Assessing Flexibility in Battery Electric Truck Charging Depots Considering Grid Impact

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Abstract

This work describes the methodology and used data to analyze the effects of charging infrastructure on service depot of Battery Electric Trucks (BETs), to quantify its potential flexibility and discuss pros and cons of Electric Vehicle Supply Equipment (EVSE) with minimized charging power. The BET will be charged on their service depot during shift change, over night or other off-duty periods. This leads to heavy load on the corresponding network infrastructure but also offers the opportunity to provide flexibility for the energy system. Quantifying the load is done by analyzing existing BET data of uncontrolled and managed charging operations and enriching it with scenario simulations. Real world data from heavy duty refuse collection vehicles as well as logistic long-haul and short distance trucks is used. The analysis quantifies flexibility potentials of service depots, which can be used to reduce the impact on infrastructure and to optimize charging costs. A short literature review is provided for contextualization. The endeavors take place in a German city.

Acronyms

BET Battery Electric Truck
BEV Battery Electric Vehicle

CP Charging Point

DNO Distribution Network Operator

EV Electric Vehicle
EVSE Electric Vehicle Supply Equipment

MAC Media Access Control

RES Renewable Energy Source
RFID Radio-frequency Identification

SNH Stromnetz Hamburg
SoC State of Charge

V2G Vehicle to Grid

1 Introduction

In terms of transport, several ways are discussed to reduce CO_2-emissions or decarbonize completely. Gaete-Morales et al. found that for decarbonising the road transport power sector costs are the lowest for flexible charged Battery Electric Truck (BET) and Vehicle to Grid (V2G) compared with e-fuels and hydrogen [4]. Transport trucks are predominantly used commercially and achieve high mileages and higher operation times in relation with passenger vehicles. However, they still have long down times depending on the utilisation profile [12]. Recharging is possible along the route, at the destination or at the depot. These charging locations have different characteristics from a grid perspective. In this work, the role of depot charging of BETs during the off-duty periods in depots regarding grid impact and flexibility is considered. A literature review in 2019 accomplished by Kluschke et al. shows that the impact on infrastructure or the energy system of BETs are not considered by the majority of the reviewed literature [9]. Since then, system integration and flexibility of Battery Electric Vehicle (BEV) and BET have gained attention.

Hertlein et al. discuss the challenges posed by the increasing demand for charging Electric Vehicle (EV) on the distribution grid level. They emphasize the need for flexibility and control on the consumption side to align power demand with supply-dependent feed-in, and present a cluster-based and incentive-oriented energy management system to achieve the flexibilization of grid usage necessary for integrating electric vehicles into the power grid. Nevertheless, BET were not within the scope of their investigation. [7]

However, Ruppert et al. find that integrating distributed flexibilities leads to a significant increase in the security of supply and a reduction in grid congestion, with the overall effect on generation adjustment being relatively small. Additionally, the comparison of results between AC and DC formulations shows significant differences in individual cases, with the AC approach generally requiring lower adjustments when considering grid losses and suitable generation locations. [11]

Gonzalez Venegas et al. underscore EVs' potential to offer Distribution Network Operators (DNOs) a range of services such as investment deferral, congestion management, voltage regulation, and backup power. While the technical feasibility of these services has been established, widespread adoption is hindered by the limited availability of bidirectional chargers, reactive power control technologies, and communication protocols necessary to fully leverage EV flexibility. BETs were not in their scope. [6]

While Hertlein et al. emphasize that flexibility is fundamentally necessary for the integration of EV into the energy system and Gonzalez Venegas et al. point out the ability of BEV to provide system services, Will and Ocker underline the ability of BET to provide flexibilities that the grid will need in the future. They state that TenneT, a German Transmission System Operator, awaits the need for flexibility for power balancing to grow by up to 3 GW and for congestion management of up to 9 GW in Germany by 2030. Will and Ocker find, that up to 23 GW of down-regulating flexibility potential can be provided by trucks and buses combined. This results in revenues which contribute to reduce operational costs for electrified heavy-duty vehicle fleets. [13]

Barthel et al. highlight the distinct characteristics of a small logistics fleet, noting its significantly longer average plug-in duration and charged energy quantity compared to other fleets, alongside a low dispersion in charging events. Moreover, analyses of idle times and shift potential offer valuable insights across the three vehicle fleets mentioned, with particular emphasis on the logistics fleet's ability to meet legal requirements, thus enabling the exploitation of flexibility as needed. [1]

