36th International Electric Vehicle Symposium and Exhibition (EVS36)
Sacramento, California, June 11-14, 2023

Impacts of inductive charging on 24h on-demand operation of shared autonomous electric vehicle fleets

Julian Brendel[1], Marcus Schober[1], Moritz Schiel[1]
[1]*Reiner Lemoine Institut (RLI), 12489 Berlin, Germany*
julian.brendel@rl-institut.de, marcus.schober@rl-institut.de, moritz.schiel@rl-institut.de

Executive Summary

Shared autonomous electric vehicles (SAEVs) can play a key role in decarbonizing the transport sector, not only by providing a resource and cost efficient solution to fulfil our mobility needs, but also by providing a flexible load to the grid and local generation of renewable energies. To leverage this potential, fleet operation and charging strategies need to react to variable signals and charging stations need to be fully automatic, as possible with inductive charging. In this work, we demonstrate a SAEV fleet simulation framework, containing modules for vehicle modeling, driving and charging simulation and applying charging strategies. In a real world based case study, we demonstrate the potentials of the approach. The results show an increase to 77 % autonomy rate with local PV using flexible PV oriented charging, compared to 0 % with depot charging, reducing the carbon emissions by 78 %. Cost oriented charging reduced costs by 25 %.

Keywords: smart charging, load management, photovoltaic, emissions, shared

1 Introduction

As a result of the battle against climate change, the transport sector is under immense transformation. Electrification of the vehicles power train in combination with a large ramp up in renewable power generation are among the main strategies towards its decarbonization [1]. Both however have a high demand in scarce resources and power generation, distribution and storage face physical, economical and political limitations. The electrification therefore has to be accompanied by a transition in transportation towards less private cars and more privision and use of public transport [2]. Shared autonomous electric vehicles (SAEVs) offer a promising perspective towards reaching these goals, while maintaining a flexible and demand oriented offer to fulfil our mobility needs.

The transformation also poses challenges for the electric grid, as simultaneously charging electric vehicles (EVs) result in high peaks on the demand side, while the high share of renewable power, mainly from solar and wind, result in high volatility on the supply side. Demand response strategies tackle this issue by proposing ways to balance demand and supply. The benefits include higher penetration of electricity from renewable resources, more efficient use of existing infrastructure, and a reduction in system operating costs. There are different options discussed how to achieve demand response. Providing economic benefit through time-variable electricity prices is regarded to be one of the most promising approaches[3].

Demand response strategies for EVs are mainly considered as so called smart charging strategies and are well researched [4]. Demand response mechanisms in the operation of autonomous fleets however are still in an early stage of study[5]. SAEVs can not only use their standing time at charging stations for flexible charging strategies, but can furthermore use idle times to relocate and connect to charging

stations. Due to the absence of personnel, the charging process should be designed to be fully automatic. Inductive charging offers a solution to this problem.
In this work, we present a flexible and modular simulation framework that contains a vehicle model, a driving simulation module and a fleet simulation tool with an adaptable charging strategy. Through this, driving and charging assignments are subjected to constraints of variable electricity costs and local renewable power. In a case study the methodology is applied to a scenario, based on the autonomous fleet operation by Regionalbus Ostbayern GmbH (RBO) in Bad Birnbach. Results are presented that show how this approach, together with automatic inductive charging stations, increases the performance of the system, measured in three key performance indicators (KPIs): Costs and CO2 emissions are decreased and the direct use of local renewable energy sources is increased. This work is embedded in the research project ADVANTAGE[1].

2 Simulation framework

To answer questions regarding the operation of autonomous vehicles, we developed a python tool which allows the simulation of different scenarios and charging strategies. Figure 1 shows the different modules that can be accessed via the simulation framework.
The scenario definition is accomplished through parsing multiple input files and creating a scenario object. This object can also start the fleet simulation module. The fleet simulation is connected with two other tools developed at the RLI. The open source tool SpiceEV[2] is handling the charging calculations. It includes a charging curve model, various charging strategies and a module for cost calculation. SpiceEV also offers depictions of the local energy systems at each grid connection, including time series of local energy production, local loads and stationary batteries. For the calculation of driving consumption, we use the model described in section 2.1.
For more details on the fleet simulation and the outputs, refer to section 2.2. The tool is still under development and will be released later this year.

