Usage Profile Rating of Suitability to E-Vehicles Utilizing a Physical Consumption Model

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Keywords: Electricity Consumption, Electric Vehicles, Simulation of Consumption, Timeseries Analytics.

Abstract: The project "Wohnungswirtschaftlich integrierte netzneutrale Elektromobilitat in Quartier und Region" (WINNER) aims to integrate shared electric vehicles, smart local grids and renewable energy in tenant households. This paper focuses on how to find the model of an electric vehicle (consumption, recharging, usage) which perfectly matches the requirements of particular carsharing stations. This approach utilizes usage profiles of conventional combustion vehicles. Each profile describes booking time and distance. Applying that information to a rating model which simulates the driving task and charges the vehicle between usages should be able to tell how much bookings might be handled by an electric vehicle. Within this paper, we give an introduction to our simulation system. This covers the data model, transforming bookings into driving tasks, and the consumption and charging model itself. Further, we validate the model by using high detailed data captured on regular routes as well as booking sets with electric vehicles. This validation shows an average relative error of 10 % for high detailed data from and an average relative error for booking information with known consumptions of 5 %. Finally, we present the application of our simulation system to make a decision based on historical booking information. This application example shows that 90 % usages at some station might be handled with electric vehicles, while others should not be replaced.

1 INTRODUCTION

Mostly stated, electric vehicles (EVs) have limited ranges until and cause the assumption that they are not universally applicable (Bundesministerium für Bildung und Forschung, 2013, S. 3). The question arises as to when an EV will become usable for private use. This issue is usually answered through generalized studies in which not everyone sees themselves reflected individually. However, the following approach implements a simulation system which helps to rate individual usage profiles. The rating weights the suitability to EVs and might help to decide if a personal vehicle usage profile can also be managed by using an EV. This simulation system utilizes a physical consumption model which provides consumptions on particular driving situations based on technical specifications of EVs as well as current real-world data, e. g., velocity, acceleration and gradient.

This approach is made within the research project WINNER (Chemnitzer Siedlungsgemeinschaft eG, 2017) which aims to integrate and coordinate electromobility, the energy consumption of tenant households and the local production of electricity, e. g., by integrating photovoltaic systems into a smart local energy grid. Within the project, EVs are used via the carsharing approach. This EV usage leads to the request about which carsharing station should use EV as well as which might be the best EV at a particular carsharing station. Vehicles used within carsharing provide perfectly documented usage profiles. They have to be our primary input, next to technical specifications of EV, to rate them.

Within this paper, we want to use such usage profiles and rate them for suitability to EV by utilizing a physical consumption model. Further, we want to give an example of how well this approach works. However, we have to implement the simulation system itself, validate the particular components. Validation is done by using detailed measurement data gathered while driving with an i-MiEV on regular routes. In addition, our project partner Mobiltiy Center GmbH provides us with a set of anonymized usage profiles with the EV e-Golf for further validation of our simulation system. Finally, we used another set of anonymized usage profiles, also from Mobiltiy Center GmbH, with various conventional combustion vehicles for final evaluations.

Hertrampf, F., Apel, S. and Späthe, S.
Usage Profile Rating of Suitability to E-Vehicles Utilizing a Physical Consumption Model.
DOI: 10.5220/0006774904460453
In *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2018)*, pages 446-453
ISBN: 978-989-758-293-6

The paper starts in Section 2 with related work about physical and statistical consumption models used in combination with EVs. Subsequently, in Section 3, details of the intended rating procedure are presented. As a result of that, the required components of our simulation systems are introduced, like data model and consumption model. The resulting system is validated in Section 5. Finally, we evaluate usage profiles of vehicles with combustion engines in Section 6 and discuss the results in Section 7.

2 RELATED WORK

The research area of electric vehicle simulation has become a well known subject in the last years. Upcoming usage of EVs improves this fact. The primary goals of research are forecasting the available ranges or the consumed amounts of electric energy. We can state three principles of doing this:

1. Standard driving cycles like New European Drive Cycle (NEDC) (Verband der Automobilindustrie, 2017)
2. Statistical analysis and artificial neural network (ANN) (Kretzschmar et al., 2013; Gebhardt et al., 2015; Ferreira et al., 2013)
3. Physical models of EV (Rami Abousleiman, 2015; Cedric De Cauwer, 2015; Schreiber et al., 2014; Fetene, 2014; Zhang and Yao, 2015)

The first mentioned variant is commonly used to get the range the car manufacturer states. The measurement occurs under standard conditions, i. e. 25 °C or 77 °F and with a mileage of 11 km. Out of that the capacity of accumulators depends on temperature. Thus, this standard driving cycle does not cover possible range decreases caused by lower ambient temperatures.