Fischer and Rudion present a method devised to assess flexibility potential using synthetically generated EV charging profiles, factoring in individual charging targets and flexibility request windows. Introducing the concept of a virtual charging management system, it aims to fulfill each EV's charging objectives while accommodating flexibility requests, although the imposition of this constraint on flexibility ultimately diminishes the overall flexibility potential. They focused on BEV. [3]

Providing flexibility needs the ability to shift loads over time and therefore needs Electric Vehicle Supply Equipment (EVSE) that can provide multiple times the minimal necessary charging power to fully charge the BET. From an operator perspective, high-power EVSE is more expensive with less to none benefits regarding operations and costs. Borlaug et al. mention in their conclusion that minimal charging power and flexibility are contrary to each other and advantages and disadvantages should be subject to further research. However, flexibility was not the subject of the analysis. [2]

Jahic et al. show the quantification of flexibility and its benefits for the grid using depot charging of electrified buses. They precisely define the various influences on the flexibility of buses. [8]

The study presented here builds on the described work.

2 Objectives

The aim of endeavours described here is to make suggestions how to build electrified service depots with a minimum of grid expansion. Therefore, the expected impact on the distribution grid of service depots has to be analysed and possible flexibilities identified. The flexibilities can be used to influence and reduce the impact on distribution grids. With the analyses made, grid operators can make suggestions or guidelines for service depots to maximize possible electrification with minimum grid expansion. BET fleet operators can use the flexibility of the fleet to reduce charging costs. With the assumption that Renewable Energy Source (RES) will be the least expensive energy source in near future, the considered goal for fleet operators is the optimization of RES rate of charged energy. However, operating schedule optimization are not in scope. Flexibility estimation is made with service schedules "as is".

Supplemented by additional BET joining the fleet from 2024, the fleet is mapped in simulations. The simulations predict the behaviour of growing fleets and fleets of logistics companies. Making these steps reproducible for further BET fleets is an objective as well. This work describes the methodology to archive this objectives.

3 Methodology

The methodology to reach the objectives is separated in the scopes *Depot* and *System*. Each scope contains empiric data, process elements and steps, which are visualized in Figure 1. Models of BET, grid and EVSE are abstracted and validated based on real world data about these entities. The data basis is described in Section 3.1 and models in Sections 3.2.1 and 3.2.2. Operational use cases are abstracted from real world usage of the BET. Models and use cases are combined to scenarios which then are simulated and evaluated.

In the system scope, the grid model is combined with estimated and real load scenarios. The results of the depot charging simulations are hand over to the power flow simulation as load time series. As part of charging simulations respective power flow simulations the models are used to compute potential flexibilities and their possible advantages as well as grid impact and its mitigation. Eventually, the scale up is made with the findings of the simulations applied to regions with several logistic hubs and depots for BET.

3.1 Empiric Data Basis

The data used in the here described method describes waste collection vehicles, small and large road sweepers as well as trucks used in freight logistics from 7.5 tons gross vehicle weight rating. BET core data (i.e. battery capacity, maximum charging power AC/DC) are available through the vehicle database in Stromnetz Hamburg (SNH) back-end system "eRound". All available data during charging is gathered by the charging infrastructure not from the BET itself. Therefore, charging power as time series with a resolution of two minutes is available, demand data for routes and topology as well as battery specific data is not, except State of Charge (SoC) which is available when BET is connected to a DC charging point. In all other cases, if a fully charged battery is recognized, SoC is calculated afterwards with the energy charged during the charging process.

BET identification is made with Radio-frequency Identification (RFID) cards or Media Access Control (MAC)-Address

