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Load Profile Generator for Electric Vehicle Home Charging

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Summary

Nowadays, electromobility is an essential part of a continuing change in worldwide mobility. Users' attitudes towards electromobility are influenced essentially by the ability to adapt to their own personal mobility needs. The subjective assessment, whether an electric car could manage familiar routes, is highly decisive for the willingness to use electric vehicles [1]. Furthermore, increasing acceptance will lead to grid relevant load peaks through the parallel charging processes. To tackle both problems, i.e. overcoming user doubts and the prediction of the electric load, the Institute of Human Research of the University of Stuttgart developed the tool "Profile Generator for Electromobile Loads"[1]. It generates a charging profile based on the individual mobility behaviour of a private electric vehicle user.

Keywords: load profile, mobility behaviour, forecast model, power demand, electric vehicle, Matlab®

1 Introduction and state of art

In order to hold "the increase in the global average temperature to well below 2 °C above pre-industrial levels" [2] and reduce air pollution caused by the transport sector, an accelerated development of electromobility is indispensable. Apart from the potential of zero direct emissions, electric vehicles (EV) can balance the fluctuating generation of renewable energies and substitute one part of backup power plants and stationary storages. Thus electromobility is a key to the sustainable global transformation of the mobility and energy sector: more climate- and environmentally friendly, more resource-friendly and more efficient. In line with these potentials, the electric car market will accelerate to a mass market adoption in the next 10 to 20 years [3]. Yet the acceptance and competitiveness of electromobility is greatly influenced by the availability of charging infrastructure, economic aspects and environmental benefits [4]. One of the most essential challenges for planning and designing charging stations is the integration of numerous stations in an existing energy system with a limited power supply, for example a residential parking garage with a multitude of parking spaces. To meet these challenges an individual load prediction for electric vehicles is required. For reconstructing energy needs and load profiles of electric vehicles two general methodologies are applied: on the one hand, historical or real data can be used [5–7], on the other hand, it is possible to simulate load flows with generic mobility behaviour of a selected user group. Valentine et. al. for example describes the vehicle usage and resulting energy demands by aggregate data; for example composed of census data and average trip distances [8]. Many simulation models use representative mobility data of conventional vehicles or

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general mobility patterns. Thereby mobility studies, such as Mobility in Germany study (MiD), national survey on transport and travel (ENTD) for France, 2000 Census Transportation Planning Package (CTPP) for the US or the study of the Austrian Motorized Individual Mobility provide the databases to identify EV charging behaviour [9]. In the current state of research a variety of authors model EV charging load based on assumptions and simplifications, for example assuming a fixed percentage of EVs, adopting a rigid EV charging schedule, assigning a certain distance traveled per day or assuming a certain mileage and corresponding fixed amount of power consumption by each EV [10].

The present paper aims to address those shortcomings by developing a load profile generator for an individual user profile and deals with economic and ecological issues. The results of the charging profile tool make private customers turn away from the thought that the range of electric vehicles might not be sufficient to cover their own mobility behaviour adequately, by applying different charging strategies and electric vehicles. The resulting load curves are also incorporated into the planning of local energy grids and can be used for overall balancing. Network operators, fleet managers and other planning services, like engineering offices, can use this profile generator for load prediction concerning electromobility and developing sustainable energy concepts according to integrated energy design.

This paper is structured as follows: Section II focuses on the methodology and introduces the main variables and general assumptions of the tool. The chapter is also intended to give an overview of the simulation process. Section III defines the case study for a selected user and a suitable electric vehicle, whereas Section IV shows the simulation results. Section V concludes the paper with an outlook and the major findings.

2 Scientific approach and general assumptions

The Load Profile Generator was developed to assist the consumer in choosing the optimal vehicle and determining the charging strategy based on his mobility characteristics. Therefore, the forecasting model is implemented in MATLAB and consists of three interactive building blocks. At first, the simulation generates a driving profile based on the user's input in the MATLAB app simulation interface. This profile includes the location of the vehicle, i.e. at home (available for charging) or at work, etc. (no charging possible), and the driving distances with a temporal resolution of five minutes over one year. Secondly, the simulation utilizes the location and route information of the user to manage the charging and calculate the resulting load profile. In this case, the generator considers the characteristics of the selected charging strategy and electric vehicle.

