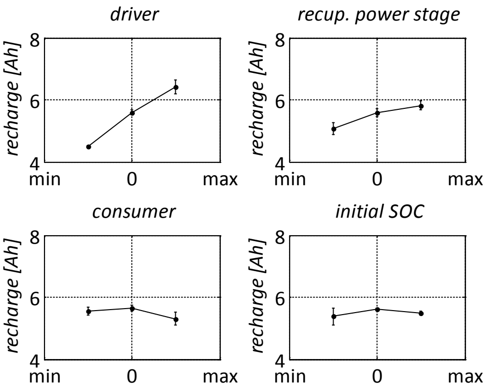

Figure 2.5: DOE parameter Influence on energy recuperation

The evaluation of experimental data shows that the driving style has a significant impact on energy consumption. Therefore, it is necessary to recognize and emulate the style of driving. In this context it is to be assumed, that the lateral and vertical vehicle dynamics are not major for long term energy consumption. Beyond this, the on board consumer have a relevant effect on energy consumption over the driving time. A clearly trend of the influences of the recuperation stage and initial SOC is not possible to detect. Except, the middle recuperation stage is the energy efficient on the Ilmenau Driving Cycle. Consequently a weaker recuperation power generates lower energy recovering and thus a higher consumption. In contrast to that a high recuperation stage causes a bigger brake torque, which is compensated by the driver. That reasons a higher consumption.

The investigation of the relevance of energy recuperation results also a biggest influence of driving behavior. As Figure 2.5 show, achieve a sportive driver more kinetic energy, which can recuperate. Regardless of that is also an impact of the recuperation stages recognizable. Consumer and initial SOC do not affect the recovering energy. Out of this issue an intelligent use of recuperation stages must be evolve. Such a detailed implementation is designed. But it will not further discussed in this work.

3. General model

For prediction system states it is necessary to known the behavior of it in future. A model-based method has been found as a reliable technique for prediction. Therefore in this chapter an implementation of a physical model for calculation the energy consumption on demand and their precision is conversed. This general model is independent of vehicle types and can adapt on other automobiles. Its model parameters are identified online. To perform the parameter identification of the mentioned models, a filter based on the least-mean-square method (see formula) was used and modified online capable. As a result a quality function ε must be defined to approximate a solution of formula 3.1. X represent the model input which generates the model output Y with parameter θ und model error $e \in R^{q \times n}$, where $X \in R^{m \times n}$, $Y \in R^{q \times n}$, and $\theta \in R^{q \times m}$ to a time sample k. The ε-function has to eliminate the error of the model. Differentiating partially the ε-function on the parameter θ results in equation 3.4 [12]. With this step, the parameters can be calculated with the least error.

$$Y_k = \theta_k X_k + e_k \qquad \textbf{3.1}$$

$$e_k = [\theta_k X_k]^{-1} Y_k \longrightarrow 0 \qquad \textbf{3.2}$$

$$\varepsilon_k = \sum (Y_k - \theta_k X_k)^2 \qquad \textbf{3.3}$$

$$\theta_k = \left(X_k{}^T X_k\right)^{-1} X_k{}^T Y_k \qquad \textbf{3.4}$$

Because the matrix representation is not effective for online parameter identification with a µ-controller a simple recursive description is needed. To introduce the online estimation of model parameter a one-dimensional model with input $x \in R^{1 \times 1}$, output $y \in R^{1 \times 1}$, parameter $\theta \in R^{1 \times 1}$ and model error $e \in R^{1 \times 1}$ should be used. Equivalent to the multi-dimensional notation following equations should be noted.

$$y_{\mathrm{k}} = \theta_{\mathrm{k}} x_{\mathrm{k}} + e_{\mathrm{k}} \qquad \mathbf{3.5}$$

$$\varepsilon_{\mathrm{k}} = \sum (y_{\mathrm{k}} - \theta_{\mathrm{k}} x_{\mathrm{k}})^2 \qquad \mathbf{3.6}$$

$$\frac{\partial q_{\mathrm{k}}}{\partial \theta_{\mathrm{k}}} = -2 \sum x_{\mathrm{k}} \left(\sum y_{\mathrm{k}} - \theta_{\mathrm{k}} \sum x_{\mathrm{k}} \right) \qquad \mathbf{3.7}$$

$$\theta_{\mathrm{k}} = \frac{\sum y_{\mathrm{k}} x_{\mathrm{k}}}{\sum x_{\mathrm{k}} x_{\mathrm{k}}} \qquad \mathbf{3.8}$$