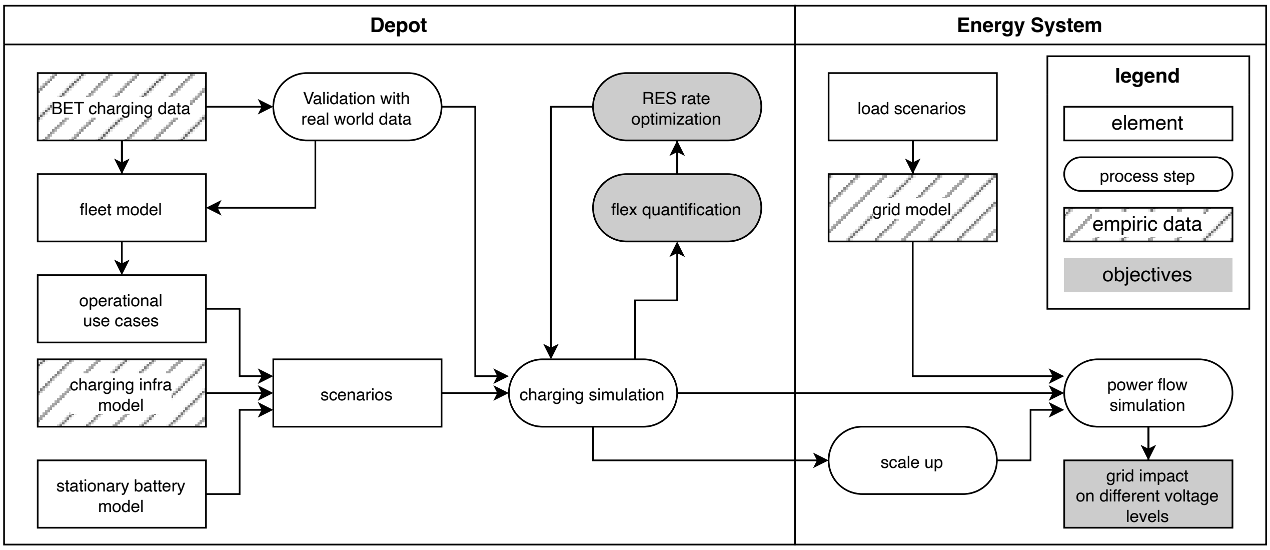

Fig. 1: Elements and processes of the analysis

of the vehicles socket. This data is provided by "eRound". From early 2023 until mid 2024, historical data of one BET is available. Data of up to 35 BET is joining during 2024 and 2025.

3.2 Charging Simulation and Synthetic Data

Simulations are written in python code and are computed with at least three components:

- BET Models
- EVSE Models (optional)
- Scenario Handler
- Distribution Grid Model

Each existing or fictional BET is represented by a parametrised instance of the BET model. Optionally models of EVSE can be added. This is necessary if the maximum charging power is limited by the EVSE instead of the BET or less charging points than BET are available.

The instances of both are created by the Scenario Handler which also handles further input parameters and constraints. The Scenario Handler - the central simulation module - then computes time series with power consumption which are hand over to the grid model and power flow calculation. The flexibilities of the BET charging process is computed by the Scenario Handler as well. The process is shown in simplified form in Figure 2. Each entity in the simulation computes its state and state changes by itself and makes the results available for other entities. This makes sure that the simulation is highly modular and with decentralized calculations. RES rate is evaluated with regional and national RES production data.

3.2.1 Model of BET: The BET are represented by a model written in python code. The model reflects the behaviour when a BET is connected to charging infrastructure, i.e. decision whether to charge depending on the SoC. The energy demand is not calculated and is given as input parameter to the model. Discharging (Vehicle to Grid) is not in scope.

On runtime the BET model receives timestamps as input. The model then calculates its parameter changes from last timestamp to the given one. Simulated parameters beside others are shown in Table 1. These are made available for scheduling several BET within the scenario simulation. A set of BET (models) represents a fleet (model).

The rolling validation on real data ensures the result quality of the analyses.

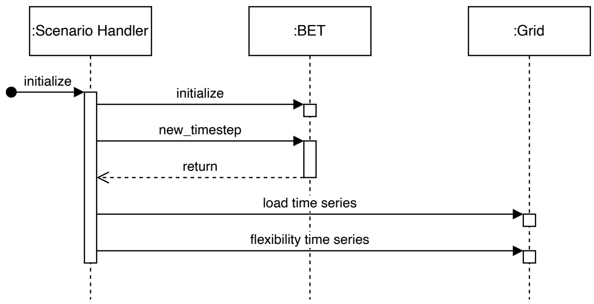

Fig. 2: Simplified representation of interaction of simulation components

3.2.2 Model of EVSE: The EVSE model describes the availability of charging points and power constraints through supply equipment. The model contains maximum active charging power per EVSE and connected Charging Point (CP). It balances the power of and over occupied CPs. When a BET model in a simulation arrives at the depot, it is assigned to an available CP. The EVSE model then determines the power for the particular CP. EVSE model therefore acts as intermediate and evaluates computed active charging power and limits it if necessary.

