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Optimized planning of e-bus charging infrastructure based on Monte Carlo Simulation

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Executive Summary

This paper investigates the effects of several interference paramters for electric bus energy systems such as delays in operation, temperature changes throughout the year and changing charging power. We use Monte Carlo simulation to alternate the different paramters and evaluate the energy system results with defined KPI. As a result we find that the charging power at high power charging stations and in the depot is the most important variable for designing a robust and reliable energy system for electric bus networks. A good system design takes the charging power as a key value into account and with that allows to compensate other disruptions during operation.

Keywords: bus, charging, infrastructure, public transport, simulation

1 Introduction

The electrification of public transportation is a key element to reduce carbon emissions in the transport sector. In Germany, the transport sector accounts for 20 % of the overall emissions. [1] The Clean Vehicles Directive drives the change towards zero-emission vehicles in this sector. All new public purchases of city buses (excluding coaches) are required to include clean and zero-emission vehicles. The German quotas is 45% clean vehicles, half of them being zero-emission, in the first phase until the end of 2025. [2] This comes as a challenge for many transport companies. The proposed technologies (e.g. hydrogen, battery-electric) are not suitable for their existing infrastructure or operation. A simple swap of buses 1-to-1 is therefore not possible. The implementation of the new technology requires careful planning. This includes analysing existing routes for their capability to allow operation with battery-electric of hydrogen buses, finding suitable locations for charging or refuelling stations and manage a completely new fleet of buses with different operational behaviour than conventional diesel buses. Planning and management tools with different methodologies and optimization algorithms are already available. [3] The calculation of electric demands for trips within the bus network is an important element. In most applications, this is the first step of the analysis. The energy demand categorizes the different trip characteristics within the network, e.g. long distance, urban environment with congestion. The categories allow the selection of fitting technologies, e.g. hydrogen for long distance. The calculation of energy consumption is therefore an important variable and appropriate assumptions are necessary to get the consumption of the electric buses. In 2020, ViriCiti released a performance report where consumption data from electric buses were analysed. The study shows, that temperature has a significant impact on consumption and thus on range. At cold temperatures, the consumption increases by 14 % to 21 %

and at hot temperatures by 9 % to 12 %. [4] This shows the strong dependence of the electrical consumption on the ambient temperature. Other than the temperature there are several parameters that influence the operation of an electric bus fleet and its energy system.

In the funded project E-MetroBus, the Reiner Lemoine Institut (RLI), together with the project partners Berliner Verkehrsbetriebe (BVG) and Technische Universität Berlin, is investigating the construction and operation of an electric bus line with articulated buses and high power charging stations (HPC). The focus of the RLI in this project is the energy system perspective. We simulate the required energy system for HPC stations on the route and charging infrastructure in the depot. A simulation model was developed within the project and tested with selected routes in the BVG network. As a next step we are using the method of Monte Carlo simulation to test the robustness of the developed system. In everday operation the energy system of the electric bus network must be able to react to interferences without compromising the operation of the routes. We vary chosen parameters and analyze the results depending on defined key performance indicators (KPI). As a result we define critical parameters which are able to disturb the operation. We develop recommended actions for bus operators to deal with these parameters to ensure a smooth operation.

2 Methodology

The analysis of interference parameters is carried out in three main steps. First, we identify specific parameters which are relevant for the operation of electric bus fleets with the special focus on energy systems. We continue with adjusting the existing simulation model to incorporate the chosen parameters and carry out a Monte Carlo simulation for parameter variation. The last step is evaluation. We define specific key performance indicators to evaluate each system of the simulation and find relevant parameters. Recommendations are derived from that.

2.1 Interference Parameters

We conducted interviews and analysis with the BVG to identify parameters that focus on the electric system for electric bus operation. During the operation of e-buses, different interference parameters can occur that lead to charging processes having to be shortened or not being able to take place at all. A total of five disturbance variables were identified, which are analysed with regard to their influence on operation.

2.1.1 Temperature

The ambient temperature is an important interference parameter. Electric bus systems are much more effected by temperature differences between the in- and outside of the bus than diesel ones. [5] Based on recorded daily consumption data of articulated buses within the project, we developed a correlation to the ambient temperature. Fig. 1 shows the results. The individual data points in blue result in a trend line (orange), which shows that consumption increases at lower and higher temperatures. This is mainly due to the additional heating or cooling demand.