Statistical analysis can be done if there are enough data to examine, e. g. when using ANNs or regression models. If this is available, we could search relations between timestamps, traffic, driver, weather and electricity consumption. Examples of approaches like this can be found in research projects, e. g., eTelematik (Kretzschmar et al., 2013) and SCL (Gebhardt et al., 2015) as well within the Electric Vehicle Assistant described in (Ferreira et al., 2013). Especially if a fleet of vehicles is available, we can think of this approach.

Taking up the position of a physicist, we could develop an EV model. Using the vehicle parameters like mass, front face or roll friction you can calculate the forces affecting the vehicle. The corresponding equations result in needed power and energy amount. Rami Abousleiman (Rami Abousleiman, 2015) follows this idea. Five different routes are used to validate the physical model. The consumption of electricity is measured and compared to the simulated one. Cedric De Cauwer (Cedric De Cauwer, 2015) not only uses a physical model, a logger for Global Positioning System (GPS) coordinates and battery data like current and voltage was used too. So very detailed information is gained, and no predefined tracks are necessary. Even the recuperation of EVs can be involved, as shown by (Zhang and Yao, 2015). They used a specific recuperation factor for regaining energy by breaking depending on the current velocity of the vehicle.

3 USAGE PROFILE RATING

In case of rating the suitability of an EV based on usages requires specifying the possible level of detail of such profiles. Within our scenario, it is necessary to limit usage profiles on a set of tuples containing start time, duration and distance to drive. This set is sorted by starting time. The resulting end time, based on start time and duration, should not be greater than the starting time of the next element. Furthermore, it is required to recharge the EV between two elements within the sets of usages. Thus, the EV rating considers that each usage can use as much energy as it could have until now. Additionally, if a single usage cannot be handled, the model should use this period as an additional recharging phase. Based on this input, our goal is to rate the suitability of an EV. A rating, in this case, describes how many elements of this set of usages can be executed by using an EV. Possible EVs might be preselected, but it is not guaranteed that there is already a significant amount of recorded data for each EV-model. Based on this restriction, we cannot easily utilize approaches like ANN or statistical analysis. We decided to create this rating approach on top of a physical consumption model which requires basic car information. Information like that can be gathered from technical specifications as well as publicly available benchmark data.

The usage profile rating can finally be described as a function which takes a vehicle configuration V and a set of usage profile tuples U_i which are defined as $(t_{\text{start}}, t_{\text{end}}, d)$, i. e. start time, end time and driven distance. The rating itself is defined as the ratio between usages which can be handled and usages which can not be done because the State of Charge (charge level of the electric vehicle) (SoC) is going to be negative. The resulting rating function $r(V, U_0, ..., U_n)$ is shown in Equation 1. It utilizes the function $d(V, U_i)$ which

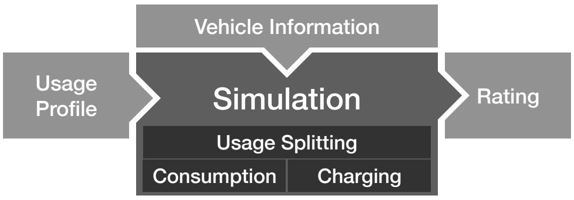

Figure 1: The basic architecture of simulation system using a usage profile and vehicle information as input and outputs rating by utilizing a consumption and charging model.

calculates the consumption within a driving task and the function $c(V, U_{i-1}, U_i)$ which handles charging tasks between two usages.

$$
\begin{aligned}
d &: (V, U_i) \rightarrow \triangle SoC_i \\
c &: (V, U_{i-1}, U_i) \rightarrow \triangle SoC_i \\
f &: (V, U_{i-1}, U_i) \rightarrow \begin{cases} c(V, U_{i-1}, U_i) + d(V, U_i) & |i > 0 \\ 1 - d(V, U_i) & |i = 0 \end{cases} \\
u &: (V, U_0, ..., U_n) \rightarrow \{j : j = \sum_{i=0}^{m} f(V, U_{i-1}, U_i) \wedge m < n\} \\
r &: (V, U_0, ..., U_n) \rightarrow \frac{|\{e : e \in u(V, U_0, ..., U_n) \wedge e \geq 0\}|}{|u(V, U_0, ..., U_n)|}
\end{aligned} \tag{1}
$$