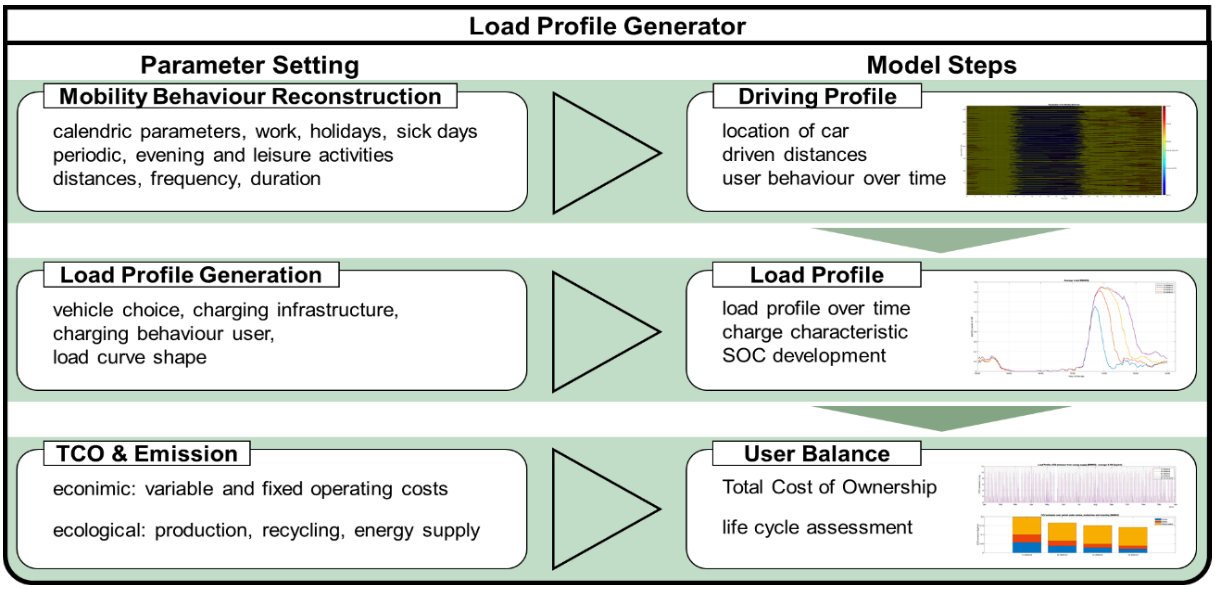

Figure 1: Methodical structure and sequence of the Load Profile Generator

Subsequently, the users' needs and the determined charging profile are balanced ecologically and economically in order to satisfy the individual mobility needs. To evaluate the results, a comparison with conventional vehicles is also possible. Fig. 1 reconstructs the schematic flow of the tool in which the left side represents the input parameters of the user interface. The right side shows the simulation steps and results. In order to support the user during personal input and to prevent misuse of the tool, general conditions for the parameters are predefined. Additional information and advice for optimal use can be viewed by pressing an information button.

2.1 Mobility behaviour reconstruction

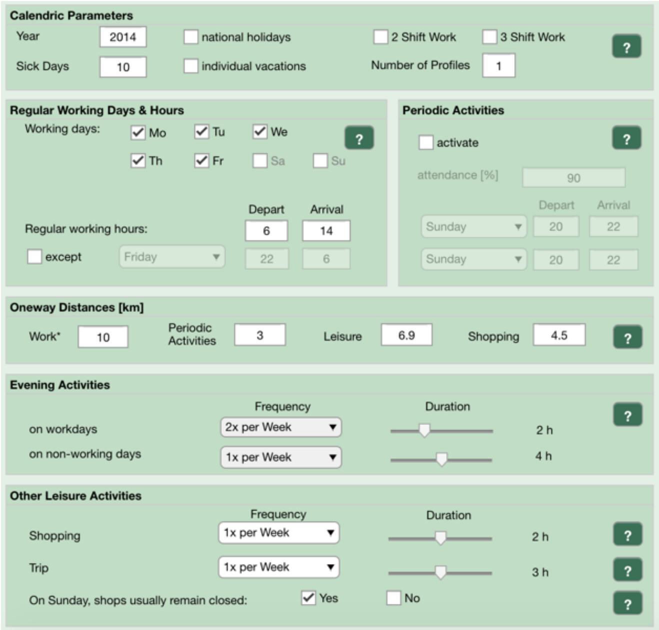

Figure 3: User interface of mobility behaviour

The modelled mobility profile of privately used vehicles is generated from the information entered by the user in the app interface and can be determined exactly by a multitude of settings. Using normally distributed variables guarantees an individual profile despite identical input parameters by the user. Fig. 2 is an illustration of the user interface with individual input of the mobility behaviour of an exemplary user. The user interface is divided into six components, which generate the driving profile. The calendar parameters form the general framework for the selected year. Optionally, national holidays and personal holidays can be taken into account. The days of illness are automatically divided into three different periods of time and distributed randomly over the year. In addition, the choice of the number of profiles is also important (e.g. for fleets). For a single driving profile the tool automatically generates two different distances to the workplace (km_{work}, km_{work}+20 km) to investigate the influence of driving length. In order to allow different routes for leisure activities, the entered information is calculated by using a continuous equal distribution. At the beginning of the mobility behaviour simulation, the event matrix contains only the status that the vehicle is at home. The idea is that events are generated and written into the matrix one after another. The structure and the calculation of the mobility behaviour follows a prioritization of the activities. This weighting of the activities prevents an overlapping of calculated events at certain times. Fig. 3 illustrates the program flow, including prioritization, after which the activities are transferred to the event matrix. The departure and arrival times for work each day are determined on the basis of core times, such as start and end of work, including an automatic spread of +-1.5 h by using a normal distribution. For each of the four possible activities, a travel distance will be specified when constructing the mobility behaviour. An automatic doubling of the distance ensures that outward and return journeys are taken into account during battery discharge. The specification of a probability of weekly leisure activities consider the probability of occurrence of the event. Irregular leisure activities of the user include the frequency and duration of the activity as information. As a result, a vector in five-minutes resolution is generated for the year (in order to match the building load) consisting of zeros (EV not at home) and ones (EV at home) only to indicate the EV's availability for charging at home.