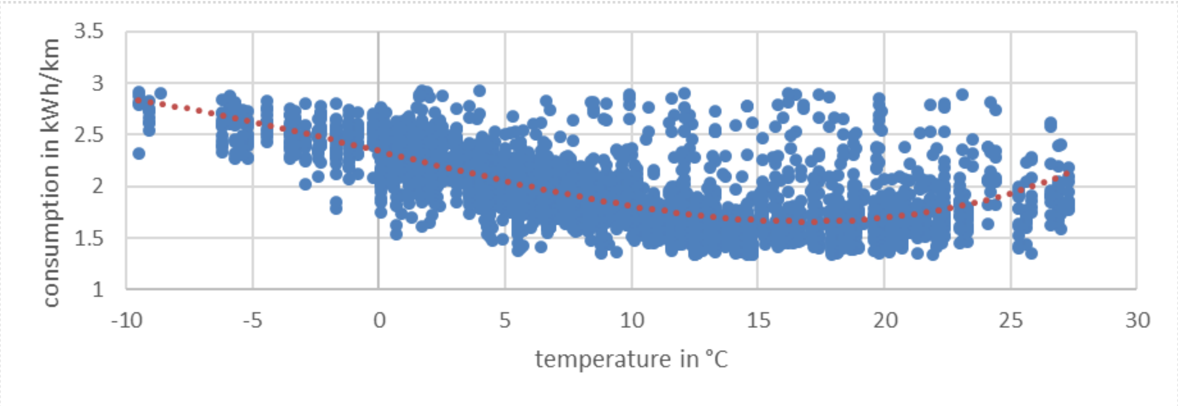

Figure 1: correlation of temperature and consumption of electric buses

2.1.2 Operational delays

Especially in the city, delays can often occur during operation because of traffic jams or construction sites. Due to these delays, buses may not be able to be charged sufficiently and thus the operation can experience disruptions. Fig. 2 shows the analysis of delay data over one week. It can be seen that especially on weekdays, delays increase at rush hour times before and after work. Furthermore, delays can also occur in the depot due to processes such as cleaning and maintenance. Again, this can cause considerable delays in the charging time available. We used analysis of our project partner Technical University Berlin to develop a range of possible delays due to processes inside the depot.

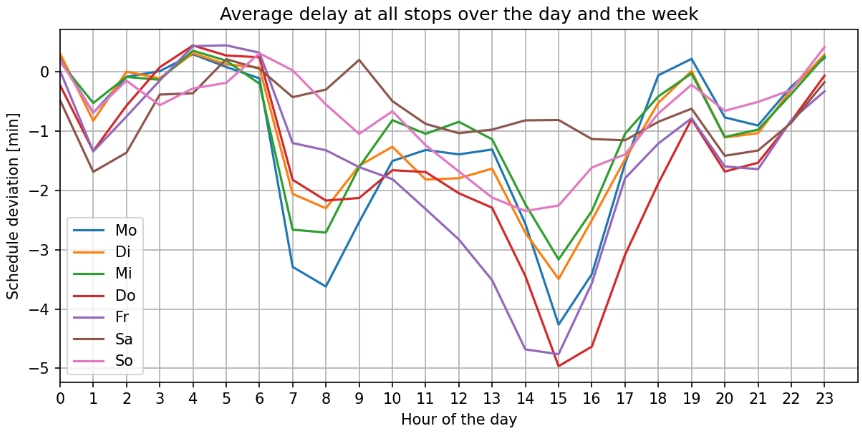

Figure 2: Average delay times over the day and the week in minutes

2.1.3 Reduced charging power

Another important parameter is the available charging power. Due to grid bottlenecks it is possible that the charging power will be lower than required. Fig. 3 shows the analysis of real charging power data at a bus depot. It shows that the maximum charging power of 150 kW is often not reached and that most charging processes only reach a plateau of 60 kW or 80 kW. This plateaus occur due to the technical restriction at the electric equipment. The variation range for the simulation is set to:

- Opportunity charging at HPC: 50 – 400 kW
- Depot charging at HPC: 30 – 120 kW (there are depots with additional HPC charging stations for fast charging possibilities)
- Depot charging at AC charging stations: 30 – 90 kW

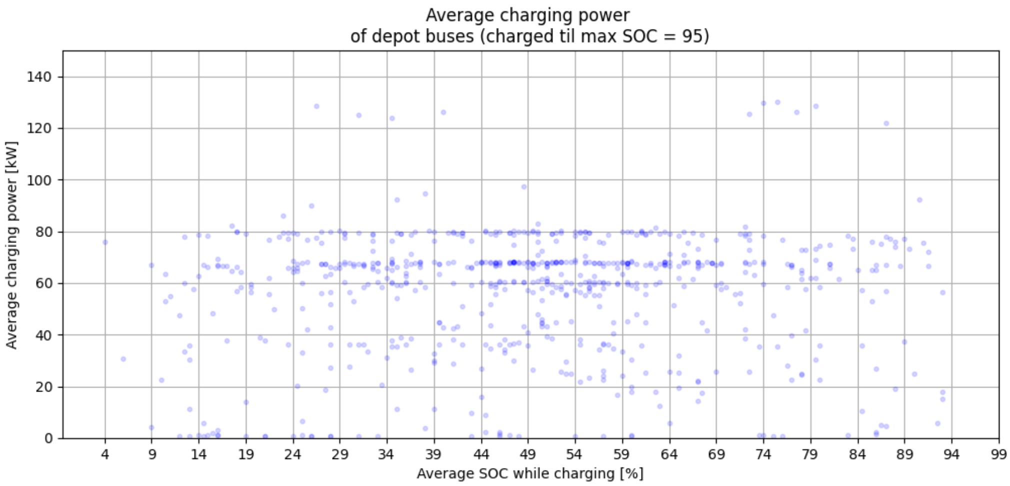

Figure 3: Average charging power at a bus depot depending on average SOC while charging

2.1.4 HPC availability

The modeled electric bus system includes charging points at end points of routes. High power charging (HPC) infrastructure is used at these stops to provide the necessary charging power during short breaks. The availability of the HPCs has effects on the operation of the whole system. HPC can be unavailable due to technical issues, maintenance or operational issues (e.g. blocked HPC with buses from previously delayed rotations). For the variation in the simulation, we consider HPC availability based on previous simulation data in the range of 1, 2, 3 or 4.

2.1.5 Battery aging

High power charging leads to a faster aging of the battery and thus to a reduced possible range of the bus due to the lower effective capacity. [6] For the simulation we consider a maximum battery capacity of 400 kWh and degradation of the effective capacity in the steps of 100, 95, 90, 85 und 80 %.

2.2 Monte Carlo Simulation

Monte Carlo simulation is a procedure in which repeated random experiments are carried out on the basis of statistical distributions. [7] In our case, the e-bus tool developed by RLI is used for this purpose. Based on the data and variation of the interference parameters, an individual scenario is created for each simulation run. Each scenario is evaluated with regard to key performance indicators (see section 2.3).

We apply the simulation for three different case studies:

- Case 1 Bus depot – the complete schedule of an entire bus depot with 268 rotations.
- Case 2 Opportunity charging – one specific line with articulated electric buses with opportunity charging ability.
- Case 3 Depot charging – one specific line with solo electric buses which are only able to charge over night at the depot.

The Monte Carlo simulation for Case 1 includes all possible interference paramters in their complete range of variation. This simulation shows the dependencies of the parameters for an entire energy system with a mix of depot and opportunity charging e-buses.

The simulations for Case 2 and 3 focus on extreme scenarios to show specific correlations for the different charging types.

2.3 Key performance indicators

The evaluation of the simulation results follows defined key performance indicators (KPI):

- KPI 1: Minimum SOC - Ratio between the number of rotations, where the minimum SOC falls below zero, and the total number of rotations (of the scenario).
- KPI 2: Remaining range - Ratio between the number of rotations where the remaining range at the end of the rotation is lower than 30 km and the total number of rotations that arrive at the depot.
- KPI 3: HPC utilization - Ratio between the daily average charging power of the bus and the maximum charging power of the charging station. This KPI is calculated for depot (KPI 3 (dep)) and opportunity (KPI 3 (opp)) charging seperatly.
- KPI 4: Full recharge at depot - Ratio between the number of charging events at the depot over night with the end-SOC reaching 100% and the total number of charging events occurring.