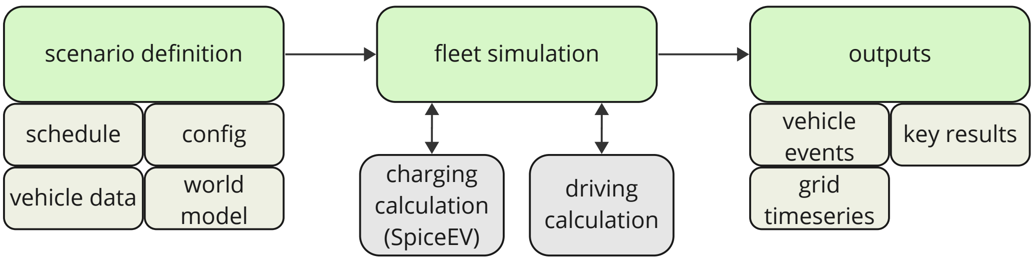

Figure 1: Components of the simulation tool

Table 1 displays the necessary input files to define a scenario. The scenario model includes vehicles and their characteristics, locations like stops and depots, and chargers. The schedule decides the route as well as the timetable of the vehicles. This information is vital to the simulation, as it creates charging demands and sets constraints on the options for charging decisions.
The configuration file defines the simulation settings and allows the parameterization of charging strategies by changing the weighting factors listed in table 2.

2.1 Driving simulation and vehicle model

The evaluation of energy consumption under varying environmental conditions is an essential part of the simulation of a vehicle fleet. RLI has therefore developed a driving simulation module, which was integrated in this framework. Both the longitudinal dynamics - in larger parts based on [6] - and heating and cooling are modeled. Vehicles can be depicted in the included modular vehicle model and are parameterized with their drive concept (battery and hydrogen), heating and cooling concept (electric resistance heater, electric heat pump, diesel powered heater) and further technical and geometrical properties. The driving simulation takes ambient temperature, level of loading, incline and driving profiles as input and carries out simulations with a second-by-second resolution to determine the momentary consumption of the modelled vehicle.

[1] `https://reiner-lemoine-institut.de/en/project-advantage-autonomous-driving-autonomous-charging/`
[2] `https://github.com/rl-institut/spice_ev`

Table 1: Scenario definition

Input file	Content
Schedule	Timetables for all buses, including destination and time for each ride
Configuration	Simulation settings like start and end date, weighting factors and charging parameters
Vehicle data	Battery capacity and charging curve per vehicle type
World model	Distance and incline between locations, charging points, various time series like temperature or energy cost

2.2 Fleet Simulation

Besides calculations of driving and charging events, the fleet simulation focuses on the evaluation of different charging options. Figure 2 describes the general simulation process. After parsing all available scenario information from the input files, objects are created to represent the given data. Locations, vehicles and chargers are all represented individually.
In a given scenario, the algorithm predicts if each vehicle is capable of completing the schedule. The delta between needed energy and available energy is considered when planning the necessary charging events. A variety of charging options is thereby created and compared using an evaluation function.
For that purpose, the simulation provides the decision-making module access to the full driving profile of the vehicles, which means that the module has perfect foresight in regard to all events of each vehicle. The available information is used to calculate optimal charging slots depending on the evaluation function.
At this development stage, the simulation is able to analyze vehicles with set timetables, as their consumption and charging patterns are predictable. In the case of on-demand services, it can be used for analysis of the charging potential and an estimation of charging behavior. Future developments will be capable of a more realistic depiction of on-demand services by replacing the known trips with projections from historical schedules. The results of the current version however already indicate the potentials associated with the charging strategies.

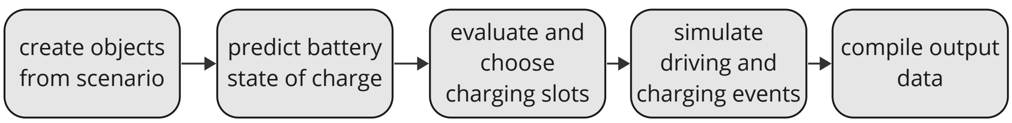

Figure 2: Schematic of the simulation process

The evaluation function for charging events is based on the following criteria:

- Amount of time and energy spent to get to the charging location
- Cost of charging energy
- Percentage of local renewable energy vs grid energy used

The user can set the weighting factors for these criteria in the configuration files of the simulation. The formula for the total score of a charging slot can be described as follows:

$$event\_score = \sum criterion\_score * weighting\_factor$$

Charging time slots are selected based on this score. Exact calculations and the corresponding weighting factor for each criterion can be seen in table 2.
After a successful simulation, the following output files are generated:

- Event list for every vehicle
- Accumulated key results
- Grid time series

Table 2: Charging slot evaluation criteria

Criterion	Weighting factor	Score calculation
Time	time_factor	$1 - \frac{driving\_time}{time\_window}$
Charging energy	energy_factor	$1 - \frac{driving\_consumption}{charged\_energy}$
Cost	cost_factor	$1 - \frac{maximum\_cost - actual\_cost}{maximum\_cost - minimum\_cost}$
Local renewables	local_renewables_factor	$\frac{local\_feed\_in}{charged\_energy}$

The event list of vehicles includes all completed driving and charging events. Every event contains information about the battery state of charge (SoC), the charged energy (split by grid and local feed-in) and energy cost and emissions. The grid emissions are calculated using a variable emission factor, while emissions from local renewable power generation are neglected, as no upstream emissions are considered. As grid emissions are rarely known in advance, they are not used as input parameters for the charging strategies directly. However, the share of renewable energies in the energy system can influence both the carbon emissions and the electricity prices. The usage of local photovoltaics can equally reduce carbon emissions. Hence the charging strategy implicitly influences the carbon emissions.
The accumulated results contain values such as total cost, total charged energy or share of charging from local feed-in, summed up over all vehicles in the simulation. These results are useful for comparing different scenarios.
The grid time series tracks the power demand of all vehicles. It tracks the total power as well as the amount of vehicles connected to a charging station per time step. The time series can be used to evaluate the impact of different charging strategies on the local electric grid.

3 Case Study - 24h on-demand fleet operation

The basis of this case study is a field test in Bad Birnbach, that is part of the research project HEAL[3]. Here, the bus company RBO, a subsidiary of Deutsche Bahn, is operating an SAEV fleet. Figure 3 shows the autonomous route network in Bad Birnbach. The considered on-demand service, where rides are flexibly booked over an app, is shown in black as line 7016. The service is currently operated with EZ10 gen 3 vehicles by the company EasyMile between 8 a.m. and 6 p.m. For charging, the vehicles are connected to a 22 kW charging station over night at the bus depot, indicated with a house symbol in the south east of the map.

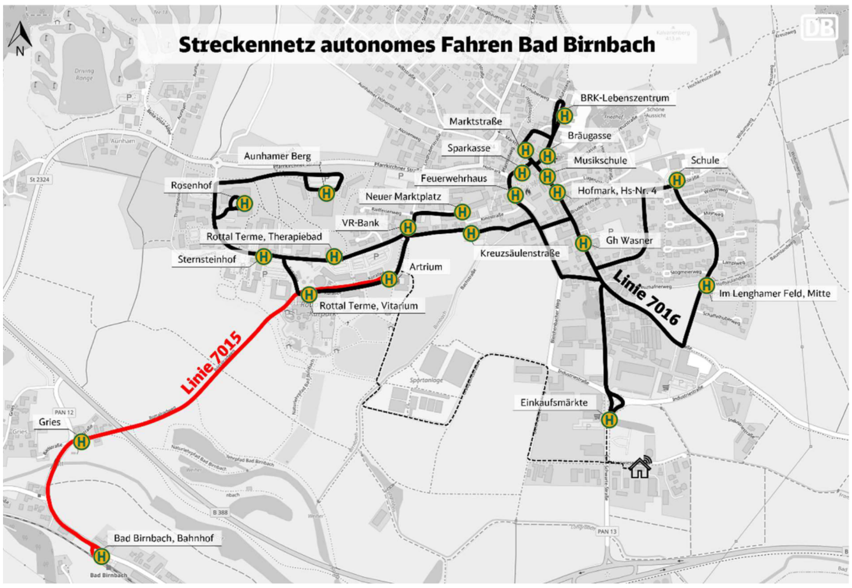

Figure 3: Autonomous route network in Bad Birnbach, ©RBO

[3] `https://www.dbregiobus-bayern.de/angebot/autonomes-Fahren/autonomer-bus-HEAL`

3.1 Scenario definition

In the analysed scenarios, the service is extended to a 24 h operation. In a reference scenario, the vehicles are charged during non overlapping fixed charging periods at the depot. Requested rides during these periods are declined. In the second scenario, automatic inductive charging stations are used for flexible opportunity charging, in order to avoid the service interruptions during depot charging. Here, the described methodology was used to determine how the fleet efficiency can be improved between automatic opportunity charging and depot charging. For the inductive scenario, three different charging strategies are compared, as described below. Table 3 summarizes the parameters used for the scenarios. For both scenarios, a minimum state of charge of 20 % is required. All further input, as described in section 3.1.2 to 3.1.4, are used consistently across the scenarios.