4 SIMULATION SYSTEM

The simulation system, as shown in Fig. 1, realizes the already mentioned workflow from Section 3. Details on the consumption are presented in Section 4.2 and charging calculation itself is shown in Section 4.3. The consumption and charging model require refining the usage profile into more specific tasks. Each task can be a driving task or a charging task. A charge task is described by time and amount of possible charging energy. A driving task is defined by a set of steps to drive by. Each step describes a time, a velocity, the temperature and gradient for this driving step. The job of the splitting component within the simulation system is to transform single usages into tasks. This splitting strategy should be configurable to reflect a different kind of situations.

4.1 Usage Splitting

Calculating consumptions based on drive tasks requires detailed information on usage. In the case of this simulation system, information should cover tuples containing speed, duration, gradient and temperature. But booking information is not that fine-grained.

The simulation system utilizes the usage splitting component to transform initial booking information to generate more detailed driving tasks. The following list will show our current available strategies to create driving tasks based on bookings.

- *Uniformly.*
  The most simple strategy to drive. Simply drive the booking duration with constant velocity.
- *Middling.*
  Adds accelerations and decelerations processes within this chain of route tasks. The number of accelerations and decelerations can be configured.
- *CommonMiddling.*
  Utilizes Middling and adds calculated mean velocities based on driven distances. E. g., drive 50 km with 40 km/h and everything further with 80 km/h. Each part can be configured with a distance to drive, a mean velocity to handle as well as the amount of accelerations and decelerations.

4.2 Consumption Model

For calculating and comparing energy consumptions, we use the equations for kinetic, potential and rotational energy. The energy budget of a single vehicle may compare well to the values of others. But the energy loss caused by friction between tires and surface or car body and surrounding air needs to be modelled as well. This can be done by using the resulting friction forces and multiplying them by the actual velocity. So we gain the currently needed power to keep a specific velocity. Multiplying by the necessary time we calculate the consumed energy. The following list gives a short overview.

- Air friction F_{air}
- Roll friction of tires F_{roll}
- Gradient of surface F_{grad}
- Inertia of vehicle F_{i}
- Wheel rotation caused by inertia F_{wheelrot}
- Engine's torque moving the vehicle F_{e}

The modelling of the formerly mentioned aspects referring to consumption needs some vehicle specific parameters. We need the mass of the car, the mass of the wheels (moment of inertia required), the measurements and drag coefficient (front face calculation for air drag) and the capacity of the accumulator. Out of that, we need the temperature of the environment and the gradient of the terrain. The latter information is used to calculate the fractions of the gravity force, which correspond with the tire friction (orthogonal force to the terrain) or the grade resistance (parallel to the terrain). The temperature is essential for the capacity of the accumulator and affects the range.

There are some problems with the formerly mentioned values. Getting the measurements etc. does not state a problem, but the dependency of capacity on the temperature may not linear. Furthermore, the mass of the engine and its rotating parts cannot be found easily in technical specifications of EV published by manufacturers. Furthermore, if we consider acceleration phases, the velocity is changing as well as the acting forces. Thus, we calculated the integrals of the forces multiplied by travelled distances to estimate the produced and consumed energies. The results are multiplied by the matching distortion factor for energy consumption or recuperation (Listing 2, (Hertrampf et al., 2018)).

$$E_{\text{air}} + E_{\text{roll}} + E_{\text{pot}} + E_{\text{kin}} + E_{\text{rotwheel}} + E_{\text{rotengine}} = \begin{cases} \Delta E_{\text{total}} \cdot \text{consumptionfactor} & |\Delta E_{\text{total}} > 0 \\ \Delta E_{\text{total}} \cdot \text{recuperationfactor} & |\Delta E_{\text{total}} < 0 \end{cases} \quad (2)$$

Finally, we use a factor to tare our model. The factor describes how much kilometres the evaluated car may travel without recharging in relation to our simulation result. In fact, this factor is multiplied by the consumed energy. For further information, a technical report is available under (Hertrampf et al., 2018). We had no chance of validating the technical details like air resistance coefficient or roll friction of the EV itself. Only manufacturer's information or general physical information was used, e. g. roll friction of standard tires.