Figure 2: Prioritization of activities

2.2 Load profile generation

The second part of the simulation includes the creation of a charging profile for the selected vehicle based on the previously determined mobility behaviour and distance profile. Fig. 4 shows the user interface of the tool as well as the setting options for the user. The user interface is divided into two sections, which serve to configure the charging process and the preferred vehicle. First, the maximum charging power is set as a representation of the household infrastructure for the charging processes. The actual charging power used in the calculation can be set in the “Load curve shape” drop-down menu, as shown in Fig. 5. It is possible to choose between a constant maximum charging power, a real charging curve [11] or a user-defined charging curve with individual shaping and adaptation. The second section allows to specify the individual charging behaviour to describe the user's behaviour as realistically as possible. As visualised in Fig. 6, the probability of a charging process is divided into four different levels and depends on the current state of charge. Irrespective of this setting, a charging process always takes place if the battery charge would not be sufficient for the next determined journey. This requirement is intended to refute the “range anxiety” and ensures that the route destinations can be reached safely. If the calculation results in an energy level that is too low to cover the next required distance, the lack of energy is noted.

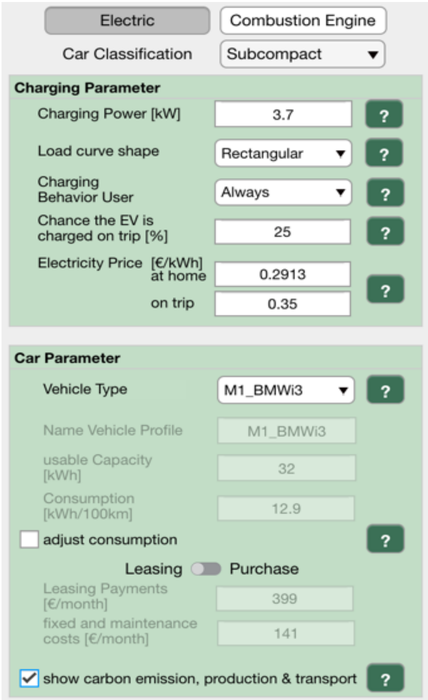

Figure 4: User interface of load profile generation

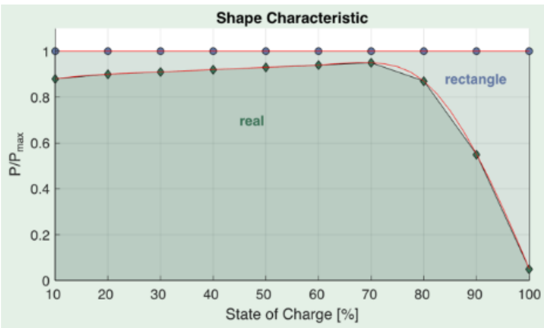

Figure 5: Load curve shape

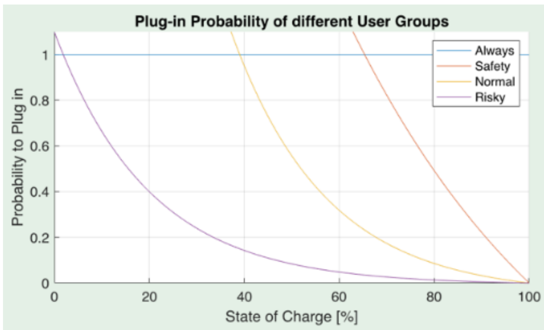

Figure 6: Charging behaviour

In addition to the charging option at home, the option of specifying a charging probability on the trip is also integrated. This modulation considers a loading process shortly before arrival or after departure. The battery model is kept simple, charging and discharging behaviour are restricted to a state of charge (SOC) range of 10% < SOC < 95% [12] (DOD = 85%). The model does not account for self-discharge losses or other non-linearities such as C-rate dependencies [13]. The configuration of the user’s vehicle takes place via real deposited vehicles or the definition of an own vehicle. In order to achieve a relevant comparison in the balancing process, the user can choose between conventional and electric vehicles, along with the determination of a charging strategy. A further subdivision is made on the basis of three vehicle classifications:

1) Subcompact
2) Compact
3) Full-size

Furthermore, the user can adjust the consumption individually. As shown in Fig. 7, the vehicles' consumption can be adapted by setting options for driving behaviour, outside temperature and driving area. The resulting factor, which is multiplied on the pre-set consumption, is indicated to the right in percent.