3 Results

3.1 Case 1

The KPIs evaluated for the Monte Carlo simulation of Case 1 is shown in Table 1. The table shows the minimum and maximum values for each KPI across all simulations.

Table 1: KPI-overview for Case 1

	KPI 1	KPI 2	KPI 3 (dep)	KPI 3 (opp)	KPI 4
Min.	0 %	1 %	0.1 %	4 %	64 %
Max.	66 %	36 %	0.5 %	12 %	100 %

KPI 1 as minimum SOC ratio has a range between 0% and 66%, with 0% representing a fully electric bus network with all buses complementing their rotations. The scenario with 66% means that over half of all rotations are not feasible under the given circumstances.

KPI 2 describes the amount of buses which arrive at the depot with a low remaining range of the internal battery. The results show ratios as low as 1% and going up to 36%. All the buses covered in this KPI are feasible but low ranges at the arrival in the depot show potential challenges when unexpected events occur. The number of 36% indicates that over one third of all buses arrive with a remaining range under 30km and need immediate charging. This can cause problems in the logistics processes inside the depot because the necessary charging points for these buses need to be provided quickly and as a priority.

The range of KPI 3 (dep) is between 0.1% and 0.5%. The simulation model uses a balanced charging strategy for depot charging. Balanced means that the maximum available charging time is calculated for each bus and the charging power is reduced accordingly to minimize the power peak for charging. This strategy reduces the required charging power for each bus to a minimum which results in low ratios between average charging power and maximum available charging power.

In contrast to KPI 3 (dep) the KPI 3 for opportunity charging has a range between 4% and 12%. Opportunity charging in the simulation model uses the maximum available power for charging to get the maximum possible SOC-gain within the short break time at end stops. The maximum ratio of 12% still represents a low number due to restrictions from the vehicle site of charging. The simulation model uses a charging curve to adjust the maximum available charging power of the bus in regard to the current SOC of the vehicle battery.

The ratios between 64% and 100% for KPI 4 are due to the mainly opportunity charging buses in the system. The buses with charging stations available on route are more likely to enter the depot with higher SOC values than depot charging buses. This results in less energy required for a full recharge and thus increase the possibility to reach that full charge at the end of the depot standing time. In the scenario where the KPI 4 reaches 100%, even all electric buses leave the depot with a full charge.

The correlation between the interference parameters and KPIs provides a good indication which parameters are more important and have a greater influence on the system. We find, that especially the charging power at end stops as a parameter for opportunity charging systems is of great importance. Fig. 4 shows the distribution of KPI 1 in the different simulations in relation to the set HPC charging power at end stops. The lowest charging power of 50 kW results in the highest default rate (represented with KPI 1) of rotations. Default rates drop with increasing charging power. The differences between 250 kW, 300 kW and 350 kW are minimal im comparison to the other steps. More and more rotations become feasible with higher charging rates and a further increase in power over 250 kW only has a minimal impacts for the feasibility of the remaining rotations with a SOC below zero.

Other interference parameters such as number of available HPC charging stations and ambient temperature show almost no correlation to KPI 1 and thus the feasibility of rotations. Fig. 5 and Fig. 6 show the distribution of KPI 1 for these two parameters. The variation of the parameters has basically no effect on the outcome of KPI 1.