Table 3: Scenario parameters

	Reference: Depot charging	Inductive opportunity charging
Nr of vehicles	2	2
Charing locations	Depot	Gh Wasner, Artrium
Charging points	2 * 22 kW conductive at depot	2 * 11 kW inductive at each location
Charging time	veh 1: 12:00 - 2:30 a.m. and 12:00 - 2:30 p.m. veh 2: 2:30 - 5:00 a.m. and 2:30 - 5:00 a.m.	flexible
charging strategy	maximum power	a) base, b) pv-proritized, c) cost-prioritized
Installed PV power	45 kWp at depot	45 kWp at Artrium

3.1.1 Charging strategies for inductive opportunity charging

For the inductive opportunity charging scenario, three different charging strategies are specified. The base strategy is designed to prefer charging events that use a large share of available time slots for charging and consume little energy for the way to and from charging locations compared to the charged energy. The PV-prioritised strategy additionally favours events with a high share of locally produced renewable energy, in this case from PV. The cost-prioritized strategy rather selects events with low costs for electricity from the grid. Table 4 shows the parameterisation of the weighting factors for each strategy, as described in section 2.2.

Table 4: Weighting factors for charging strategies

	time	energy	cost	local renewable
base	1	1	0	0
PV-prioritised	1	1	0	1
cost-prioritised	1	1	1	0

3.1.2 Input time series

The simulation requires several input time series to model the energy system. These are the cost of electricity from the grid, the local PV power and the ambient temperature. For the evaluation of the results, also the grid emission factor is used. Figure 4 shows these values over the simulation time of 48 hours beginning at 21st of May 2021. The electricity cost is calculated as

$$cost_{el} = cost_{el,basis} + cost_{el,procurement} \tag{1}$$

where $c_{el,basis} = 8ct$, which represents all cost components except for procurement as in [7, p.119]. Energy procurement $cost_{el,procurement}$ is modeled as time series of the day-ahead energy prices for german-luxembourg at the EPEX energy exchange market as described in [8]. The hourly specific emission factor is based on the electricity mix in Germany and the specific emission factors of each energy source neglecting upstream emissions [8]. The temperature data originates from Fürstenzell, which is

20 km away from Bad Birnbach, and is measured and provided by the German meteorological service Deutscher Wetterdienst (DWD). At this site, the DWD also provides data for solar irradiation, which was used to model a 45 kWhp photovoltaic system (PV) using the open source tool feedinlib[4]. The resulting feed-in timeseries was used at both stations, "Depot" and "Artrium". As no upstream emissions are considered in the analysis, energy from local PV is considered to be CO2 emission free. When local PV energy is used for charging, the missed revenues of assumed 5 ct/kWh is considered as costs.
Due to the high penetration of renewable energies, mainly wind and solar, in the German electricity grid, costs and emissions strongly depend on their variable supply. Figure 4 shows, that during times of high supply of solar energy during the day, both the grid emission factor and the electricity cost decrease. At the same time, the cost depends on demand, which is why price increases can often be observed in the morning and evening, less visible on the morning of 22nd of May 2021, as this was a Saturday.