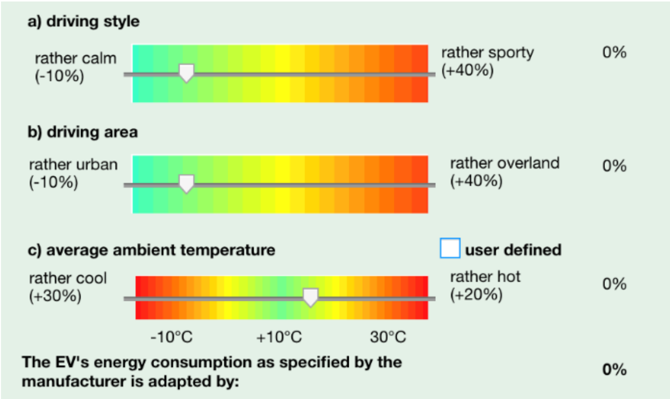

Figure 7: Adjusted consumption

The modelling of the load profile is based on the user's parameter settings, i.e. vehicle type and charging strategy, and the previously determined reconstruction of the mobility behaviour, which provides the information on the vehicle position and the distances taken. At the start, the assumption is made that the vehicle is at home with a fully charged battery.

2.3 Ecological and economic balancing

The final step of the simulation balances the user's modelled mobility and charging behaviour from an ecological and economic point of view. The previously determined route requirements, the user's choice of vehicle and the load flow serve as a basis. The modelled mobility behaviour remains constant over the period under review.

2.3.1 Life cycle assessment

The life cycle assessment [14] considered in the context of this work, primarily deals with climate-relevant carbon dioxide emissions (CO2). Air pollutants and resources are not part of this study. However, in order to fully assess the environmental performance of different propulsion technologies, an analysis of the entire life cycle is required. This so-called life cycle assessment takes all emissions into account - from raw material production, manufacturing, operation and maintenance up to the disposal of a vehicle. The determination of CO2 emissions during the use phase is based on the previously modelled mobility and charging behaviour of the user. The CO2 emissions generated by production, including recycling, are categorised by vehicle class and depend on the total capacity of the battery. Tab. 1 contains the subdivision and sources of the data basis determining the CO2 balance. The following equation is used to determine the total CO2 emissions:

$$EM_{p,a,n}^{i} = \sum_{y}^{y+n} (i_{veh}^{p,a,y} + i_{bat}^{p,a,y} + i_{elec}^{p,a,y} + i_{fuel}^{p,a,y} + i_{exh}^{p,a,y}) \quad (1)$$

$EM_{p,a,n}^{i}$:	CO2 emission for driving profile p and propulsion a in period under review n [kg]
$i_{veh}^{p,a,y}$:	vehicle production and recycling CO2 emission using propulsion a [kg]
$i_{bat}^{p,a,y}$:	battery production and recycling CO2 emission using propulsion a [kg]
$i_{elec}^{p,a,y}$:	CO2 emission from electricity supply for driving profile p and propulsion a in year y [kg]
$i_{fuel}^{p,a,y}$:	CO2 emission from fuel supply for driving profile p and propulsion a in year y [kg]
$i_{exh}^{p,a,y}$:	CO2 emission from exhaust for driving profile p and propulsion a in year y [kg]

Table 1: Data basis for determining climate relevant emissions

	Source
production incl. recycling	Institute for Energy and Environmental Research Heidelberg [15]
fuel supply (Well-to-Tank)	Joint Research Centre-EUCAR-CONCAWE [16]
power supply	Umweltbundestamt (Federal Environment Agency) [17]
Tank-to-Wheel	ADAC EcoTest [18]

2.3.2 Total Cost of Ownership

In order to compare the costs of battery-electric and combustion-engine vehicles, it is advisable to consider the overall costs. Therefore, all costs of use over the entire holding period of the vehicle have to be taken into account as precisely as possible. While an electric vehicle often has higher investment costs than its conventional counterpart, it can have considerably lower operating costs. The applied Total Cost of Ownership (TCO) [19] model considers all relevant cost parameters during the vehicle holding period. The holding period must be specified by the user in the user interface. The considered economic input parameters for conventional and electric vehicle variants are listed in Tab. 2 and deal with the following fixed and variable cost parameters:

Table 2: Cost parameters of Total Cost of Ownership

Capex	Opex
purchase price	fuel/energy cost
tax depreciation	vehicle tax, insurance, costs for main/exhaust emission test
residual value at end of holding period	costs for vehicle maintenance and services
charging infrastructure costs	costs for services/maintenance of charging infrastructure

The following equation is used to determine the total operating costs:

$$TCO_{p,a,n}^{j} = \sum_{y}^{n+y} \left(j_{capex}^{p,a,y} + j_{opex}^{p,a,y} \right) \tag{2}$$

$TCO_{p,a,n}^{j}$: discounted TCO for driving profile p and propulsion a in period under review n [€]

$j_{capex}^{p,a,y}$: discounted annual investment j_{capex} for driving profile p with propulsion a in year y [€]

$j_{opex}^{p,a,y}$ discounted annual operating costs j_{opex} for driving profile p with propulsion a in year y [€]

In order to establish comparability between the expenses, all incoming costs were discounted to the total cost calculation for the year under review. The probable development of energy prices according to the energy reference prediction are included.

