Modeling Storage Characteristics of Electric Vehicles in the Grid

M. Sc. K. Lipiec Kamil.Lipiec@iff.fraunhofer.de
Dr. -Ing. Przemyslaw Komarnicki Przemyslaw.Komarnicki@iff.fraunhofer.de

***Abstract*- The modeling of complex systems always presents challenges when the intention is to predict the systems' future performance. The mounting number of electrical cars entails growing interest in grid integration and vehicle performance. Modeling will have to address aspects of personal mobility such as vehicle range and availability. A standardized model is needed, which is able to deliver the proper data for other types of simulation, e.g. impacts of high electric vehicle penetration on a distribution grid. A model of electric vehicle performance under development simulates a single electrical vehicle or a vehicle fleet in an electrical network. The model incorporates different battery types' performance and vehicles' physical properties as well as different user profiles. The simulation results from the model are also employed to analyze storage performance.**

I. INTRODUCTION

Mobility is a distinctive feature of modern society. 24% of households in Germany own at least one car [1]. Car traffic contributes to climate change and resource depletion. Therefore, the European Commission adopted a guideline for the reduction of CO2 emissions caused by passenger cars, which account for 12% of the total European emissions [2]. New basic concepts that conserve fossil resources and step up the use of renewable energies are needed to achieve the EC's goals. Moreover, system integration of renewable energy sources will have to be facilitated and options for the storage of excess power developed. electromobility represents a promising solution to both challenges.

The total number of electric vehicles (EV) in Germany is expected to reach between 1 and 4 million in 2020 and 6 to 15 million in 2030 [11, 12 and 13]. Such rapid development of electromobility will enable utilizing aggregate batteries for mobile storage in the grid, e.g. to store excess energy from renewable energy sources.

However, charging large numbers of batteries generates an additional load that can trigger critical events in a distribution grid. This necessitated the creation of electric vehicle simulation models that enable analyses from the perspective of electrical and logistical infrastructures (networks) and are intended to facilitate the use and implementation of electromobility in fleet operation. One such electric vehicle simulation model is presented here. Furthermore, the simulation model may also be employed to analyze the impact of high electric vehicle penetration on a distribution grid.

This paper is divided into eight sections. Sections II and III describe the tasks and principles of vehicle modeling. Battery modeling is divided between section III, which describes discharging mode and additionally presents driving schedules, and section IV, which uses charging characteristics to describe a charging process. Section V outlines the principles a vehicle's daily load characteristic and section VI presents the results for a single vehicle. Section VII is a summary and conclusion.

II. AIMS AND PRINCIPLES OF MODELING

The model being developed is intended to deliver a load characteristic for an aggregate battery in order to analyze the potential to store energy, especially when a power system is oversupplied. The aggregate battery storage characteristic developed for the model is a function of the temporal distribution of vehicle availability. Vehicle availability is defined as the vehicle's status when an electrical connection exists between the grid (charging spot) and the traction battery (electric vehicle). This would facilitate verifying that electric vehicles translate into better utilization of renewable energies.

The model's second purpose is to analyze the influence of electromobility on a power supply network. This will allow an analysis of any additional power requirement or parallel effects when several EV are being charged at one network node.

Such events can overload grid components, e.g. transmission lines and transformers. A method to forecast the aggregate battery load characteristic at a particular network node is being developed in order to observe these events. A map of the load characteristic should also include a conceptual analysis of the distribution of the electric vehicle fleet based on simulation scenarios. The future number of electric vehicles is not inferable from different studies published by governmental and nongovernmental organizations [11, 12, and 13].

The model also supports an analysis of demand on electromobility engendered by personal mobility. Driving schedules have been analyzed and employed in the modeling. User profiles derived from these driving schedules are used to map and group human behavior (e.g. commuter traffic, urban traffic and company cars). This will facilitate further analyses of the ranges and service lives of the electric vehicle's different subcomponents.

The electric vehicle model is based on separate modeling of vehicle and battery performance. To meet the aforementioned aims, the modeling process was divided into

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two parts: (1) the electric vehicle's driving mode, which facilitates calculation of driving load and analysis of the discharging process, and (2) the vehicle battery's charging mode based on collected data on the charging process of a lead-acid battery.

III. DRIVING MODE MODELING

Driving mode modeling is divided into (1) vehicle performance and (2) battery performance during discharge. Steps to calculate the power required to propel a vehicle are described first.