Table 1 Parameters of BET model (selection)

Name	Description	Type	Codomain
	Specifying Parameters		
max. charging power	maximum permissible power to charge the BET	float	$[0, \inf)$
capacity	Energy capacity of the battery	float	$[0, \inf)$
service schedule	When the BET is connected to the charging point, energy use when not connected	list[datetime], list[float]	<ISO timestamps>, $[0, \inf)$
	Input Parameters		
timestamp	The model calculates changes of all parameters from the previous timestamp to the new one.	datetime	$(\inf, \inf)$
	Simulated Parameters		
SoC	SoC at end of time step	float	$[0, 1]$
charging power	charging power at end of time step	float	$[0, \inf)$
charging	Whether charging at end of time step	boolean	$\{true, false\}$
connected	Whether connected at end of time step	boolean	$\{true, false\}$

3.3 Flexibility Quantification

In the context of the energy market, flexibility describes the possibility to shift load over time. Regarding BET the main dependency is the connection to the charging infrastructure. Load shifting can only be done, when the BET is plugged in and if time of upcoming departure is known.

The role of flexibility in this analysis is minimizing necessary grid expansion for depot charging in urban and suburban grid topologies. This leans on findings of Will and Ocker which state that “waste collection in urban environments [. . .] [is a] further prime use cases for electrification” [13, p. 4] and the possible providable flexibility reaches from 4 GW up to 23 GW.

The flexibility is qualified with a flexibility frame and is visualized with a flexibility matrix (Equation 1 according to [8, eq. 6]) and a graph according to Gerritsma et al. [5].

$$F = \begin{bmatrix} P_{t_0,cat0} & \dots & P_{t,catn} \\ \vdots & \ddots & \vdots \\ P_{t_0+m,cat0} & \dots & P_{t+m,catn} \end{bmatrix} \quad (1)$$

$$\text{with} \qquad cat = t_d - \Delta t_{c,min} - t \qquad [min]$$

$$\text{where} \qquad \Delta t_{c,min} = \frac{\Delta SoC}{\bar{P}} \qquad [min]$$

cat describes the amount of time the flexible load could be shifted ahead in minutes. $\Delta t_{c,min}$ is minimum required charging time to fully charge, t_d is the time of next departure, t is the time step in the simulation from initial time stamp (t_0) over the number of time steps in the simulation m, ΔSoC is the remaining energy to fully charge and $\bar{P}$ is the mean maximum charging power.

An example of a flexibility matrix graph is shown in Figure 3. The bars indicate at which time charging power is demanded. Each BET is represented by a bar which stack when occurring during the same time period. The colour indicates the number of minutes (= category) the charging power could be shifted to later time periods. Bars coloured red represents low numbers of minutes and shades to blue the more minutes would be available for shifting the load. The limitation for shifting is the next time the BET leaves the depot. Flexibility matrix and graph are subject to the assumption that the occurring load is shifted unchanged. Additional flexibility can be achieved with varying the charging power. A reduced charging power can lead to more semi-charged BET with an overall maximum load constraint or few RES available. With a higher charging power, fast charging BET can make full advantage of high RES availability. Therefore, the amount of energy needed has to be taken into account. This information is available in the flexibility frame. The flexibility frame can be used to make the flexibility data available in a structured form. It contains information about energy demand, maximum power as well as earliest and latest time to charge as shown in Table 2, where *latest* represents the time where charging must be started to reach demanded SoC until departure. Flexibility quantification is based on [5, 8] and is accomplished by analysing real world data of an existing BET fleet.

Table 2 Flexibility frame example

ID	name	energy [kWh]	power [kW]	earliest	latest
0	BET1	200	180	2023-01-01 16:00:00	2023-01-02 08:00:00
1	BET1	200	180	2023-01-02 16:00:00	2023-01-02 23:45:00
2	BET2	200	180	2023-01-01 16:00:00	2023-01-02 08:00:00
3	BET2	200	180	2023-01-02 16:00:00	2023-01-02 23:45:00