3 Case study

In the following, an example scenario is used for the validation and entered into the user interface in order to illustrate the opportunities and results that can be achieved with the tool. The mobility behaviour is mapped by a standard commuter whose mobility behaviour is shown in Tab. 3. The route information is based on the mobility behaviour MIB 2008 [20]. As previously explained in Chapter two, a distinction is automatically made between two working distances when generating the distance profile. For the first scenario the one-way distance to work is 10 km. To investigate the effects of the commute on the load curve, a second distance of 30 km is simulated. The two scenarios are described below with “distance 1” and “distance 2”.

The focus is on charging at home, therefore 3,7 kW is selected as the charging power. Some studies also discuss a charging capacity of 7,4 kW or 11 kW, but a peak power of up to 3,7 kW is recommended by the authors of this paper and considered sufficient for charging at home [21]. Tab. 4 shows the electric (BEV) and conventional (ICE) vehicles used for the exemplary balancing of mobility behaviour. In order to enable a direct comparison, the VW e-Golf and a petrol-driven Golf were investigated and compared. The manufacturer's guarantee for the battery is 160.000 km or eight years [22]. In this case study the observation period is exactly eight years, so all CO2 emissions resulting from production and recycling are balanced.

Table 3: Input parameters for mobility behaviour

Mobility Behaviour	Assumption
Calendric Parameters	
Year	2014
National holidays	German
Individual vacations	20.03 15:00 - 28.03 15:00, 08.08 14:00 - 16.08 11:00
Sick Days	10
Period under Review	8 years
Number of Profiles	1
Regular Working Days & Hours	
Work	Mo-Fr, 6:00-14:00
One-way Distance	1) 10 km 2) 30 km
Periodic Activities	
Attendance	90 %
Point in time	Tuesday, 18:00-20:00
One-way Distance	3 km
Evening Activities	
On workdays	2x per Week, 2h
On non-working days	1x per Week, 4h
One-way Distance	6,9 km
Other Leisure Activities	
Shopping	1x per Week, 2h
One-way Distance	4,5 km
Trip	1x per Week, 3h
One-way Distance	80 km

Table 4: Data set for charging infrastructure, BEV and ICE

	Parameters
Load Profile	
Charging Power	3,7 kW
Load curve shape	Real
Charging Behaviour User	Always
EV is charged on trip	25 %
Electricity Price at home	0,29 €/kWh
Electricity Price on trip	0,35 €/kWh
BEV	
Name	VW e-Golf
Usable Capacity	35,6 kWh
Consumption	12,7 kWh/100km
ICE	
Name	VW Golf, Petrol
Consumption	5,9 l /100km
direct CO2-emission	141 g/km

4 Simulation results

After entering all parameters into the user interface and a subsequent start command, the Load Profile Generator calculates the mobility behaviour, the charging strategy as well as the balancing of the user. All results are automatically presented in a clear and understandable way in tables and diagrams. Furthermore, it is possible to view explicit times of the simulated year in detail by using the zoom-in function. In the presentation of the results of the example scenario, the first working week of the simulated year 2014 is explicitly depicted. Fig. 8 illustrates the generated mobility behaviour from 6 January to 13 January in 2014 and provides information on the status of the user and the location of the car.

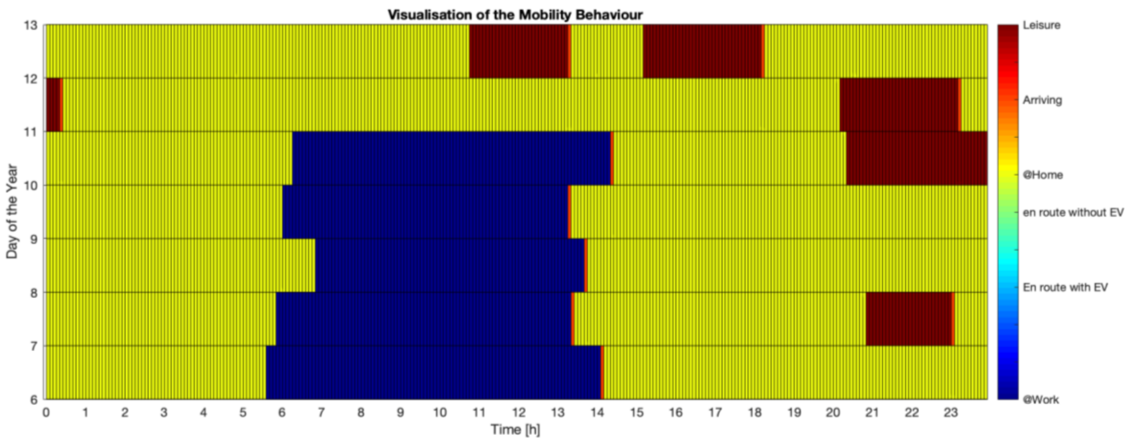

Figure 8: Generated mobility behaviour

The resulting route profile achieves a total mileage for the simulated year 2014 of

- distance 1: 9570 km
- distance 2: 19370 km.