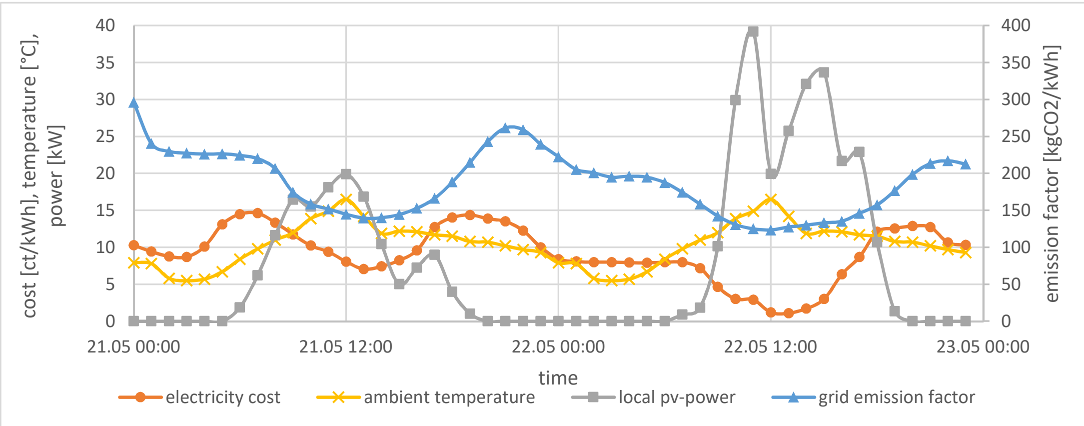

Figure 4: Boundary conditions of simulated scenario

3.1.3 Demand profile

On-demand services don't have a fixed schedule and respond on the go to incoming ride requests. The simulation with the described "perfect foresight" model requires a synthetic schedule. An agent-based pooling algorithm developed by RLI is used for this purpose. We generated a synthetic profile for the 24 hour services using MID-data [9] and statistical data from the HEAL-project in Bad Birnbach (fig. 5) to create ride requests. Start and end strops of every trip are chosen accordingly to the probability derived from the HEAL-data. These ride requests are then assigned to the vehicles via a pooling decision without perfect foresight, by evaluating possible variations of start and end of already assigned trips and the new request. The algorithm aims for a high pooling rate and low delay for passengers. If trips can not be assigned to any vehicle in a given time period, they are rejected.

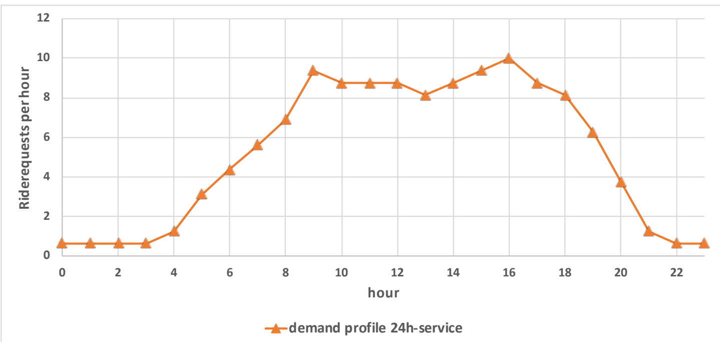

Figure 5: demand profile for 24-h operation

[4]https://github.com/oemof/feedinlib

3.1.4 Vehicles and consumption

The vehicles were simulated using the aforemetioned methodology. For this purpose, the modular vehicle model was parameterized for the vehicle class used in Bad Birnbach. However, the model could not yet be validated with real data and is therefore preliminary. Each vehicle is equipped with a battery capacity of 32 kWh. Figure 6 shows the consumption of the modelled vehicle for three driving profiles with varying mean velocities. Additionally the resulting specific consumption for the simulation of each trip of the demand profile is depicted.