However, if counter k running to infinity the sum $\sum y_{\mathrm{k}} x_{\mathrm{k}}$, sum $\sum x_{\mathrm{k}} x_{\mathrm{k}}$ also converge rapidly against infinity. Accordingly an advance modification is set. A time-weighted factor should be introduce, which forgot the past data. Out of this conclusion an observer is designed to estimate online one-dimensional parameter based on a recursive filter. This design has also the canceling property to improve noisy data. Wherein, T_w is a time design factor which respect data T_w seconds ago. T_s is the sampling rate. Note this method works only for linear combined model equations. Please pay also attention to ${}^{x}_{x}\epsilon_{\mathrm{N}} = \sum_{\mathrm{k}=1}^{\mathrm{N}} x_{\mathrm{k}} x_{\mathrm{k}}$ and ${}^{x}_{x}\epsilon_{\mathrm{N}} = \sum_{\mathrm{k}=1}^{\mathrm{N}} x_{\mathrm{k}} x_{\mathrm{k}}$.

$${}^{y}_{x}\epsilon_{\mathrm{k}+1} = \frac{1}{T_w + T_s} \left(T_w \, {}^{y}_{x}\epsilon_{\mathrm{k}} + T_s y_{\mathrm{k}+1} x_{\mathrm{k}+1} \right) \qquad \mathbf{3.9}$$

$${}^{x}_{x}\epsilon_{\mathrm{k}+1} = \frac{1}{T_w + T_s} \left(T_w \, {}^{x}_{x}\epsilon_{\mathrm{k}} + T_s x_{\mathrm{k}+1} x_{\mathrm{k}+1} \right) \qquad \mathbf{3.10}$$

$$\theta_{\mathrm{k}+1} = \frac{{}^{y}_{x}\epsilon_{\mathrm{k}+1}}{{}^{x}_{x}\epsilon_{\mathrm{k}+1}} \qquad \mathbf{3.11}$$

Since an electric vehicle is an electromechanical system an electrical and mechanical model and their coupling are propose. For the reason that the calculation performance and accuracy are more important there is no need to physical modeling of parameters.

3.1 Energy storage model

The energy storage model estimates the actual storage state of the battery. Out of this initial condition the maximal state of charge and transient discharging while driving are approximate. An equivalent circuit diagram of a widely used model is suggested by Figure 3.1 [8], [13]. This commonly model consists out of the SOC-Model on the left-hand side and V-I-Characteristic on the right-hand side. In this context the large influence of temperature on maximum state of charge is to be observed. This phenomenon is also considered by the online estimation filter because the battery capacity is identified dynamically.

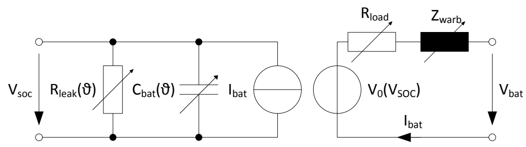

Figure 3.1: Battery equivalent circuit diagram

3.1.1 *SOC-Model*

This part of the commonly model calculates the battery state of the charge represent by C_{bat}. The battery capacity is discharged by a current source which signifies the consumer current I_{bat}. Additional, since the internal insolation of the battery is not ideal a small leakage current is flowing through electrical conductivity. The sum of leakage is considered by the leakage resistance R_{leak}. The SOC-Model transformation in Laplace notation corresponds with equations 3.12 to 3.16.

$$V_{\mathrm{soc}} = \frac{R_{leak}}{\mathrm{s} R_{leak} C_{bat} + 1} I_{bat} \qquad \mathbf{3.12}$$

$$I_{\mathrm{c}} = \mathrm{s} C_{bat} V_{soc} \qquad \mathbf{3.13}$$

$$I_{\mathrm{c}} = \frac{\mathrm{s} R_{leak} C_{bat}}{\mathrm{s} R_{leak} C_{bat} + 1} I_{bat} \qquad \mathbf{3.14}$$

$$Q_{\mathrm{soc}} = Q_{bat} - \mathrm{s}^{-1} I_{\mathrm{c}} \qquad \mathbf{3.15}$$

$$soc = \frac{Q_{\mathrm{soc}}}{Q_{max}} 100\% \qquad \mathbf{3.16}$$

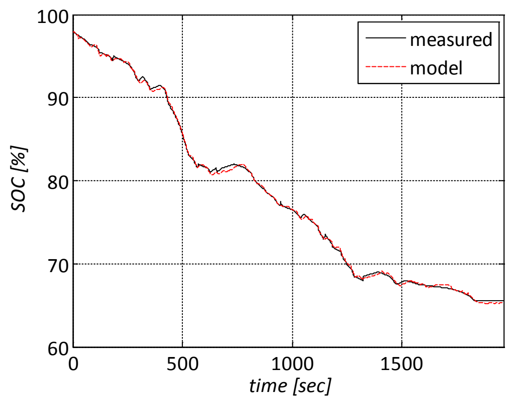

Figure 3.2: Battery SOC model

The valuation of the introduced SOC-Model is shown in Figure 3.2.