Based on the route profile, the next step is to develop a charging strategy for the consumer. Fig. 9 outlines the resulting charging and SOC curves of the charging strategy developed for the electric vehicle. All targets of the reconstructed mobility task are safely achieved. The peak load for both distances is 3,55 kW. The capacity of the vehicle battery is sufficient for all calculated routes and there is no lack of energy at any time. The minimum state-of-charge level is 58 % for distance 1 and 28 % for distance 2 and therefore never falls below the defined boundary of 10% in the example scenario.

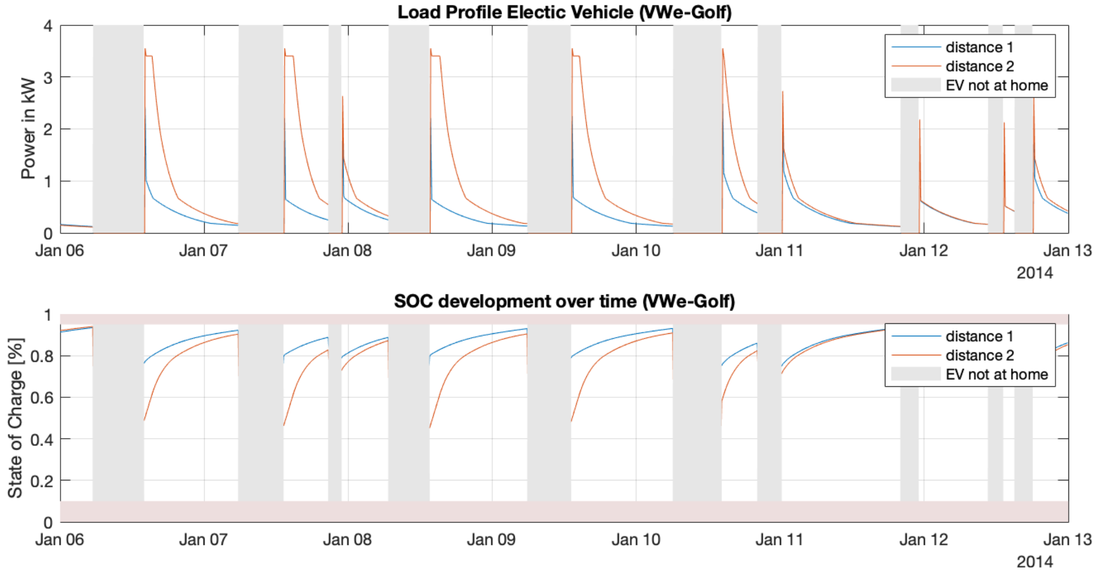

Figure 9: Generated load profile and SOC (06.01.2014 - 13.01.2014)

To provide the user a better overview of his charging behaviour, the average load and start times of his charging operations are listed. Fig. 10 illustrates the average load curve of the user's charging station over one day. In addition, the total of 525 charging processes with a total energy demand of 1.771 kWh for distance 1 and 3.684 kWh for distance 2 are plotted. The load profile shows peak loads and a frequency of the start time at 3 p.m., which is related to the arrival after work. The number of charging processes is the same for both distances, as the electric vehicle is always connected to the charging station when it arrives at home.