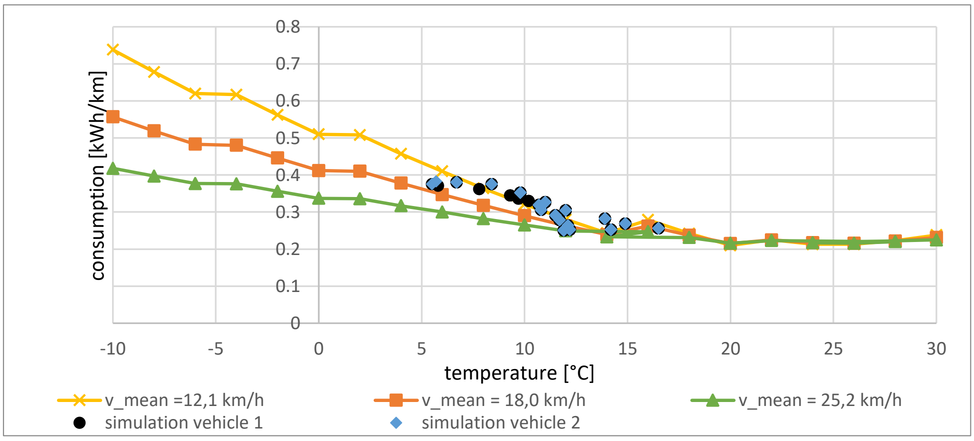

Figure 6: Simulated consumption of vehicles

3.2 Results

In the reference depot charging scenario, the vehicles charge during the defined breaks. Opportunity charging allows the charging processes to be distributed flexibly, as shown in figure 7. The figure shows SoC of one of the two vehicles, where charging events are indicated by a rising SoC-curve. Different charging times are thus selected depending on the charging strategy pursued. Following the base charging strategy, vehicle 1 charged 11 times over the entire simulation period. If the PV-based charging strategy is followed, the number of charging processes increases to 19, and for cost-based charging to 12. The selected charging times also change depending on the strategy followed. For example, with PV-based charging, the charges are mostly distributed during daytime to take advantage of solar production. Moreover, the results show that the minimum SOC is higher when inductive charging is applied. This allows a higher safety of the system against increasing consumption at low temperatures, or the use of smaller traction batteries.

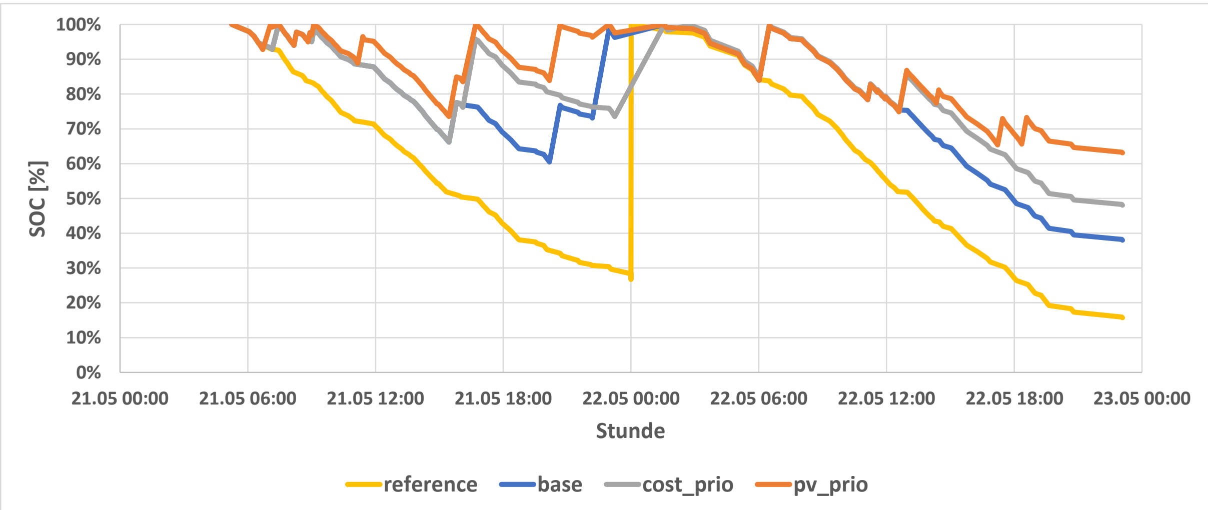

Figure 7: SoC course of the different scenarios for vehicle 1

To compare the results of the different scenarios, KPIs are used which are described in Table 5.

Table 5: KPIs for comparing the different scenarios

KPI	description
Distance	Distance traveled to fulfill ride requests and reach charging stations
Costs	Cost for the amount of energy recharged
Self sufficiency	Percentage of energy drawn from local PV
Emissions	Emissions of the amount of energy recharged

The charging strategy also affects the distance traveled by the vehicles during the two days simulation time. While 316.9 kilometers were traveled in the depot scenario, the distance traveled decreased to 313.1 km for the inductive base scenario. If certain charging strategies are pursued, the distance traveled increases because additional trips are made in order to reach the desired charging location. Therefore prioritizing local PV-power increases the distance by another 14.2 km to 327.3 km, compared to the inductive base scenario.