3.1.2 V-I-Characteristic

Batteries also exhibit very pronounced hysteresis behavior while charging and discharging. The V-I-Characteristic model describes this complex specific. Therefore it use the by SOC-Model calculated state of charge. The nonlinear relation between the open circuit voltage and state of charge is represented as SOC-voltage controlled ideal voltage source V_{soc}. R_{load} represents in the model the internal resistance of the battery. While operating the terminal voltage battery response is transient. A Warburg Impedance stays for an appropriate model to characterize this behavior. Basically it is a network of several RC-circuits. For prediction of the residual range is this part of the battery model not require. Because of completeness was this mention.

$$V_{\mathrm{bat}} = V_0(V_{soc}, \vartheta) - (R_{load} + Z_{warb})I_{bat} \quad \mathbf{3.17}$$

$$V_0(V_{soc}, \vartheta) = \sum_{k=0}^{n=3} \xi_k {Q_{soc}}^k \quad \mathbf{3.18}$$

$$R_{load} = \sum_{k=0}^{m=3} \alpha_k {Q_{soc}}^k \quad \mathbf{3.19}$$

$$R_{warb}(V_{soc}, \vartheta) = r_0 + r_1 e^{-r_2 Q_{soc}} \quad \mathbf{3.20}$$

$$C_{warb}(V_{soc}, \vartheta) = c_0 + c_1 e^{-c_2 Q_{soc}} \quad \mathbf{3.21}$$

3.2 Energy consumption model

In this chapter an energy sink model is suggest. It considers the main elements consumer and powertrain for calculation electric charge consumption equivalent to energy consumption. Beyond a method for classifying the driver behavior is mentioned.

3.2.1 Consumer

The consumer model is a simple sum of all small aggregate currents. Usually consumers are switching periodic on/off, they running permanent or their dynamic is very low. For this reason all consumer currents are summarized in a mean model I_{con}.

A big difference to the powertrain is the dependency of time. Whereas the electric motor only consumes energy while driving consumers need energy although standing. Out of this context there is a need to predict the time during driving and standing. The consumed electric charge calculates by equation 3.22.

$$Q_{\mathrm{con}} = \int_{t_0}^{t_1} I_{con}\, \partial \mathrm{t} \quad \mathbf{3.22}$$

3.2.2 Powertrain

It was already discussed that the energy consumption is essential depending of the longitudinal vehicle dynamic. On this account only the driving resistances are part of the model [14], [15]. Equation 3.23 represents the important resistances:

- Aerodynamic drag force
- Hill climbing force
- Rolling resistance
- Acceleration force and
- Rotatory inertia of powertrain.

$$F_{\mathrm{mech}} = \tfrac{1}{2}\rho_{air} c_w A_\perp \dot{x}^2 + mg\sin\alpha + mg\varkappa_r + m\ddot{x} + J i_{gear}\dot{\omega} \quad \mathbf{3.23}$$

$$F_{\mathrm{mech}} = \tfrac{1}{2}\rho_{air} c_w A_\perp \dot{x}^2 + mg\sin\alpha + mg\varkappa_r + \left(m + \frac{J i_{gear}}{r_{wheel}}\right)\ddot{x} \quad \mathbf{3.24}$$

Where the traveled way x, the altitude z and rotary motor speed ω are involved. The Ilmenau Driving Cycle is well suited to research the influence of slopes. Figure 3.3 shows the clearly distinct height profile which results a significant hill climbing force.

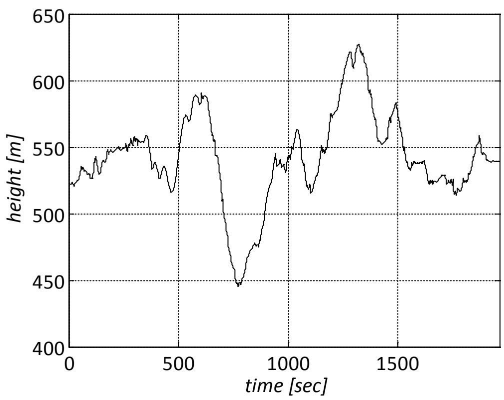

Figure 3.3: Height profile of Ilmenau Driving Cycle

Furthermore allows the splitting in three equivalent driving sections it is possible to evaluate the influence of vehicle speed. That means, that on the highway section especial the aerodynamic drag force has a high implication.