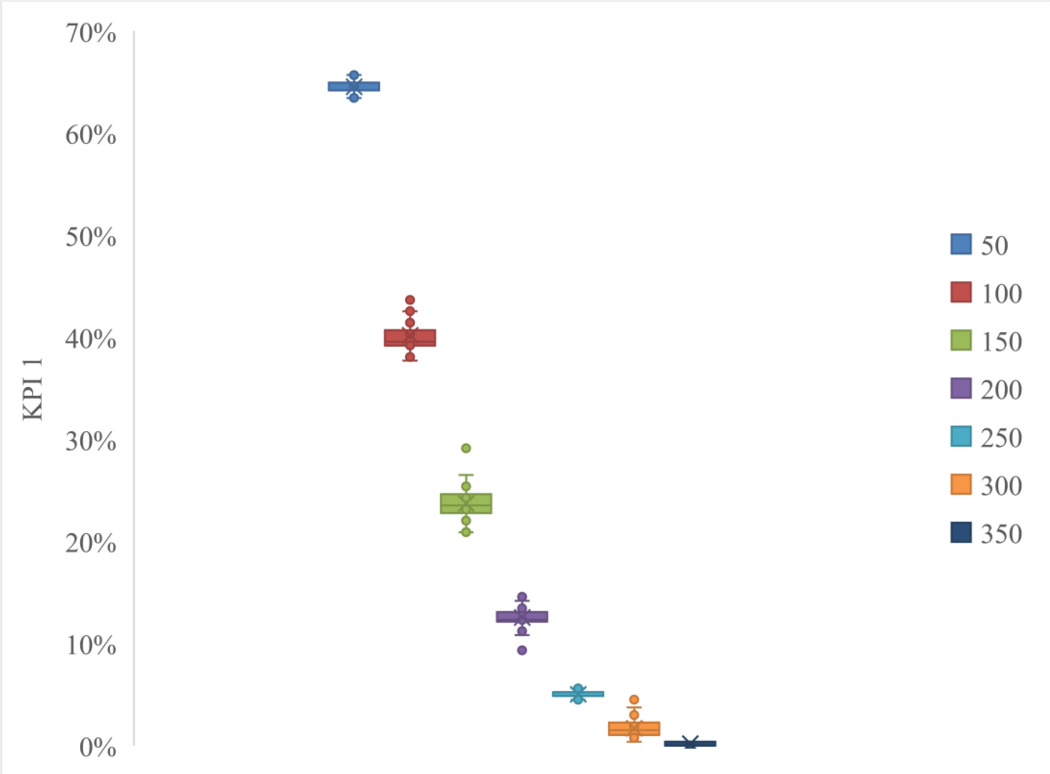

Figure 4: Distribution of KPI 1 depending on HPC charging power in kW (range 50 kW to 350 kW)