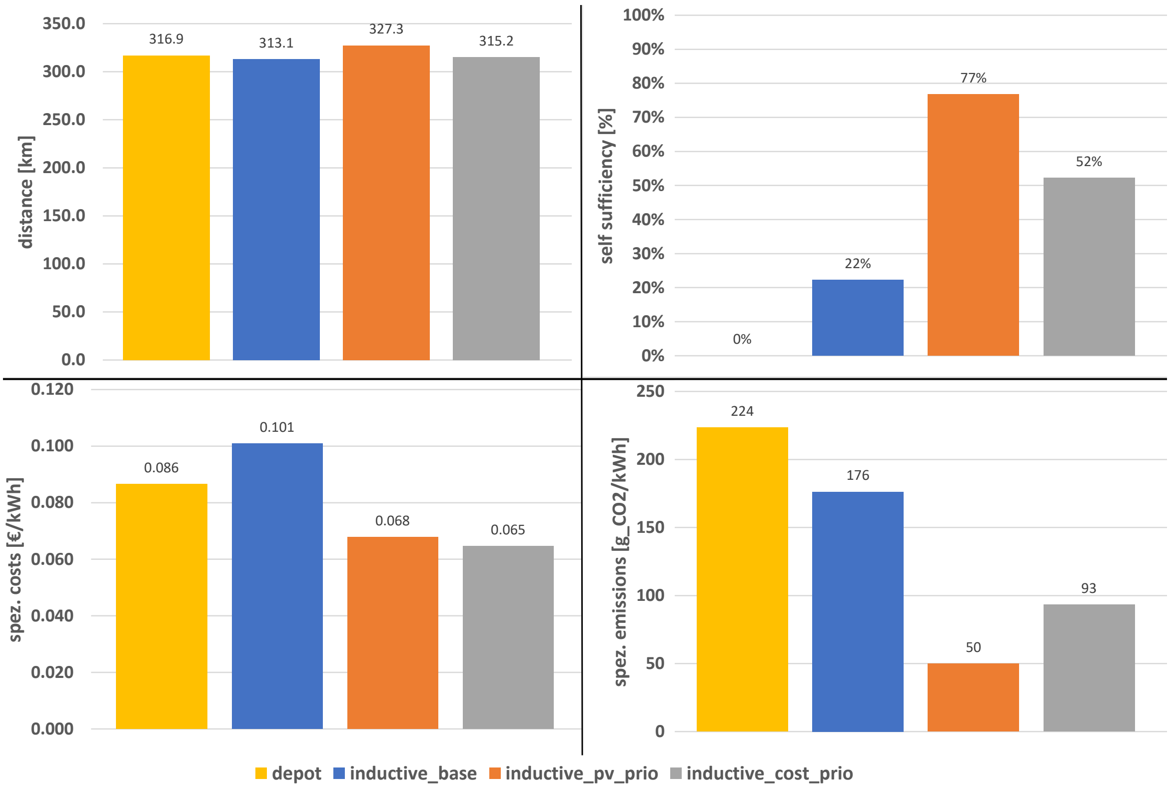

Figure 8: KPIs for the different scenarios

Due to the charging pause during night period with no solar irradiation, no energy could be obtained from local PV systems in the depot-scenario. In comparison, the share used in the inductive base scenario was increased to 22 %. If a PV-based charging strategy is pursued, the share can be increased to 77 % while in the cost prioritized strategy it could be increased to 52 %.

This is also reflected in the carbon emissions, because local PV systems are assessed as emission-free. Each charged kilowatt-hour caused emissions of 224 $g_{\text{CO2-eq}}$/kWh in the depot-charging case. In the inductive base scenario, emissions decreased by 21 % to 176 $g_{\text{CO2-eq}}$/kWh, mainly due to the higher utilization of PV systems. The PV charging strategy reduced these emissions to 50 $g_{\text{CO2-eq}}$/kWh and cost-optimized charging to 93 $g_{\text{CO2-eq}}$/kWh.

The costs of the purchased electricity reflect the grid efficiency of the charging process. In the depot-scenario, the average cost of electricity was 8.6 ct/kWh. In the inductive base scenario, these costs were increased by 14 % to 10.1 ct/kWh. The costs compared to the depot-scenario could be reduced by 1.8 ct/kWh to 6.8 ct/kWh through a PV-based charging strategy. With the cost-optimized strategy these costs could be reduced by a further 0.3 ct/kWh to 6.5 ct/kWh, resulting in the most cost efficient scenario. Here specific costs are decreased by 25 % compared to the reference scenario.

In summary, the results show that the followed charging strategies can improve the results in the desired categories. Thus, the specific costs and emissions during charging can be reduced.