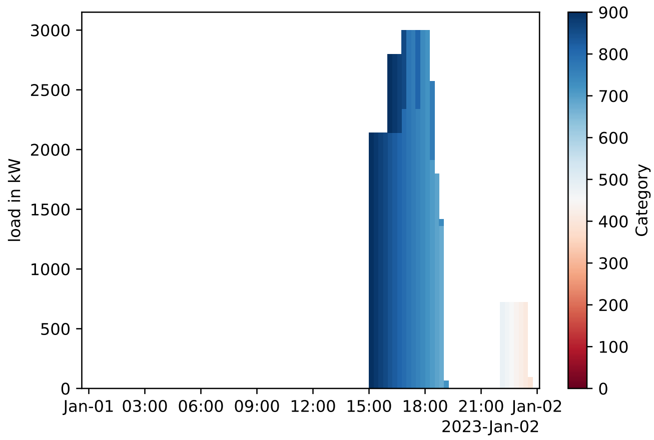

Fig. 3: Example of a flexibility graph based on the flexibility matrix (according to [5, 8])

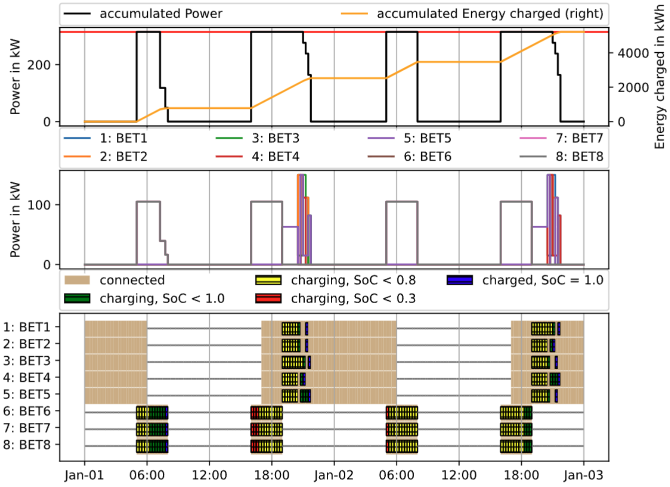

Fig. 4: Visualisation of an example simulation with scheduled charging process

3.4 Model of Electricity Grid and Power Flow Simulation

Grid impact is analysed considering data of the existing corresponding grid where the service depots are located at and validated by IEEE standard grid models. However, the grid data can not be published since its critical infrastructure. For publications and in terms of reproducibility standard grid models from simbench [10] will be used. The depots are connected on the 10 kV voltage level in urban grid topologies. With the results of charging simulation, power flow simulations will reveal the impact of depot charging. As reference case, the BET will be charged without any use of flexibility. The results of the reference case are then the basis of optimizing the use of flexibility.

3.5 Process

The simulation and its modules allow to build fleet models after real world data or ramp-up scenarios. It gives the ability to simulate several use cases with the same or different fleet models, combine it with models of charging infrastructure to scenarios which than give detailed results and load time series. For each BET an operation schedule can be defined as hard constraint. The over-all maximum load can be limited and is satisfied by shifting charging operations based on priorities of individual BETs to make sure the most important BET are charged first and power limits are not exceeded. The priority ψ is calculated for each BET with Equation 2 where ψ is the charging priority as a fraction of the remaining time until departure which is needed to charge the BET:

$$\psi = \frac{\Delta t_{c,min}}{t_d - t} \qquad D : \{t < t_d\} \quad W : \{0 < \psi < \infty\} \qquad (2)$$

Both, input and output data are time series for each BET as well as cumulated across all vehicles. Figure 4 shows a result visualisation of an example simulation with 8 BETs. The three shown graphs share an x-axis which represents the time. On top is the over-all power consumption and accumulated energy demand during the simulated time period. The red line indicates the maximum available power on the grid connection point. The example shown here includes a scheduler which makes sure, that the available maximum power never is exceeded and shifts charging operations if necessary.

The second and third graphs show how this was accomplished: The second graph shows the power consumption separated per BET. The graph at the bottom indicates whether the BET is connected to an CP, whether its charging and in which range its SoC is. It can be seen, that - in this example - shifting charging operations was necessary to keep power consumption below the limit: BET1 to 5 start their charging operations not immediately when connected to a CP because the available power is already fully occupied by BET6 to 8. Instead charging starts as soon as BET6 to 8 are disconnected from the CPs (not fully charged) and power is available again.

These results can be used for power flow analyses, flexibility quantification and RES optimization. The results from power flow simulations then can be used to modify and adapt the input data for the fleet models to differ the simulated grid impact.

This process ensures a modular, branched analysis for *charging simulation*, *RES optimization*, *flexibility quantification*, *scale-up* scenarios and *power flow* simulations, which can easily be adapted to several use cases and objectives.