We expand equation 3.23 with the vehicle velocity $\dot{x}$, which results the power consumption in equation 3.26. For a better performance and quality of the later introduced prediction of the power consumption is integrated. It should be noted that the highest derivative of the corresponding terms are integrated. This approach allows a higher precision. Moreover the correlation between the integrated signals and the charge state of battery is much higher.

$$P_{\text{mech}} = F_{\text{mech}} \frac{\partial x}{\partial t} \qquad 3.25$$

$$E_{\text{mech}} = \tfrac{1}{2}\rho_{air} c_w A_\perp \dot{x}^2 \int \dot{x}\, \partial t + mg \sin\alpha \int \dot{x}\, \partial t + mg\varkappa_r \int \dot{x}\, \partial t + \left(m + \frac{Ji_{gear}}{r_{wheel}}\right)\dot{x} \int \ddot{x}\, \partial t \qquad 3.26$$

The model parameters in equation 3.26 are still oriented on physical quantities. For the online identification it is not interesting to know such details. Finally the physical based parameters are replaced by coefficients. Besides, the slope $\sin\alpha$ is substitute by the altitude z since both correlate.

$$E_{\text{mech}} = \beta_1 \dot{x}^2 x + \beta_2 z x + \beta_3 x + \beta_4 \dot{x}^2 \qquad 3.27$$

3.3 Coupling

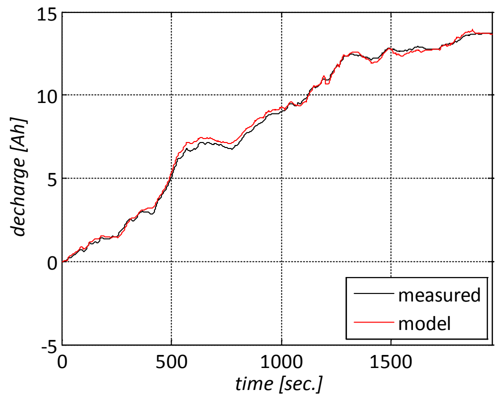

Figure 3.4: Validation of energy model

The model approaches for energy consumption and storage must to be combined. Thus the energy efficiency coefficients η_{PT} and η_{CON} are established. Likewise the coefficient β_0 was introduced to convert the energy unit to a charge unit. To reduce the model error there is the option to recirculate the fault. In order not distort the results it was not decided to use the error recirculation $\int e\, \partial t$.

$$Q_{\text{bat}}(t) = \frac{1}{\eta_{PT}} \beta_0 E_{mech}(t) + \frac{1}{\eta_{CON}} Q_{con}(t) + \int e\, \partial t \qquad 3.28$$

$$Q_{\text{bat}}(t) = \Lambda_1 E_{mech}(t) + \Lambda_2 Q_{con}(t) + \int e\, \partial t \qquad 3.29$$

$$Q_{\text{soc}}(t) = Q_{\text{soc}}(t_0) - Q_{\text{bat}} \qquad 3.30$$

After all Figure 3.4 shows a very well agreement between model and measured data. That means a high trustworthy in this model approach.

3.4 Driver behavior

As Figure 2.4 and Figure 2.5 show is the driver a very important protagonist. He controls the vehicle in dependency of his physical and psychical condition. With his driving behavior, he has a major influence on the longitudinal and lateral dynamics of the vehicle. In addition, the driving style is a key factor for power consumption. Here, the driving behavior and thus the execution of driving tasks the driver constitution heavily influenced. In the literature, the holistic behavior of the driver is represented as the so-called control model [16].

Hence, for prediction problems it is useful to know how the driver's behavior will be in future. This approach classifies the behavior in the three categories defensive, normal and sportive driving.

The driver model presented here is limited to the human-machine-interaction between driver and vehicle. Because in particular the driving pedal position represents the longitudinal vehicle dynamic it was mentioned to use the activity of the drive pedal as an indicator for classifying the behavior. In dependency of the vehicle speed $\dot{x}$ and the drive pedal position γ the classifier in Figure 3.5 was developed.