A. *Vehicle behavior*

To estimate driving load, vehicle performance must be predicted. A single vehicle's performance depends on parameters such as motor power, driving performance and battery type and capacity. First, driving effort is calculated. Then, driving schedules are applied to estimate driving load. If a vehicle with a given mass m is proceeding at a velocity υ, the force propelling the vehicle forward is calculated as a sum of the following forces:

Rolling resistance

Rolling resistance is approximately constant and proportional to vehicle mass as indicated by (1), where μ_{rr} is the rolling resistance coefficient dependent on the type of tires. It is estimated to be 0.0015 for tires developed especially for electrical vehicles [6]. *g* being the gravitational acceleration (9.81m/s^2):

$$F_{rr} = \mu_{rr} mg \quad [\text{N}] \tag{1}$$

Aerodynamic drag

Aerodynamic drag is the force required to overcome the friction a vehicle encounters when travelling through air. It is a function of the frontal area (A), car shape and velocity υ and is produced by (2), where ρ is the density of air. The drag coefficient C_d is estimated to be 0.4 [5]. The vehicle has a frontal area of 2.5m^2 [5].

$$F_{ad} = 0.5 * \rho A C_d v^2 \quad [\text{N}] \tag{2}$$

Acceleration force

Acceleration force represents a vehicle's linear acceleration *a* and is produced by (3).

$$F_{la} = ma \;\; [\text{N}] \tag{3}$$

The contour must be allowed for to calculate a vehicle's acceleration more accurately. The model presented here disregards these forces and employs Eq. 1-3 to calculate the total driving effort.

$$F_{te} = F_{rr} + F_{ad} + F_{la} \;\; [\text{N}] \tag{4}$$

Total driving effort is used in every simulation step to calculate the power P_{te} required to move a vehicle. Mechanical and electrical efficiencies are allowed for when calculating the power P_{batt}, which was used to determine the battery's current I_{batt}. Finally, the state of charge (SOC) was calculated.

B. *Battery behavior*

The modeling of the battery performance is limited to lead-acid battery type. Battery performance is modeled in order to simulate battery operation at a specific set power and to estimate the SOC in every simulation step.

To estimate it, the SOC is assumed to be approximately proportional to the open circuit voltage OCV [8], which is calculated as follows [3]:

$$OCV = \big(2.15 - (1 - SOC) * (2.15 - 2.0)\big) \;\; [V] \tag{5}$$

The SOC is dependent on battery capacity and discharge current. Battery capacity drops as the discharge time decreases and the discharge current increases.

Peukert's model is employed to model battery capacity [8]. Equation 6 delivers the battery's Peukert capacity, where T is the rated discharge time.

$$Cp = {I_{batt}}^{k} T \;\; [\text{kWh}] \tag{6}$$

Assuming a certain current *I* flows from a battery, then the current that flows out of the battery is calculated with usage of the Peukert coefficient *k* and designated by I^k. The Peukert coefficient for a lead-acid battery is 1.107 [8]. Equation (7) delivers the battery's current, where R_{batt} is the battery internal resistance.

$$I_{batt} = \frac{-OCV + \sqrt{OCV^2 + 4 R_{batt} P_{batt}}}{2 R_{batt}} \;\; [\text{A}] \tag{7}$$

When the charge removed from the battery *CR* is proportional to the discharge current ($CR \sim I_{batt}$), then the depth of discharge (DOD) is the ratio of the charge removed from the battery to its Peukert capacity as in (8)

$$\text{DoD} = \frac{\text{CR}}{\text{C}_\text{p}} \tag{8}$$

Then, the SOC is calculated with (9)

$$SOC = (1 - DoD) * 100 \;\; [\%] \qquad (9) \tag{9}$$

C. *Driving schedules*

The driving schedules were employed to incorporate aspects of personal mobility. The speed stipulated by the driving schedules for each simulation step is utilized to calculate the total tractive force. Driving schedules provide a basis for analyzing requirements of personal mobility. Driving schedules are used to reproduce driver-specific performance and properties (e.g. drive dynamics, speed and typical driving time). The schedules were developed to objectively estimate the fuel consumption of cars with internal combustion engines and are available from the literature. A set of schedules used for other simulation is presented in Table I. However, schedules have not been developed for electric vehicles.