A brief validation between real charging processes and the simulation was performed with data from March 2023. Energy demand as well as departure and arrival information was given as input for the simulation. In both cases 47 charging operations was executed. Figure 5 shows the cumulated charged energy over time for the simulation and the measured operation and its deviations. The overall charged energy of the measured charging operations is 3,280 kWh and in the simulation 3,278 kWh. It can be seen, that during charging operations deviations occur but disappear until the end of the charging operations. The maximum deviation per time step amounts to 120 kWh. These are caused by the differences in the charging behaviour and the time resolution of the simulation: In this case, the time step size in simulation is 15 minutes. An event with start time between quarter-hour-steps is performed at the approaching quarter of an hour. For charging periods with duration of several hours, this effect has no impact. Events with a duration of less than an hour can have relatively bigger deviation when start time is closer to the beginning of a quarter and the end time is closer to the end of a quarter. Since this is only an issue when simulating real events with random time stamps, a solution for this is increasing the resolution and accept the performance drop for the validations. Figure 5 shows, that over long periods the deviation does not cumulate.

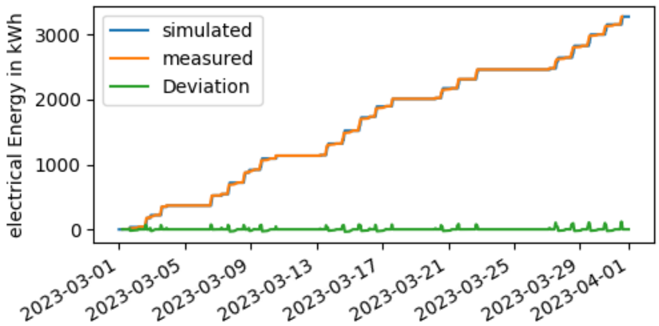

Fig. 5: Comparison of cumulated energy charged over time and the Deviation between both

4 Discussion

The assessing process introduced here ensures a highly modular and flexible analysis of grid impact of BET depot charging. It emphasizes incentives to optimize charging processes and helps to evaluate advantages of high power charging equipment. It closes the gap between fleet operation with its electrification challenge [1, 7], flexibility identification [11] and its usage and benefits for the system [6]. However, only active power is considered by now. Adding reactive power to the simulation is planed in the future as well as V2G models. With considering V2G, more flexibility can be reached with depot charging.

A brief validation based on charged energy over one month shows a good coverage of the charging simulation of real charging processes. However, further validation with measured data is needed to minimize deviations in every time step of the simulation.

Concerning maximum available power at the grid connection, non-BET demands (i.e. office, IT, cantine etc.) have to be considered as well. This relies on the availability of this data. Modules to assess RES usage of own production are not yet addressed but should be objective of further investigations.

Although the method aims to describe most cases of depot charging, its flexibility and grid impact of BET, it is build with and upon data of waste collection vehicles and road sweeper. Further work is planed to verify it with other BET use cases like freight logistics.

5 Conclusion and Outlook

The method described here makes it possible to simulate and analyse both, the flexibility of depot charging of BET as well as the possible advantage for the energy system. The process is set up and validated with real data from a logistic company and a waste disposal company. This makes it possible to run the analysis for different fleets and charging infrastructure. With flexibility and grid impact analysed in this way, advantages and drawbacks of EVSE designed to operate at minimal necessary power levels can be discussed in terms of both grid integration and truck operation. Further analyses are planned with small mid and large sweeper and higher number of electric waste collection vehicles as well as BET for logistic purposes to refine the process. Further research is needed to connect the results to several distribution grid topology as well as V2G representation.

Results of using the shown method are introduced in further studies.

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[1] V. Barthel, J. Schlund, P. Landes, V. Brandmeier, and M. Pruckner. Analyzing the charging flexibility potential of different electric vehicle fleets using real-world charging data. *Energies*, 14(16), 2021. ISSN 1996-1073. doi: 10.3390/en14164961.

[2] B. Borlaug, M. Muratori, M. Gilleran, D. Woody, W. Muston, T. Canada, A. Ingram, H. Gresham, and C. McQueen. Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems. *Nature Energy*, 6(6):673–682, 2021. doi: 10.1038/s41560-021-00855-0.

[3] Nelly-Lee Fischer and Krzysztof Rudion. Forecasting the Flexibility Potential of Electric Vehicles Limited by Individual Charging Targets. In *2023 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, pages 1–5, October 2023. doi: 10.1109/ISGTEUROPE56780.2023.10407761. URL `https://ieeexplore.ieee.org/document/10407761`.