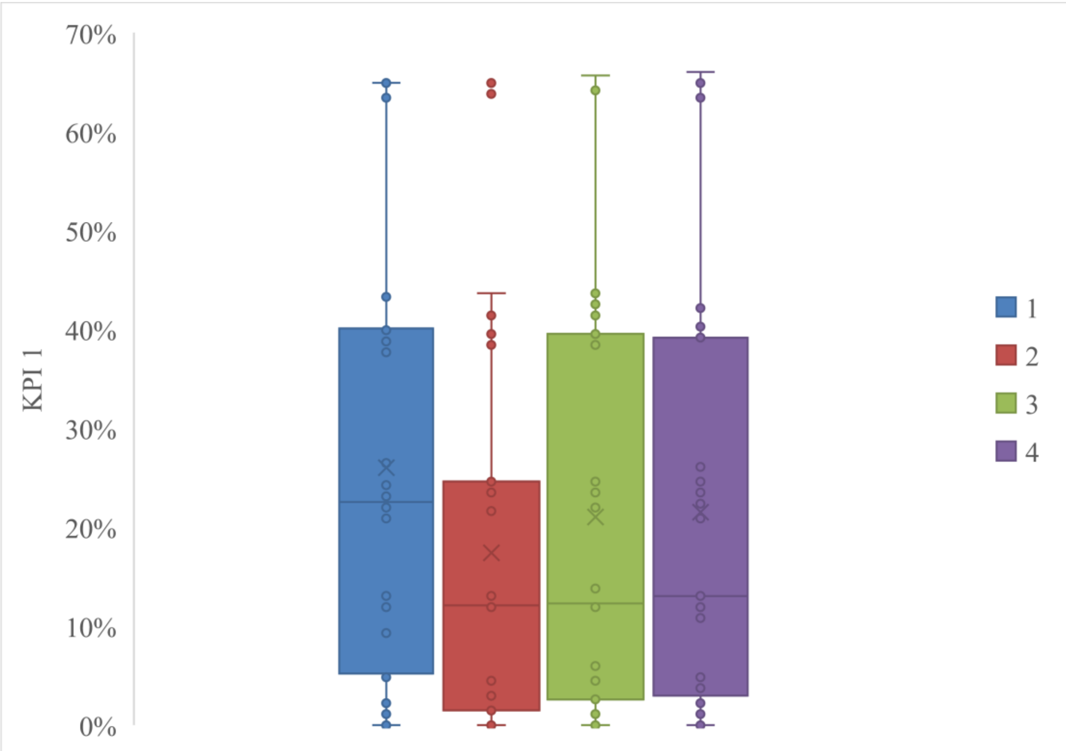

Figure 5: Distribution of KPI 1 dependening on number of available HPC charging stations (range 1 to 4)

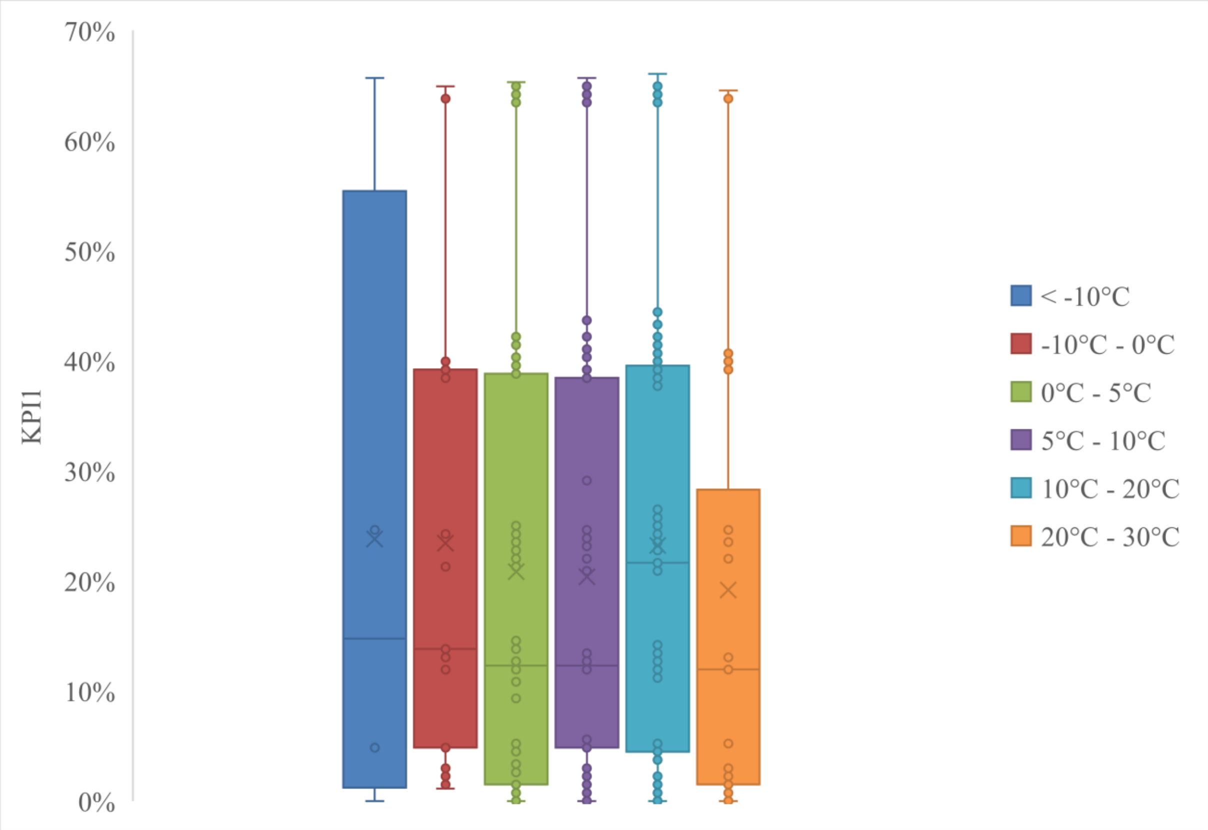

Figure 6: Distribution of KPI 1 dependening on ambient temperature (range -10 °C to 30°C)

The correlation of KPI 1, KPI 3 (opp) and the charging power shown in Fig. 7 confirms our findings of the importance of the parameter charging power at HPC charging stations. There is a clear link between the two KPIs and the charging power. The graph also shows that low charging power result in high default rates (represented with KPI 1) and a high utilization of the HPC charging stations (represented in KPI 3 (opp)). High utilization means that the average power over all daily charging events is high in comparison to the maximum charging power at the station. With lower charging powers more buses are able and need to charge longer with the maximum power available, thus resulting in more charging events with maximum power.