TABLE I.
COMPARISON OF DIFFERENT DRIVING SCHEDULES

Schedule	Duration [min]	Distance [km]	Consumption [kWh/100km]	Power P_{av} [kW]	Energy [kWh]
UN/ECE 15	20.5	10.9	19.5	6.8	2.32
IM240[1]	4.00	3.20	22.5	10.6	0.71
UDDS[2]	22.8	12.0	19.5	6.2	2.34
FTP[3]	31.0	17.8	20.0	6.8	3.60
HWFET[4]	25.8	33.0	18.7	14.4	6.17
NYCC[5]	10.0	1.90	33.4	3.8	0.63
US06[6]	10.0	12.9	34.4	26.6	4.44
HDUDDS[7]	18.0	8.90	20.7	6.3	1.85
UN/ECE LP[8]	6.70	6.60	17.5	10.4	1.15

Calculations of the values in the Table I assume a vehicle weight of around 1400kg. Consumption and the total energy requirement for a single schedule (see Table 1) do not include braking energy recovery.

For purposes of modeling, schedules were divided into three groups, i.e. city 1, city 2 and commuter. Each group maps different mobility requirements.

The city 1 group includes driving profiles with low speeds, e.g. UN/ECE LP for small vehicles, NYCC with numerous stop-and-go sequences and the UN/ECE 15 urban schedule.

The city 2 group includes a profile that describes urban movement patterns with higher speeds and rapid acceleration sequences, e.g. the US06 schedule.

The commuter group includes higher speed driving profiles used to map highway mobility, e.g. the UN/ECE 15 commuter schedule and the HWFET schedule that simulates highway driving.

Fig. 1. presents a UN/ECE 15 driving schedule as an example. Assumptions are applied to calculate the power required from the battery for this schedule.

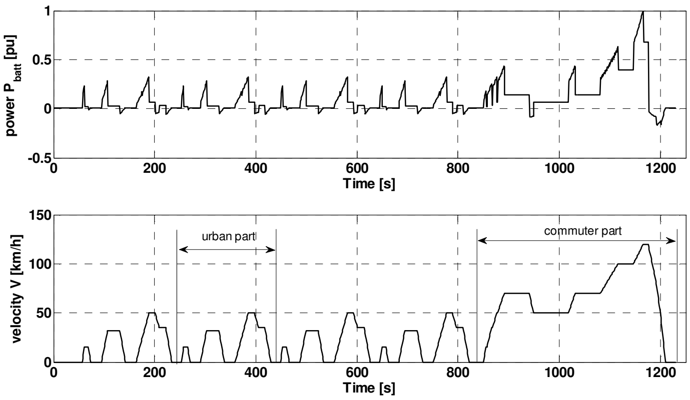

Fig. 1. Speed, time and power characteristic on the New European Driving Cycle based on ECE 15.

The profile consist of an urban part with four equal sections of accelerating and braking sequences and a single commuter part that allows for higher speeds. Speed values were used to calculate the acceleration in each simulation step. The tractive force was calculated with equations (1-3). The power required for additional equipment P_{ac} was estimated to be 0.5kW. This value is derived from an assumed total peak power of additional equipment of 8.3kW and a coincidence factor established as 0.006 [3].

Finally, the efficiencies of the individual components, e.g. battery, drive train η_{sys} and the engine η_{eng} are incorporated to calculate the power required from the battery P_{batt}. The transmission efficiency fluctuates between 70 and 80% and is dependent on the vehicle class. Electrical engine efficiency is estimated as a linear function of the rated engine power [3]. The recovery efficiency during the braking phases was found to be 50% [3] and is factored into the model presented here. Fig. 2. presents the power flow and a schematic model with input and output parameters. (See section V for a description of the input parameters.)