4.3 Charging Model

The energy consumption can be modelled by using an efficiency factor within our stepwise simulation. In contrast, the charge task is not mapped onto steps. This is caused by the lack of charging information on the EVs. We would not have been able to check our model according to the considered vehicles. Fortunately, there is some research on this term. Mohammad Chahgrkhgard (Charkhgard and Farrokhi, 2010) states a root-shaped profile for the SoC over time. According to this result and empirical values, we use a double-linear charging profile. Up to a threshold of refilled capacity the model charges with a high efficiency, afterwards, the efficiency is reduced. This simple charging model accounts for the fact, that vehicle manufacturers often state charging times up to 80 % and the remaining time up to 100 %.

4.4 Reality Distortion Factor

One factor can modify the consumption model of Section 4.2. This factor might be used to overcome the gap between the physical consumption and the real consumption of an EV. However, the goal of this paper is to rate usage profiles of suitability to EV utilizing. Further, this rating is done without having recorded driving data. To solve the problem of missing driving data, the idea is to get this factor by using available information driving results and compare them to consumptions made by our consumption model.

The NEDC (Verband der Automobilindustrie, 2017; Nations, 1995) is a standardized driving cycle with a distance d_{NEDC} of 11022 m which takes 1180 s to drive. Manufacturers mostly provide results as consumption per kilometre or driving range in kilometres. The NEDC cycle measures the energy consumed after driving the cycle two times on a roller dynamometer. This measurement is done after a full discharge and recharge of the vehicle.

Within our simulation system, we use this cycle to get the energy consumption ΔE_{Model} based on our model as it would be with a specific car mass, front face and air drag coefficient. Afterwards, we calculate the max range of this consumption and the vehicle capacity C as the NEDC does it and compare this result to the NEDC-range R_{NEDC} a vehicle should have:

$$RDF \cdot \frac{C}{\Delta E_{\text{Model}}} = \frac{R_{\text{NEDC}}}{d_{\text{NEDC}}}$$

The resulting ratio is used as our reality distortion factor (RDF). This factor should compensate specific efficiencies of the EV as well as various loss factors between the point of measurement used by the NEDC and the point of the simulation. The equipment is placed between vehicle charger and main socket to measure consumptions afterwards. Our consumption model calculates energies required to change the moving state and position of the EV.

Getting the RDF has to be an iterative process. The NEDC causes this. We do not know the technical efficiency of an EV, which handles the driving cycle. So we assume at first an RDF of 1, that means, we estimate a model consumption equal to the real consumption. After driving the NEDC, we compare the manufacturer's given range and the simulated and calculated range. Depending on this comparison we gain a new value for the distortion. Using this number, we rerun the simulation and use the next distortion value obtained in this way. The steps are repeated up to such time as we get no difference between start distortion and end distortion. Finally, we get the vehicle specific RDF that we can use for the further evaluation of usage profiles. Fig. 2 shows the progress of the factor calculation. You can see, that 10 to 20 cycles are enough to get a value changing no longer. The i-MiEV reaches a value of approx. 1.09 for example.

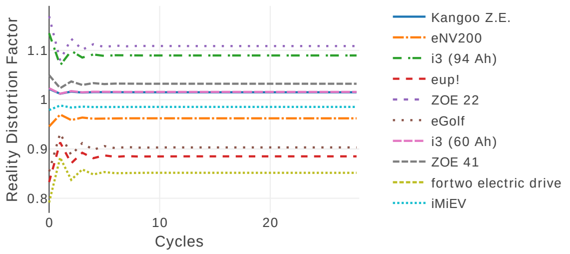

Figure 2: Distortion factor plotted over number of repetitive calculations.

5 VALIDATION

We have to show the usefulness of our model. For this approach, we used data from tracks collected in 2013. The tracks run from Jena to Weimar and back as well as from Jena to Golmsdorf and back. In this section, we give a short description of this information and identify problems.

5.1 Specific Validation

The validation of our physical model is done by using data from a Mitsubishi i-MiEV. We use the OBD2 Port to access CAN-Bus data, i. e. the current velocity, the measured state of charge of the battery and the needed current and voltage at a specific time. Additionally, we have added the current GPS position. Using the position data we called an elevation web service (Google, 2017) to gain information on the current gradient. The time resolution is one second. At this point, we must state, that the quality of data is not perfect. If we compare the velocity calculated by the GPS locations and the velocity measured recorded from the OBD2 Port we get differences. Furthermore, there is a mismatch between the measured SoC and the iterative summed up energy. So we have to choose one single data source, or we have to interpolate between various values. We do not consider current weather conditions or driving characteristics of specific car drivers. This validation utilizes the already mentioned RDF.