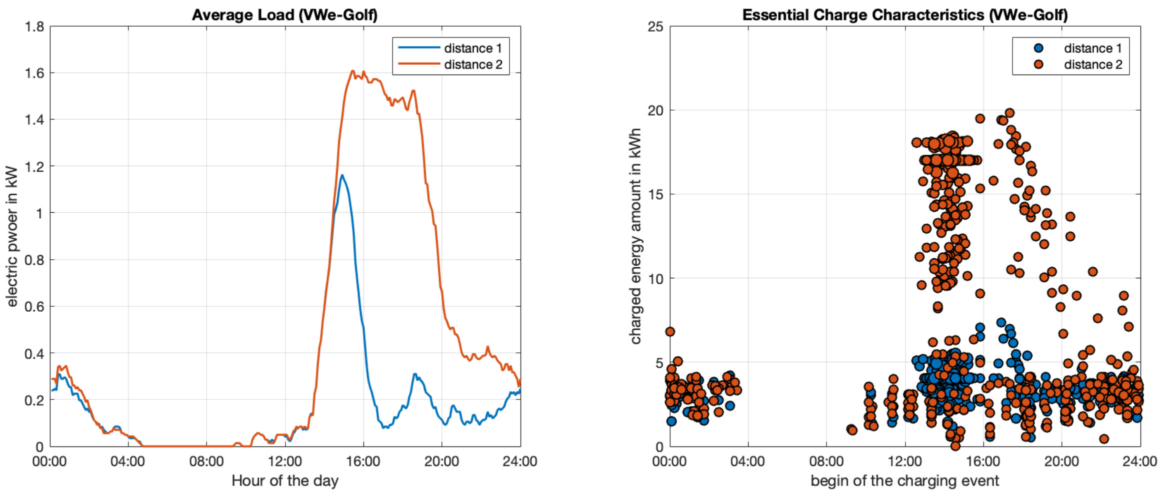

Figure 10: Overview of generated charging behaviour

The following bar chart of mobility behaviour in Fig. 11 compares the absolute values over the observation period in order to illustrate the ecological and economic consequences to the user. A comparison of different electric models across vehicle classes shows, that the CO2 balance of an electric vehicle is determined in particular by the high CO2 emissions from battery production and by the CO2 emissions from power supply. Particularly electric models with high battery capacities and high power consumption have an unfavourable CO2 balance. Only with the possible use of renewable energy, a clear improvement can be seen. Based on the German electricity mix, CO2 emissions for the use of the BEV will amount to 0.104 kg/km for energy supply in 2014. The economic comparison of the drive concepts shows higher purchase costs with lower usage costs for the BEV. In general, a high annual mileage is an essential key to the economic efficiency of electromobility.

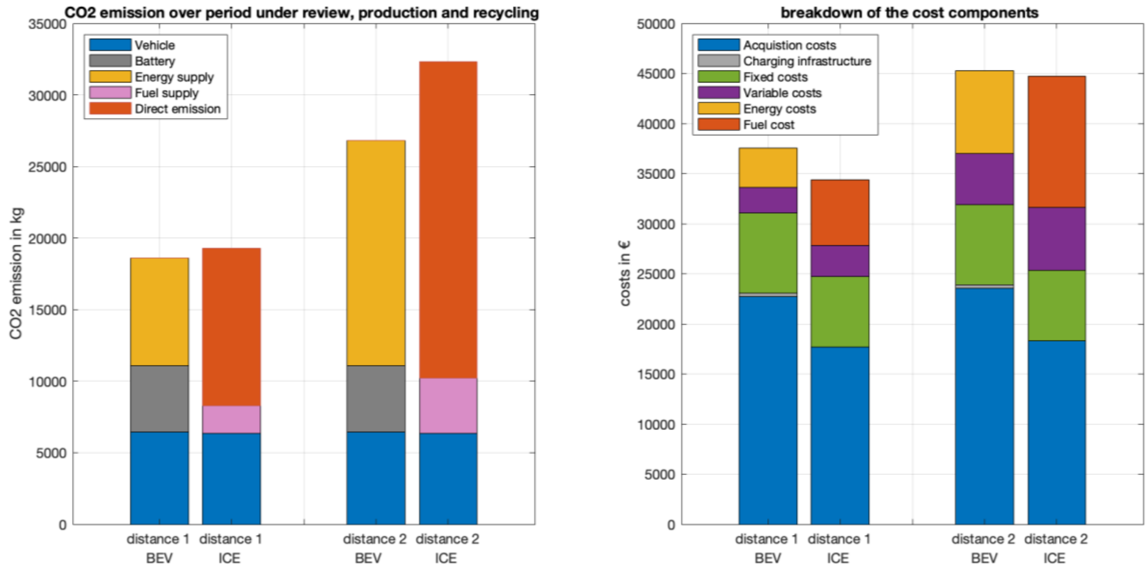

Figure 11: Ecological and economic balance

Additionally, the tool offers the option of reading in several predefined user profiles and combining the resulting load profiles. This option can be used, for example, in the layout of micro smart grids or car parks. Fig. 12 shows the total load curve of 30 different user profiles with up to 11 kW per charging station. The load profile reflects the resulting energy demand of 30 different mobility characteristics, from student to manager. 21 charging stations offer an output of 3,7 kW and 9 stations 11 kW for charging the battery. For this case study the maximum power requirement is up to 59 kW with a total installed power of 176,7 kW.