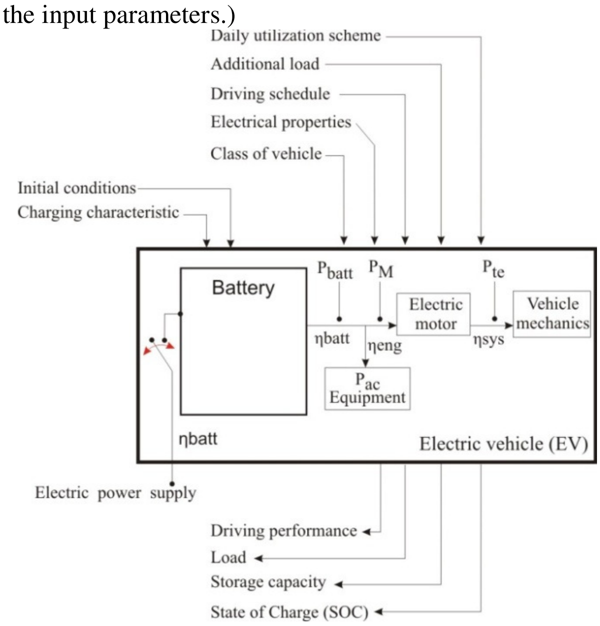

Fig. 2. Schematic model with input and output parameters

1 Inspection and Maintenance Schedule
2 Urban Dynamometer Driving Schedule
3 Federal Test Procedure (FTP)
4 Highway Fuel Economy Driving Schedule
5 New York City Cycle
6 US06 or Supplemental FTP driving schedule
7 Heavy Duty Urban Dynamometer Driving Schedule
8 Extra-Urban Driving Cycle (for Low Powered Vehicles)

IV. BATTERY CHARGING MODE MODELING

Measured data from two lead-acid batteries is utilized to describe battery performance during charging. The lead-acid batteries are well established and widely used for low cost automotive applications chiefly because of their: low cost, commercial availability and reliable performance. A Hawker Genesis (model G26EP) battery was used for further simulation [10]. It weighs 140kg and its charging characteristic is presented in Fig. 4. The battery-pack was fitted to a compact car with a total maximum weight of 600kg. Practical tests not detailed in this paper estimated the total energy stored in the battery during seven hours of charging to be 5.74kWh.

Data was collected from a second battery used for simulation, an AGM battery with an energy storage capacity of 10kWh and a total weight of 350kg. The battery's nominal charging time is 10h. It is found in commercially available electric vehicles such as the Mega eCity [10], the charging characteristic of which is presented in Fig. 3. The charging characteristic greatly depends on the charging method. The model presented utilizes the CCCV[9] method, which charges a battery with constant current (I-Phase) to just below gaseous voltage.

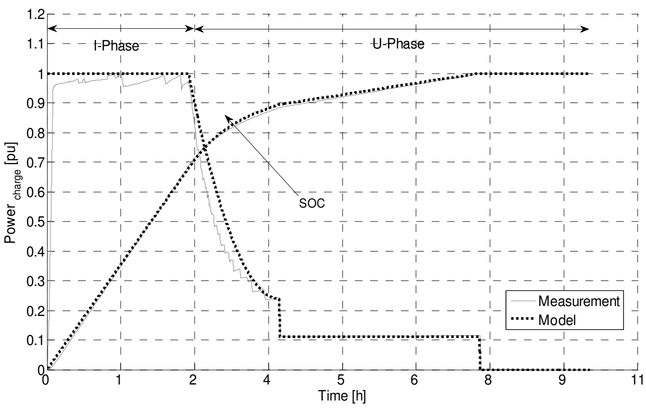

Fig. 3. Charging characteristic of lead battery type 1

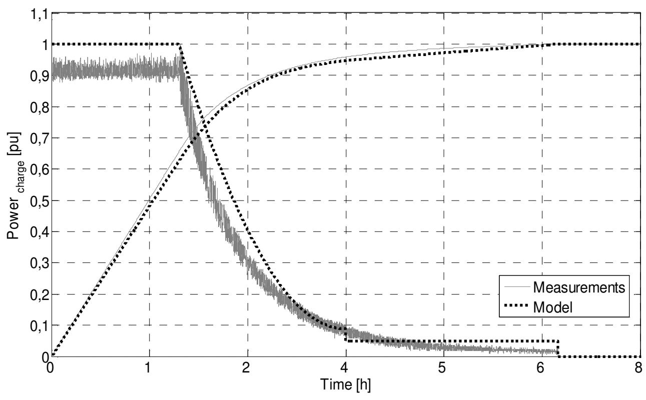

Fig. 4. Charging characteristic of lead battery type 2

The output voltage is maintained for a set period at the end of which the constant voltage is reduced to trickle voltage (U-Phase). Current drops exponentially during the U-Phase. Figs. 3 and 4 present the product of voltage and current during the CCCV charging and, in addition to real charging characteristics, modeled values for charging power as well.

Charging is assumed to take place at a standard socket with a 16A cutout current, thus providing a maximum connection power of approximately 3.7kW. The base power for the AGM and Hawker Genesis batteries is 3.6kW and 1.6kW respectively.