Situations, like driving uphill, while decelerating or driver specific behaviour, cause problems and an error of energy consumption forecast. Driving uphill or downhill with a large gradient is not modelled perfectly. For lower gradients, the prognosis gets better.

Finally, we want to present the overall error for the i-MiEV on various tracks. Fig. 3 shows that we get results differing from the measured consumptions by an amount of 10 %. The error is not increasing

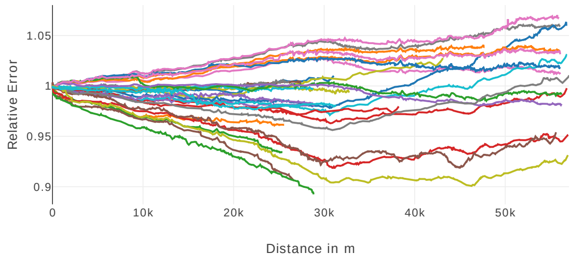

Figure 3: Evolution of errors on various tracks depending on track distance (vehicle i-MiEV).

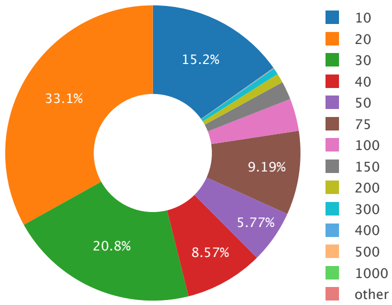

Figure 4: Grouped distances in usage profiles (15.2 % is smallest category 10, other categories anti-clockwise).

constantly. Some tracks show an increasing and decreasing evolution. We assume that the weather conditions and the driver behaviour are responsible for this irregular process in addition to the insufficiencies mentioned above. Considering these inaccuracies, the error has got a small value.

5.2 Splitting

Until now, we have validated that our consumption model calculates consumptions which are comparable to measured ones. We want to use this validated part of our simulation system and take a closer look at the splitting component. As mentioned, this splitting is used to get an approximated list of driving tasks based on a usage profile U. This profile is a tuple of distance, start and end time defined as $(t_{\text{start}}, t_{\text{end}}, d)$.

Our validation is done by using real usage profiles from EV bookings. Those bookings contain the start and end SoC also. Thus, we know how much energy is used by this booking. However, these information does not include details about charging processes.

Fig. 4 visualizes more than 4.300 usages grouped by distances done with an E-Golf which has a range of 190 km measured by NEDC. As shown, most usages are below 100 km. We decided to drop usages with unrealistic consumptions, i. e. consumptions per kilometre lower than 0.5 % and higher than 1.5 %. This drops approx. 350 usage profiles and finally removes such ones, which include recharging tasks. These

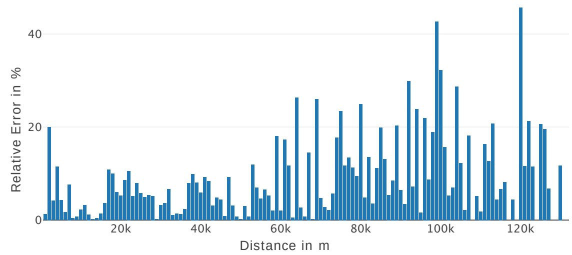

Figure 5: Average relative error per distance with finally configurated CommonMiddling splitting strategy.

cannot be validated.

Making use of the splitting strategy Uniformly (see Section 4.1 for an overview of strategies) results in an average error of 197 %. The more distance a usage profile handles, the lower the error will be. Utilizing middling strategy with acceleration and deceleration phase, called cycle, with 60 s, 30 s and 10 s results in a slightly improved average error ranging from 172 % to 51 %. However, these strategy indicates better errors in particular distances as well as much too low velocity values. Thus, we have used the CommonMiddling strategy configured with 50 km at 40 $\mathrm{km/h}$ and everything further at 80 $\mathrm{km/h}$. The first 50 km uses 5 s cycles and the remaining distance uses 60 s cycles. This strategy results in an average error of 68 %. Further, analyses show hot spots in various distances. Thus, we optimized the configuration of our CommonMiddling strategy with five states. They are shown ascending in the following list. The resulting average error is 5 % and is visualized in Fig. 5.