[4] Carlos Gaete-Morales, Julius Jöhrens, Florian Heining, and Wolf-Peter Schill. Power sector effects of alternative options for de-fossilizing heavy-duty vehicles—Go electric, and charge smartly. *Cell Reports Sustainability*, 1(6):100123, June 2024. ISSN

2949-7906. doi: 10.1016/j.crsus.2024.100123. URL https://www.sciencedirect.com/science/article/pii/S2949790624001964.

[5] Marte K. Gerritsma, Tarek A. AlSkaif, Henk A. Fidder, and Wilfried G.J.H.M. Van Sark. Flexibility of Electric Vehicle Demand: Analysis of Measured Charging Data and Simulation for the Future. *World Electric Vehicle Journal*, 10(1):14, March 2019. ISSN 2032-6653. doi: 10.3390/wevj10010014. URL https://www.mdpi.com/2032-6653/10/1/14.

[6] Felipe Gonzalez Venegas, Marc Petit, and Yannick Perez. Active integration of electric vehicles into distribution grids: Barriers and frameworks for flexibility services. *Renewable and Sustainable Energy Reviews*, 145:111060, July 2021. ISSN 1364-0321. doi: 10.1016/j.rser.2021.111060. URL https://www.sciencedirect.com/science/article/pii/S1364032121003488.

[7] T. Hertlein, J. Ochs, T. Blenk, and C. Weindl. Grid serving charging control of electric vehicles. In *27th International Conference on Electricity Distribution (CIRED 2023)*, volume 2023, pages 1174–1178, June 2023. doi: 10.1049/icp.2023.0673. URL https://ieeexplore.ieee.org/document/10267667.

[8] Amra Jahic, Felix Heider, Maik Plenz, and Detlef Schulz. Flexibility Quantification and the Potential for Its Usage in the Case of Electric Bus Depots with Unidirectional Charging. *Energies*, 15(10):3639, May 2022. ISSN 1996-1073. doi: 10.3390/en15103639. URL https://www.mdpi.com/1996-1073/15/10/3639.

[9] Philipp Kluschke, Till Gnann, Patrick Plötz, and Martin Wietschel. Market diffusion of alternative fuels and powertrains in heavy-duty vehicles: A literature review. *Energy Reports*, 5:1010–1024, November 2019. ISSN 2352-4847. doi: 10.1016/j.egyr.2019.07.017. URL https://www.sciencedirect.com/science/article/pii/S2352484719301167.

[10] Steffen Meinecke, Džanan Sarajlić, Simon Ruben Drauz, Annika Klettke, Lars-Peter Lauven, Christian Rehtanz, Albert Moser, and Martin Braun. SimBench—A Benchmark Dataset of Electric Power Systems to Compare Innovative Solutions Based on Power Flow Analysis. *Energies*, 13(12):3290, January 2020. ISSN 1996-1073. doi: 10.3390/en13123290. URL https://www.mdpi.com/1996-1073/13/12/3290. Number: 12 Publisher: Multidisciplinary Digital Publishing Institute.

[11] Manuel Ruppert, Viktor Slednev, Rafael Finck, Armin Ardone, and Wolf Fichtner. Utilising Distributed Flexibilities in the European Transmission Grid. In Valentin Bertsch, Armin Ardone, Michael Suriyah, Wolf Fichtner, Thomas Leibfried, and Vincent Heuveline, editors, *Advances in Energy System Optimization*, Trends in Mathematics, pages 81–101, Cham, 2020. Springer International Publishing. ISBN 978-3-030-32157-4. doi: 10.1007/978-3-030-32157-4_6.

[12] Daniel Speth and Patrick Plötz. Depot slow charging is sufficient for most electric trucks in Germany. *Transportation Research Part D: Transport and Environment*, 128:104078, March 2024. ISSN 13619209. doi: 10.1016/j.trd.2024.104078. URL https://linkinghub.elsevier.com/retrieve/pii/S136192092400035X.

[13] Christian Will and Fabian Ocker. Flexibility Potential of Smart Charging Electric Trucks and Buses. *World Electric Vehicle Journal*, 15(2):56, February 2024. ISSN 2032-6653. doi: 10.3390/wevj15020056. URL https://www.mdpi.com/2032-6653/15/2/56. Number: 2 Publisher: Multidisciplinary Digital Publishing Institute.