The SOC is proportional to the integral of the charging power allowing for the charger efficiency η_{batt} (85%) [8]. This assumption facilitates an estimation of the SOC after every charging period. It is also used to define the starting charging power when a vehicle is connected to the grid after completing a selected driving schedule.

V. VEHICLE DAILY LOAD CHARACTERISTIC

The vehicle's load (from the perspective of the grid) can be determined from the daily load characteristic. The load calculation allows for vehicle availability over 24h. The storage capacity of a single battery while connected to the network connection can be estimated with this information. The characteristic is a function of specific battery parameters, e.g. initial conditions such as SOC at the start of the simulation (see section II and IV for the model of battery the charging and discharging characteristics), vehicle parameters (e.g. class, load of additional equipment, etc.) and the daily vehicle utilization scheme. The model is simulated by Matlab® simulation software. (See Fig. 5 for the simulation steps.)

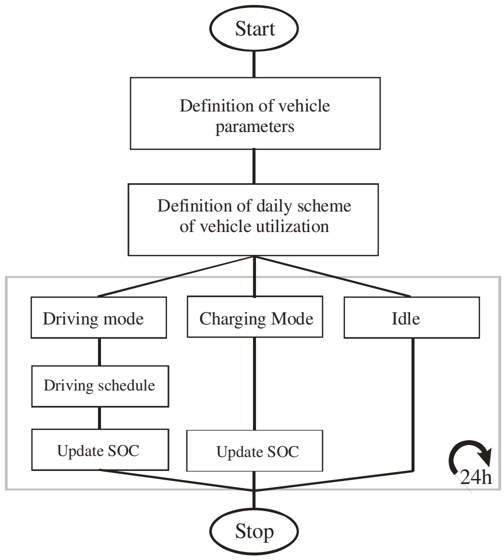

Fig. 5. Simulation steps

Vehicle parameters are defined in three groups. The vehicle's class is defined at the start of the simulation. The three options are: compact car, midsize car and plug-in hybrid. Certain vehicle class parameters are automatically defined, i.e. weight, frontal area, electric motor efficiency and rated power and recovery efficiency. Table II presents typical

[9] Constant current-constant voltage

values used in the compact car simulation and defined battery parameters including capacity, type, rated discharging time, charging mode and overall efficiency.

TABLE II.
BATTERY AND VEHICLE PARAMETERS

Vehicle class: Compact Car		
Vehicle weight	700	[kg]
Frontal area	2.0	[m^2]
Electric motor efficiency	85	[%]
Recovery	50	[%]
Rated electric motor power	15	[kW]
Battery parameters		
Type	Lead	-
Battery capacity	15	[kWh]
Rated discharge time	10	[h]
Charging method	UI	-
Charging/discharging efficiency	85	[%]
SOC at start	100	[%]
Additional Load:	1.28	[kW]

It also presents the defined load of additional vehicle equipment, which has been divided into three sections that define the frequency of equipment usage. The first group is event triggered and includes brake lights or windshield wipers for example. The second group includes every load used during vehicle driving mode (e.g. board display and computer). The third group includes sporadically used energy-consuming loads, e.g. electrically operated window regulators. Every load group affects a vehicle's energy consumption with different coincidence factors.
The simulation incorporates sporadically used loads with a factor of 0.1, event-triggered loads with a factor of 0.2 and permanent loads with a factor of 0.9. Fig. 6 pictures the graphical user interface (GUI) used to enter vehicle, additional equipment and battery parameters.

The second simulation step is to define the daily vehicle utilization scheme. In order to meet vehicle users' requirements, one day was divided in to three parts (morning, afternoon and evening) when different mobility events take place. Every time of day was divided into 2h periods. The vehicle's state (driving mode, charging mode and idle) can be defined for each 2h interval. Once the driving mode has been selected (on the GUI), a driving schedule is selected from the aforementioned groups. Then, one of the driving schedules is assigned to the simulation step, which is set to 15min. Fig. 7 pictures the GUI used to define the daily vehicle utilization scheme. The GUI in step two delivers different mobility patterns that are used to estimate daily load and battery storage availability.

Once the vehicle, battery and additional load parameters and daily utilization scheme are defined, the simulation is run. The results of the simulation are the battery's SOC, the vehicle's electrical load in the grid and the energy stored by the battery over 24h.