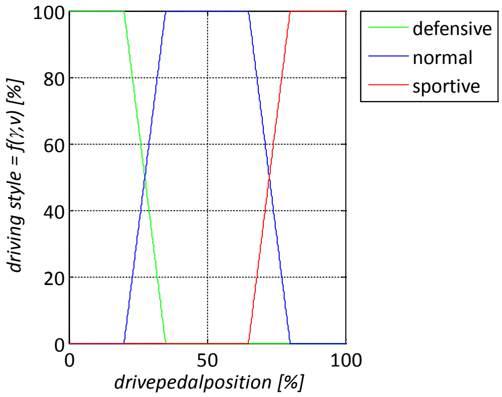

Figure 3.5: Driver classification

Their thresholds are moving with the vehicle speed. Using the drive pedal has particular advantages over other equivalent indicators such as vehicle acceleration. In particular, the specific system boundaries between 0% and 100% should be mentioned, which make it much easier to assign the type of driver. Furthermore, a general methodology has been created, which is independent of the vehicle types in contrast to other indicators as acceleration. The result of the classifier is the factor ${}^{D,N,S}_{t}\delta = f(\gamma,\dot{x})$ for transient behavior:

- D – defensive,
- N – neutral and
- S – sportive.

For a long term prediction this factor is filtered to indicator ${}^{D,N,S}_{f}\delta$ comparable with equation 3.32. As in equation 3.32 only the behavior which not passing T_w is high weighted.

$$ {}^{D,N,S}_{t}\delta = f(\gamma,\dot{x}) \qquad \textbf{3.31}$$

$$ {}^{D,N,S}_{f}\delta_k = \frac{1}{T_w+T_s}\left(T_w\,{}^{D,N,S}_{f}\delta_{k-1} + T_s\,{}^{D,N,S}_{t}\delta_k\right) \qquad \textbf{3.32}$$

Figure 3.6 introduce the convergence of the mentioned factor ${}^{D,N,S}_{f}\delta$. It is shown that the driver behavior establish basically on quasi-static threshold what facilitates the prediction of driver behavior.

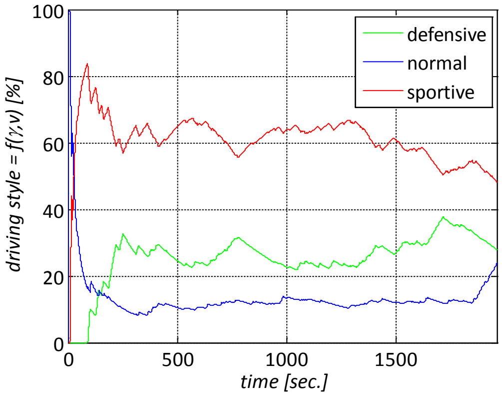

Figure 3.6: Online driver-classification driving across the Ilmenau Driving Cycle

4. Methodology of prediction

In combination with an intelligent energy saving route planning the future energy state of the EV can be calculated and predict the remaining range to offer the driver a range safety. An approach of this work is shown in Figure 4.1. First with the use of GPS-data the route should be planed. From this preliminary planning the topology of the track should estimate. From there all model inputs like altitude, vehicle speed, distance and driving time are known for energy calculation equation 3.27. For unknown routes this chapter introduces an alternative methodology.

4.1 Prediction of residual range using route planning

It is a big problem that the route is in most cases not known since the routing data are inputs for an energy consumption forecast. Because in the most cases the route is not known, in this section a prediction for an unknown track is discussed.

4.1.1 Route forecast

For the reason that usually the driving route is unknown an approach for an intelligent track scheduler is discussed. The first scheduler suggestion is an assigning priority in dependency of road types. Beginning from the starting point the scheduler estimates the track for road types with the highest priority (see Table 1).

Table 1: Assigning of road priority for track prediction

road category	priority
highway	very high
expressway	high
country road	middle
main road	low
secondary roads	very low

If one road leads into another with the same priority, then the track is taken that leads on the shortest way to the nearest roads with the larger priority. This scheduler represents the strategic logic for a long trip.