4 Conclusion & Outlook

It was shown, that flexible opportunity charging with inductive chargers can overall increase the SoC during operation compared to scheduled depot charging thus making the system more robust against increased consumption e.g. due to cold temperatures. As charging now takes place during the day, locally generated PV-power can be used for charging. Under variable electricity prices, the charging strategy should however consider these, as charging while the global demand is high can otherwise result in increased costs for charging. When applying the proposed charging strategy to maximize local PV use in the inductive charging scenario, up to 77 % of the charging energy could be provided by local PV compared to 22 % in the base strategy. This leads to a reduction of carbon emissions induced by charging can by 72 %. The cost prioritized strategy reduces costs by 36 % compare to the base strategy. To reach these improvements, the locations and times of the charging events were adapted, demonstrating the capability of the proposed approach to utilize the flexibility inside the systems to the desired behaviour.
With the expected growing share of renewable energy in many countries electricity systems, also the variability in electricity prices and emissions over the day will increase and spread. This will also intensify the shown effects of reducing carbon emissions and costs through the proposed approach. Fleet operators of SAEVs should therefore consider deploying opportunity charging strategies with automated charging stations, as is possible with inductive chargers. This can also support the grid integration of electric autonomous fleets, if time-variable electricity prices are designed to serve the grid.
There are still many open questions for future research. The potentials of using the flexibility in the system could be further investigated by incorporating vehicle-to-grid into the model. As the availability of autonomous vehicles in public transport is still low, the data on the demand is still scarce. In order to generate valid data for the upscaling phase of these sytems, developing and validating transport demand models could help to close this gap. The data basis could be further improved by providing publicly available validated consumption data for this vehicle class, that does not exist to our knowledge.

Acknowledgments

The research was supported by the Federal Ministry for Economic Affairs and Climate Action of Germany through funding the project "ADVANTAGE". We are grateful for the support of the DLR Projekttträger (https://projekttraeger.dlr.de).

References

[1] *Global energy transformation: A roadmap to 2050.* Abu Dhabi: IRENA, 2019, oCLC: 1337455620.

[2] A. Brunnengräber and T. Haas, *Baustelle Elektromobilität: Sozialwissenschaftliche Perspektiven auf die Transformation der (Auto-)Mobilität*, ser. Edition Politik. transcript Verlag, 2020. [Online]. Available: https://books.google.de/books?id=7ajpDwAAQBAJ

[3] N. O'Connell, P. Pinson, H. Madsen, and M. O'Malley, "Benefits and challenges of electrical demand response: A critical review," *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 686–699, Nov. 2014. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032114005504

[4] Hildermeier, Kolokathis, Rosenow, Hogan, Wiese, and Jahn, "Smart EV Charging: A Global Review of Promising Practices," *World Electric Vehicle Journal*, vol. 10, no. 4, p. 80, Nov. 2019. [Online]. Available: https://www.mdpi.com/2032-6653/10/4/80

[5] S. Narayanan, E. Chaniotakis, and C. Antoniou, "Shared autonomous vehicle services: A comprehensive review," *Transportation Research Part C: Emerging Technologies*, vol. 111, pp. 255–293, Feb. 2020. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0968090X19303493

[6] O. A. Hjelkrem, K. Y. Lervåg, S. Babri, C. Lu, and C.-J. Södersten, "A battery electric bus energy consumption model for strategic purposes: Validation of a proposed model structure with data from bus fleets in China and Norway," *Transportation Research Part D: Transport and Environment*, vol. 94, p. 102804, May 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1361920921001085

[7] M. Faltenbacher, “Abschlussbericht - Programmbegleitforschung Innovative Antriebe und Fahrzeuge,” https://www.now-gmbh.de/wp-content/uploads/2022/04/NOW_Abschlussbericht_Begleitforschung-Bus.pdf, Bundesministerium für Digitales und Verkehr (BMDV), Berlin, Abschlussbericht, Aug. 2021.

[8] F. Hein and H. Hermann, “Agorameter – Dokumentation,” https://static.agora-energiewende.de/fileadmin/Projekte/Agorameter/A-EW_Hintergrunddokumentation_Agorameter_v37_web.pdf, Oct. 2020.

[9] infas, DLR, IVT und infas 360, “Mobilität in Deutschland,” 2018.

Presenter Biography

Julian Brendel holds a Master of Science degree in physical engineering from Technische Universität Berlin (Berlin Institute of Technology) and has been employed as research assistant at Reiner-Lemoine-Institute since 2020. His main field of research is the electrification of public transport bus fleets with an emphasis on the energy supply, the use of renewable energies and grid integration. The methodologies used focus on the development of open-source modelling and simulation software.