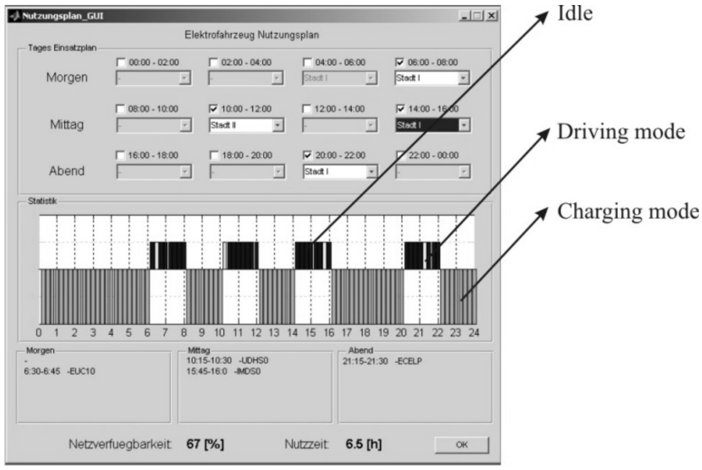

Fig. 7: Step 2 - GUI for defining the daily vehicle utilization scheme

VI. RESULTS FROM A SINGLE VEHICLE

A one-day profile of a specific vehicle was mapped to test estimated battery parameters and routine vehicle operation. The results included profiles of load, stored energy and SOC. Fig. 8 and 9 present the results for two different vehicles. The vehicle parameters and the daily utilization schemes were fitted to reproduce two common mobility characteristics, i.e. commuter and company car characteristics. The company car is characterized by multiple routes driven daily. The vehicle (Fig. 8) completed nine different driving schedules that entailed city as well as suburban mobility. The vehicle weight is 1300kg and the battery capacity was adjusted to 25kWh. The load of additional equipment for this type of electric vehicle was estimated to be 1.65kW. The simulated vehicle drove a total distance driven of 91.3km and consumed 22kWh/100km on average.

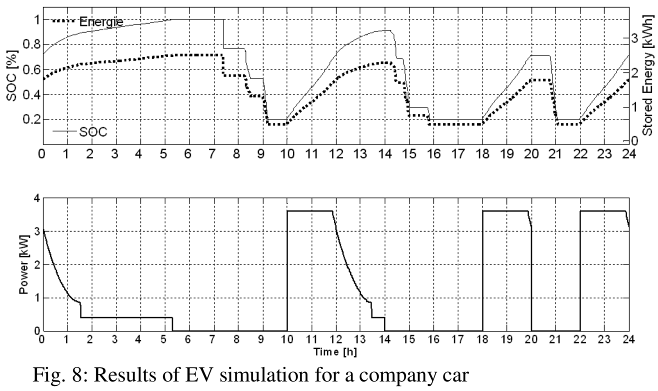

Fig. 8: Results of EV simulation for a company car

During its operation, the battery reached the 20% SOC three times but this did not prevent the vehicle from completing the planned driving schedule. The vehicle's availability to the grid is 58%. The vehicle consumed 28kWh over 24h.

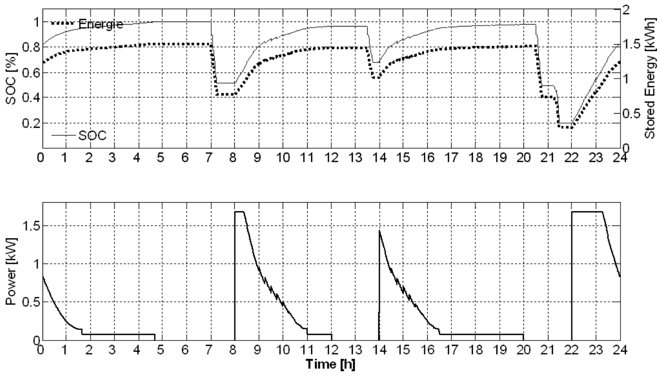

Fig. 9: Results for EV simulation for a commuter car

The second simulated vehicle was a typical commuter vehicle. Vehicle utilization is limited to a maximum of four routes, i.e. two suburban and two urban routes. The vehicle weighed 700kg, thus less than the preceding vehicles. The smaller vehicle's battery capacity was 15kWh. The additional load was estimated to be 1.22kW. In the simulation, the vehicle drove a total distance of 47km and consumed 14.8 kWh/100km. The battery charged 20% only once at the end of its operation. The vehicle's availability to the grid is 67%. The vehicle consumed 7.4kWh over 24h.