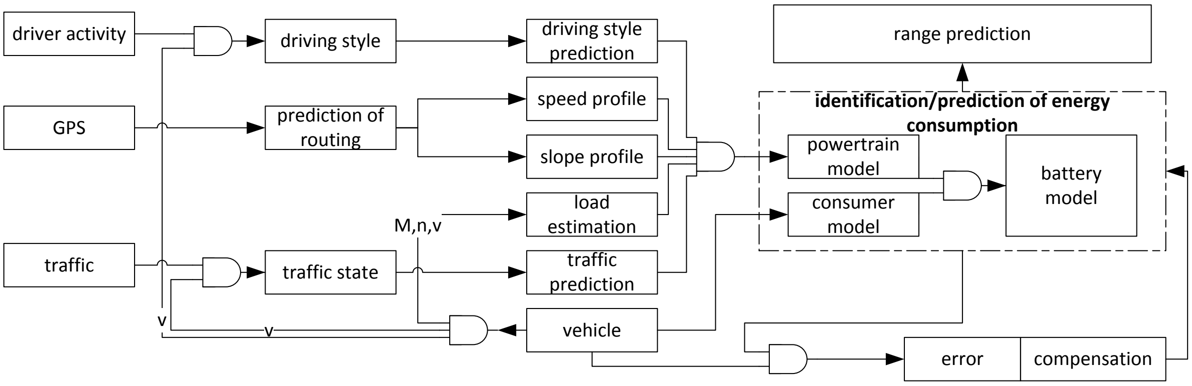

Figure 4.1: Range prediction procedure

As a second scheduler suggestion is based on data statistic data collection of driven routes. The tracks with the highest frequency are more prefer for a route planning. For vehicles which are moved in the near located environment with small driving ranges is this method very efficient. But in this case electric vehicles can be charged to the local charging stations. Probably there is no need for a precise range prediction. It makes more sense for longer ranges. Eventually the data collection needs a big data memory. If both schedulers fail the method in chapter 4.2 should use.

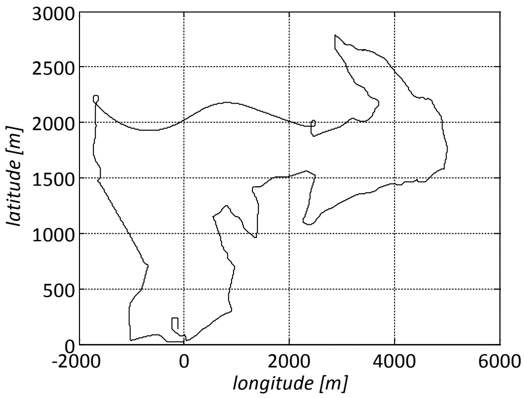

Figure 4.2: Route of Ilmenau Driving Cycle

The further considerations of this work are based on Figure 4.2. The Ilmenau Driving Cycle was adopted as a given planned route by the scheduler.

4.1.2 Speed profile prediction

Assuming the scheduled route the sped profile can create from navigation device data. For this, the speed limits $\dot{x}_{GPS}$ of road signs stored on a central database are used. To fit the speed limit profile $\dot{x}_\delta$ to the expected real driven velocity $\dot{x}$ the driver behavior model is used.

$$\dot{x} \overset{\text{def}}{=} \dot{x}_\delta \qquad \textbf{4.1}$$

$$\dot{x}_\delta = [\kappa_D\, {}^{D}_{f}\delta_k + \kappa_N\, {}^{N}_{f}\delta_k + \kappa_S\, {}^{S}_{f}\delta_k]\dot{x}_{GPS} \qquad \textbf{4.2}$$

The result of such an estimation of the speed profile $\dot{x}_\delta$ is shown in Figure 4.3. Hence the GPS-data speed limits assume only the target speed without to regard acceleration and the actual speed. The driver model takes this into account.

The estimated speed profile continues to be used in for calculation the driving distance. In Figure 4.4 it can be seen that the deviations are marginal.

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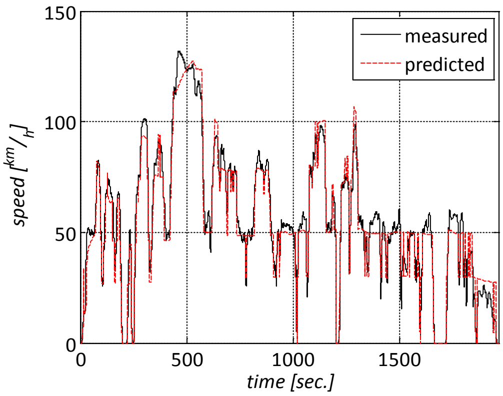

Figure 4.3: Speed prediction

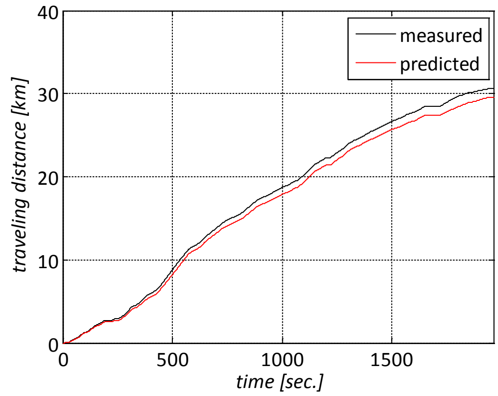

Figure 4.4: Travel distance prediction

4.1.3 Altitude prediction

The prediction of the altitude is the same procedure as the driving profile. With the preplanned track we can assume their altitude profile out of navigation device data.