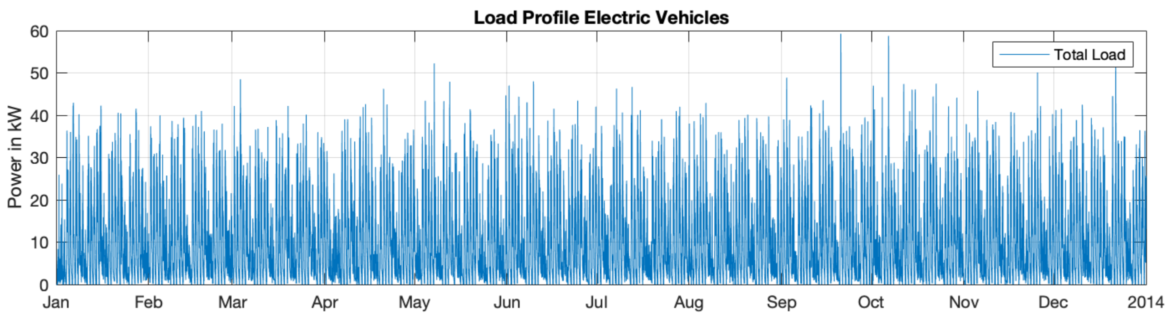

Figure 12: Total load profile of 30 electric vehicles

Compared to the annual peak load, a maximum output of 43 kW is achieved in the exemplary week. Thereby Fig. 13 illustrates the load curve from Monday till Sunday in five-minutes resolution. Since this case study is about home charging and standard commuters are considered, the load peaks are normally in the afternoon. This example shows that the charging behaviour is not the same every day. On Thursday and Friday the charged amount of energy is significantly lower.

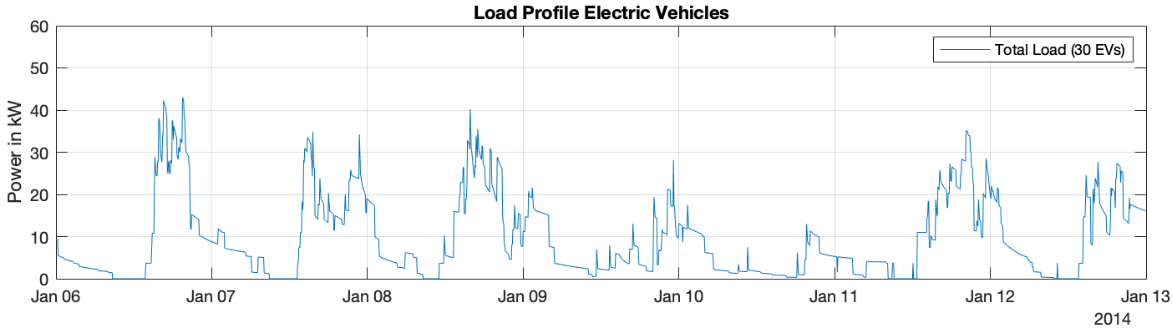

Figure 13: Total load profile of 30 electric vehicles (6.01.2014 - 13.01.2014)

5 Conclusion

To conclude, the charging profile generator can cope with two application goals. It enables the consumer to perceive the opportunities and risks of electric mobility by directly balancing his personal mobility behaviour from an ecological and economic point of view. Additionally, the Load Profile Generator can be used to determine the energy demand and load flow curve for the mobility sector, e.g. in micro smart grids. The setting options of the tool aim for a realistic representation of the behaviour. In the following, two different application possibilities are summarized: on the one hand the added value for the private user to verify, if an electric vehicle will satisfy his mobility needs. On the other hand network operators and planners of charging infrastructure can benefit from the load profile prediction for a whole vehicle fleet.

- **Profile for the private consumer**
  After entering the personal mobility behaviour and vehicle selection, the load profile generator develops a charging strategy. The development of this charging strategy by means of a load flow calculation shows the charging process for the considered year and aims to take away the consumer's “range anxiety”. The final comparison between electric and conventional vehicles based on the calculated mobility behaviour reflects the two most important success and decision factors when choosing a vehicle: environmental friendliness and economy.
  Today, electric vehicles are already more climate-friendly than comparable combustion-engine vehicles. This also applies if vehicle production and the German electricity mix dominated by fossil fuels are taken into account and real energy consumption is included in the calculations.
  Profitability depends strongly on external factors such as the development of energy prices and of the residual value of the vehicle. To act economically, electric vehicles have to be driven a lot in order to amortize the higher purchase costs through lower consumption and maintenance costs. In fact, the decision is strongly dependent on whether the driving profile can be mastered purely electrically. With relatively even daily driving cycles and sufficient annual mileage, electric vehicles are the most economical choice.

- **Profile for integration in the power sector**
  By defining different user profiles with mobility behaviour, vehicles and charging stations, the load profile generator develops a load demand out of the sum of the individual profiles. The resulting load profile can provide information for the dimensioning of neighbourhoods or multi-storey car parks with regard to temporal power demands and load peaks. The possibility of generating individual mobility needs of the individual users make it possible to estimate the load profile for a specific case.

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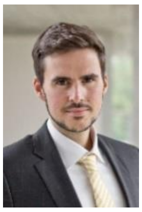	**Georg Göhler** studied Sustainable Energy Competence at the University of Applied Sciences Stuttgart. In April 2014 he started working at the Institute of Human Factors and Technology Management IAT at the University of Stuttagrt. His research activity focus, i.a., on issus such as 'Sustainable Energy Concepts' and the 'Interaction between Energy and Electromobility Infrastructures'. He developed several planning tools for cross-sector energy and elektromobility systems to design components in the Smart Grid and evaluate technical, economical and ecological effects.
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