VII. Conclusion

The approach presented by this paper describes a method to simulate electric vehicles by employing different driving schedules, daily vehicle utilization profiles and battery charging characteristics.

User profiles have been developed and researched with an eye toward electric vehicle features in order to analyze electromobility's fulfillment of human needs. Typical user categories, e.g. commuters and company cars, entered into the development of the profiles.

This approach makes it possible to simulate the performance of electric vehicles in a distribution network and thus estimate additional energy consumption and identify potential challenges related to future electric vehicle penetration. The model presented in this paper may also be used to simulate a vehicle fleet. This enables organizing a fleet based on different battery characteristics (including charging and discharging characteristics) as well as a temporally and spatially variable number of electric vehicles.

Further development of the model shall incorporate different types of batteries, e.g. ZEBRA[10] or lithium-iron-phosphate ($LiFePO_4$) batteries. Their charging and discharging characteristics could be implemented in the model to allow a wider selection and thus produce better conditions for simulating an electric vehicle fleet.

Dedicated control signals can be implemented in the daily utilization scheme to influence charging times and starting times. One such a signal could be a variable energy price. Then, potential to shift loads with a large number of electric vehicles could be analyzed

[10] Zero Emission Battery Research Activity

VIII. References

[1] Bundesministerium für Verkehr, Bau und Stadtentwicklung: "Mobilität in Deutschland-Ergebnissbericht", Bonn, 2008

[2] Regulation (EC) No 433/2009 of the European Parliament and of the council, "Setting emission performance standards for new passenger cars as part of the Community's integrated approach to reduce CO2 emissions from light-duty vehicles", Strasbourg, 2009

[3] J. Larmine, J. Lowry: Electric Vehicle Technology Explained, Oxford, 2003

[4] J. Grassin: Vehicle-to-Grid Improving wind power integration, Lyngby, Denmark 2007

[5] M. D. Galus, G.Andersson: Power System Considerations of Plug-In Hybrid Electric Vehicle based on a Mulit Energy Carrier Model, Zurich, Switzerland

[6] K. T. Urlich: Estimating the technology frontier for personal electric vehicles, University of Pennsylvania, January 18, .2006.

[7] Jossen, W. Weydanz: Moderne Akkumulatoren richtig einsetzen, ISBN: 3-939359-11-4, January 2006.

[8] D. Heinemann: Strukturen von Batterien- und Energiemanagementsystemen mit Bleibatterien und Ultracaps, Berlin, 2007

[9] Data specification sheet of HawkerGenesis battery

[10] Data specification sheet of eCity electrical vehicle

[11] Bundesregierung: Sachstand und Eckpunkte zum Nationalen Entwicklungsplan Elektromobilität. Nationale Strategiekonferenz Elektromobilität. Berlin, November 19, 2008

[12] Shell Pkw-Szenarien bis 2030. Fakten, Trends und Handlungsoptionen für nachhaltige Auto-Mobilität. Shell, Hamburg, 2009

[13] Reichert, Carolin: Elektromobilität – Chancen, Herausforderungen und Beitrag RWE. In: *Erster Deutscher Elektromobil-Kongress*. Bonn, June 16-17, 2009

[14] Kempton, W., Tomic, J. (2005): Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. In: Journal of Power Science.

[15] Kempton, W., Tomic, J. (2005): Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. In: Journal of Power Science.

IX. Biographies

Kamil Lipiec earned a dual Master's of Science from Wroclaw University of Technology in Poland and Otto von Guericke University Magdeburg in Germany in 2007. Since then, he has been a research manager in the Process and Plant Engineering Business Unit of the Fraunhofer Institute for Factory Operation and Automation in Magdeburg, Germany. His special fields of interest include electrical vehicle modeling and power systems monitoring.

Przemyslaw Komarnicki earned a dual Master's of Science from Wroclaw University of Technology in Poland and Otto-von-Guericke University Magdeburg in Germany in 2004.

Since 2004, he has been a research manager and, since 2008, the manager of the Electric Power Systems Group in the Process and Plant Engineering Business Unit of the Fraunhofer Institute for Factory Operation and Automation in Magdeburg, Germany. Parallel to his work, he earned his doctorate from the Department of Electric Power Networks and Renewable Energy Sources at Otto von Guericke University in 2008 and is an assistant lecturer at the Otto von Guericke University in 2008 and is an assistant lecturer at the university since then.