4.1.4 Driving time

The accuracy of the prediction of the driving distance affects a higher precision for calculating of consumer energy consumption. Out of the speed profile and route distance forecasts the travel time is estimated. Wherein the traffic can influences the travel time and real speed profile strongly. An additional traffic model could this respect.

4.2 Prediction of residual range for unknown routes

Usually modern cars include a navigation device from which one the database could use. But not every vehicle has access to navigation-database.

For this and for predicting the residual range after arriving, this chapter discusses a linear extrapolation method.

As already mentioned the driver expects after arriving final information about the residual range of the vehicle. Consequently a method for extrapolating prediction was developed. A range weighted filter is designed according to equation 4.3. It describes any model input or parameter represented by φ_{k} at a sampling k that is filtered to a extrapolating long term value φ_{k}^{*}. For prediction the residual range x_r^* every model input and parameter is filtered and substitute in equation 3.27, 3.29 and 3.30, which results in equation 4.4. To approximate the residual range the remaining charge must be assume as zero. Change to x_r^* gives equation 4.5.

$$\varphi_{\mathrm{k}}^{*} = \tfrac{1}{x_w+\partial x}\left(x_w\varphi_{\mathrm{k}-1}^{*} + \partial x\varphi_{\mathrm{k}}\right) \qquad \textbf{4.3}$$

$$0 = Q_{\mathrm{soc}}(t_0) - \Lambda_1^*\left[\beta_1^*\dot{x}^{*2}x_r^* + \beta_2^* z^* x_r^* + \beta_3^* x_r^* + \beta_4^*\dot{x}^{*2}\right] - \Lambda_2^* Q_{con}^*(t) \qquad \textbf{4.4}$$

$$x_r^* = \frac{Q_{\mathrm{soc}}(t_0) - \Lambda_1^*\beta_4^*\dot{x}^{*2} - \Lambda_2^* Q_{con}^*(t)}{\Lambda_1^*\left[\beta_1^*\dot{x}^{*2} + \beta_2^* z^* + \beta_3^*\right]} \qquad \textbf{4.5}$$

This is an operative way for recursive estimation with a high performance for example with a µ-controller. However, in exchange also GPS-data are required.

5. Impact

Finally the impact of the presented work will discussed. For assessment of the precision and quality of the methods the absolute error definition is used. In addition, the qualitative and quantitative approach performance is shown and evaluated on the basis of curve running. Because of overview both methods were plotted after different time windows.

$$\text{absolute error} = \sqrt{(Y_{\mathrm{k}} - Y_{\mathrm{k}}^{*})^2} \qquad \textbf{5.1}$$

Figure 5.1 shows that after 5 and 10 minutes of model identification the model differ rapidly. Note that before that no parameters are estimated. A reason for this deviation could be the highway between range kilometer 10 and 20. On this section the velocity is very high and velocity depending resistance like aerodynamic force couldn't identifying very well. Anyway has the wind direction a big influence. On the Ilmenau highway the direction changes quickly. Further the actual vehicle speed could not predicted exactly by Figure 4.3. In order to it causes a bigger error. After 20 and 30 minutes this error impacts are also obvious. Nevertheless the charge prediction for the final value of the driving cycle is accurately, since the route scheduling procedure is designed for this.

In contrast to the energy consumption model is the range prediction very accurately. Over the whole driving cycle a range prediction error less than 1.5 km was achieved (see Figure 5.2). The main impact on this error is the driver behavior prediction in combination with the speed profile prediction.