1 Up to 10 km at 25 $\mathrm{km/h}$ with 5 s cycles
2 Up to 30 km at 32 $\mathrm{km/h}$ with 15 s cycles
3 Up to 60 km at 70 $\mathrm{km/h}$ with 45 s cycles
4 Up to 90 km at 70 $\mathrm{km/h}$ with 360 s cycles
5 Up to ∞ km at 70 $\mathrm{km/h}$ with 1000 s cycles

5.3 Usage Profile Rating

Finally, after validating consumption model and usage profile splitting, we like to take a closer look at the usage profile of a dataset where we know that EV uses it. Fig. 6 visualizes the same dataset as used in Section 5.2 splitted according to used vehicles. The final rating is done as introduced in Section 3. This validation intends to check if this data produces ratings at nearly 100 %. The figure shows that the implemented simulation system creates a rating of an already substituted EV at an average of 97.4 %.

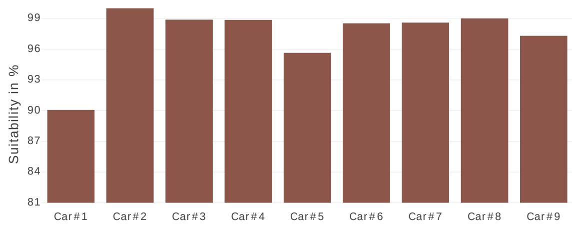

Figure 6: Usage profile rating of an EV.

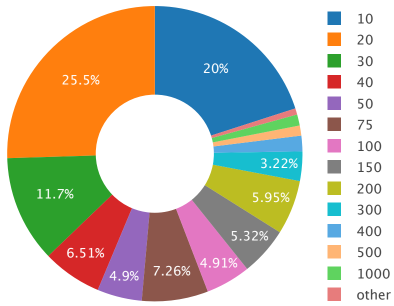

Figure 7: Grouped distances of usage profiles of combustion vehicles (20 % is smallest category 10, other categories anti-clockwise).

6 EVALUATION

After showing the usefulness of our model, we want to consider some more vehicles. The usage data of conventional combustion vehicles of a car sharing service were used to create usage profiles. Our aim is to show, which of these profiles could be handled by an EV. First, we take a look at the usage profiles of the combustion vehicles.

As you can see in Fig. 7 the distances mentioned above of EV bookings are applicable for conventional cars too. There is an amount of approx. 18 % of tracks that are longer than 100 km. So, we expected a good rating result for the EVs during our research. The usages of them and conventional vehicles are similar in general.

We used the formerly mentioned rating index (Section 3) to evaluate the possibility of replacing combustion vehicles with EV. In Fig. 8 you can see the rating index in percent for various EV. The rating is calculated for many combustion vehicles (1 to 49). The indexes 21 to 27 show a low suitability value. This might be caused by many long-distance tracks, which had to be handled by the cars. In contrast, the vehicle index 35 shows a high rating of 95 %. This car could have been replaced by an EV, i. e. there were many shorter tracks to drive. An interesting case can be found referring to car 36. We can see, that some EV got a rating of approx. 50 %, some others of approx. 90 %.

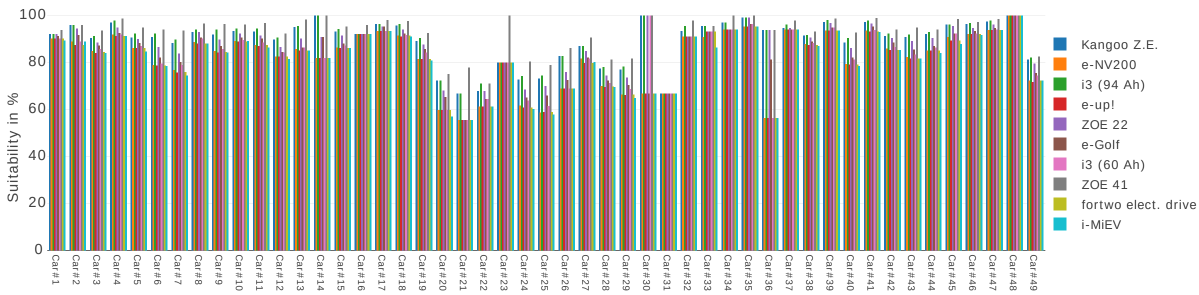

Figure 8: Suitability factor for various EV.