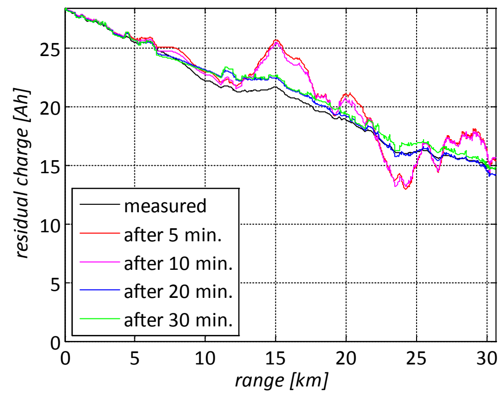

Figure 5.1: Prediction of residual range using route planning

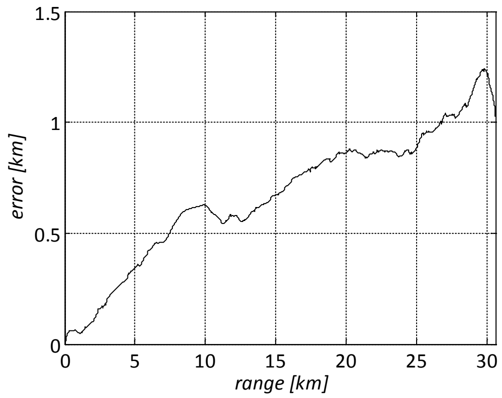

Figure 5.2: Prediction error of residual range using route planning

The linear extrapolating prediction according to equation 4.5 is presented in Figure 5.3. It is clearly recognizable that time have not a significant effect. A clearly improvement trend after a longer or shorter time window is not observable. However, the tendency of model and measurement is congruent. The essential issue of this procedure is the residual range which negligible variants between 59 and 61.5 km.

The mentioned influence of the identification of the aerodynamic resistance is similarly perceived in Figure 5.4. After 10 minutes driving the error is rising. On the other hand does the absolute error not exceeds 3.5 km. This is an extraordinary quality. For low velocities the prediction error is a smaller amount of 1.5 km.

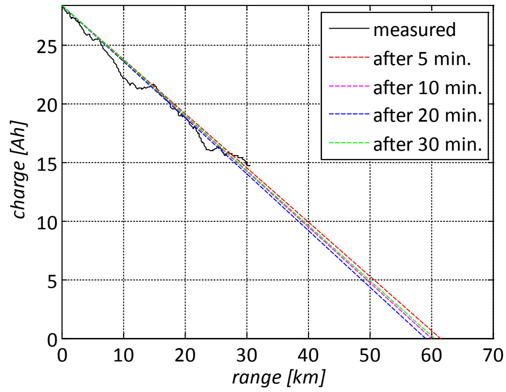

Figure 5.3: Extrapolating prediction of residual charge

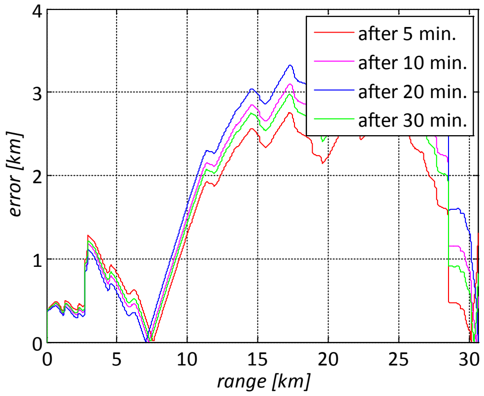

Figure 5.4: Extrapolating prediction error of residual charge

6. Conclusion

This work presents a model-based approach for a high precision prediction of residual range of electric vehicle. Therefore an energy storage and energy consumption model was established. Its general property allows an easy plug-play adaptation on different vehicle. In particular, a methodology for classification of driver behavior has been created, which is independent of the vehicle types. In extension to the vehicle energy model it was advanced to involve the driving performance for accurately prediction. For the reason that the calculation performance and accuracy are more important there was no need to physical modeling of parameters. To perform the parameter identification of the mentioned models, a factor weighted filter was evolved and modified online capable. For calculate the residual range two methods are presented. The first procedure estimates with high probability selected track and their topology. The second procedure proposes a recursive estimation technique. However, in exchange also GPS-data are required. The impact of the recommended process evaluates a very small deviation a smaller amount than 4 km.

The evaluation of the results reveals a better consideration of traffic state. Moreover, a recirculation of model error should be implemented.

7. Acknowledge

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Besides the mentioned work, a methodology has been developed, which use reduces the energy consumption by up to 10% by providing the electrical power in terms of a rule-based strategy. In this regard, there is always a conflict between the minimization of energy consumption and the driving dynamics which is to be solved. Therefore, the acceleration and jerk were chosen as an indicator to evaluate the drivability and comfort. On this foundation the energy consumption of the powertrain was minimized and optimized. On top, assistance functionality was developed to extend the range, which supports the driver using the recuperation power stages. Concurrently the test vehicle and the test cycles were modeled detailed in a simulation environment to develop new strategies for the operation of an electric vehicle. Thus the simulation tools IPG CarMaker, Matlab/Simulink and AVL-Cruise are used.

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