All in all, we can state, that over 50 % of the tracks driven by conventional vehicles could have been driven by EV too. There are some distances electric driven cars cannot handle, but it depends on the type of EV. The capacity of the accumulator may be a primary factor. The ZOE 41 has got the accumulator with the highest capacity and reaches the best suitability values (Fig. 8).

7 DISCUSSION

Even if we got simulated energy consumptions matching measurement values (Fig. 3 and Fig. 6), there are some problems although. We used the NEDC to get RDFs for our considered EVs. At this point, we are simulating the consumptions within the car, not the energy we have to recharge after driving the tasks of the cycle. This way of proceeding results in systematic errors, which impact all the following steps. The process of measurement of the NEDC does not happen within the car; it only evaluates supplied electric energy.

Another problem is caused by the external influences of a driving task. At now, we do not consider weather conditions like rain or wind. Watching these factors, we get higher energy consumptions if there is a headwind or if we have to use the wipers. Especially the lights of the car are not only turned on during the nighttime period. The modelling of the recuperation while driving uphill or downhill is not easy because we would have to know if the EV is recuperating or not. But this often depends on the state of the throttle pedal, not the velocity of the car or other macroscopic measurement values.

The aforementioned sources of errors refer to various driven tracks. The longer the distance a car drives, the harder it gets to model recharging and driving. On short tracks, there are not that many possibilities of taking breaks for recharging. The behaviour of the driver is tough to estimate, referring to configurated breaks and accelerations. While working, we found tracks of equal length which were driven by a specific energy amount and the half of this value. Guessing the energy economy causes errors.

A very system specific problem lies in the "CommonMiddling" (section 4.1). We got the strategy in Section 5.2 by try and error. It was calibrated using a vehicle type with about 4.000 usages. But we are not sure if this strategy is vehicle-specific or a more generic approach. The values reflect a plausible driver behaviour, but we were not able to check them against other vehicle models. Out of that, we did not consider recharging during a driving task. Our model only recharges between two tasks. The long-distance tracks are not well evaluated in this way. Such tasks need recharging by the driver, and so they get undervalued.

As mentioned before, there are problems of modelling driving uphill or downhill. The reached error level will be hard to underbid. If we correct the model referring to higher gradients, we get worse results for lower ones. The physical model forces us to keep the physical plausibility, i. e. adding correction terms, maybe depending on time, must have a physical justification.

Although, we reach a high precision level, especially if we think of the non-existent, precise track data for each considered vehicle.

8 CONCLUSION

Our approach aimed to decide if an EV could have overcome the usage profile of a vehicle with a combustion engine. We used a physical energy model to describe the electricity consumption of EVs. Furthermore, a model for splitting up usages into driving tasks was used to guess the behaviour of a driver (driving and charging tasks) on a specific track. Finally, we simulated the driving of EVs on them and calculated a rating that represents the possibility of replacing the formerly used combustion vehicle by an EV.

We were able to show the possible precision of a physical model in combination with a clever-guessed user behaviour. Within the i-MiEV validation, a limit has been reached at least if we think of the poor data input we used. The physical model is configurable but needs an RDFs in the end. To overcome this problem, additional energy consumptions must be added like lights or air conditioning system. Furthermore, other measurements should be done so that further energy terms can be added. Out of that, the specific consumption behaviour depending on temperature and gradient is needed. These measurements should take place for every considered EV.

Referring to the aforementioned additional measurements we have to think of the model in general. Maybe we should not use a physical model reflecting energies. Another way could be the use of average consumption depending on manufacturer given values. With a more significant amount of data, an artificial intelligence could be used as well. Further, an advantage would be the more precise knowledge of the behaviour of drivers. Especially people frequently using EVs are experienced in a recuperation-enhancing driving tactic.

However, that was not the primary question within this approach. As shown, it seems to be possible to rate usage profiles by utilizing a physical consumption model. Such methods have to take into consideration an average relative error of approx. 10 % of the physical consumption model itself, which might be optimized by adding more accurate measurement data, as well as an error of approx. 5 % when guessing driving tasks within our splitting component. This application example shows that 90 % usages at some station might be handled with electric vehicles, while others should not be replaced.

ACKNOWLEDGEMENTS

The research project WINNER is funded by the Federal Ministry for Economic Affairs and Energy of Germany under project number 01ME16002D. We would like to thank especially the Mobility Center GmbH for the provision of anonymised booking data.

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