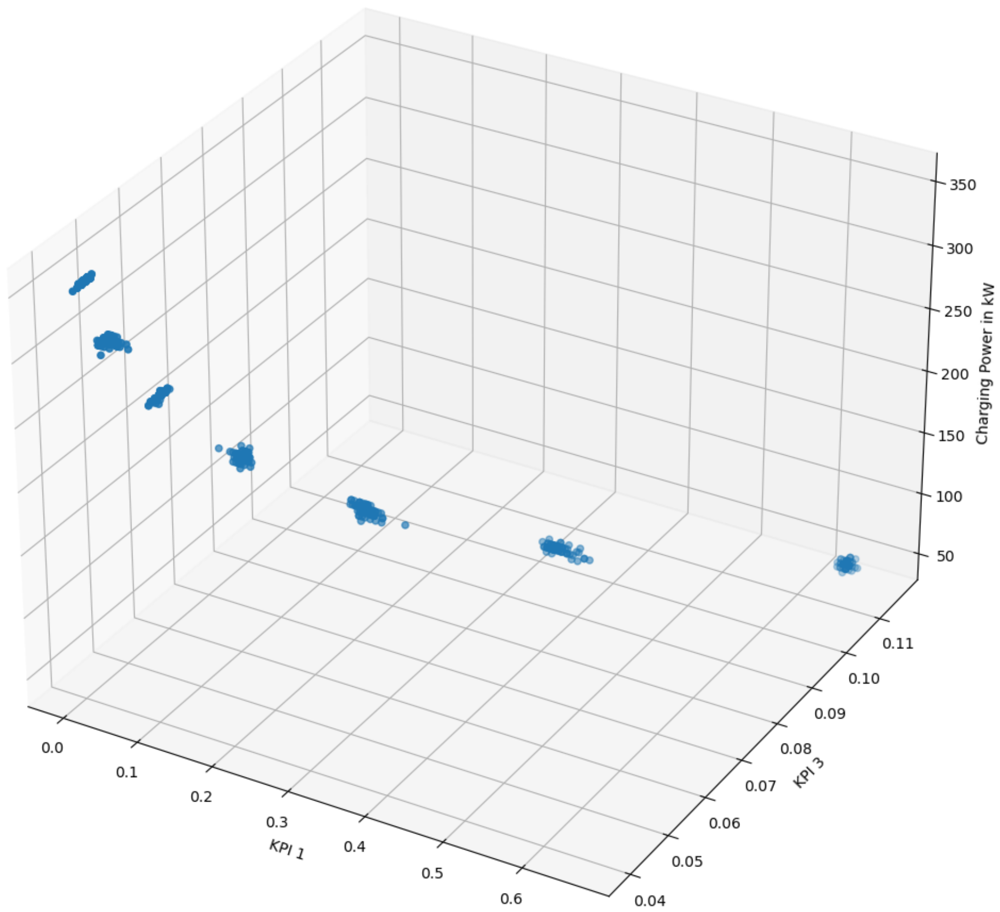

Figure 7: Correlation of KPI 1 and KPI 3 in relation the charging power at HPC charging stations (range 50 kW to 350 kW)

3.2 Case 2

Case 2 focuses on a line with opportunity charging buses. The simulations were done with maximum/minimum values of the different interference parameters, to see the system response for extreme (worst-case) scenarios. Each simulation had one value changed while the others stayed the same. This way the effects of individual parameters were analysed. One worst-case simulation was done with all parameters being at their extreme values.

The results for the KPI 1 and KPI 3 (opp) are shown in Table 2.

Table 2: KPI evaluation for Case 2 simulations

Scenario	KPI 1	KPI 3 (opp)
Wort-case (all parameters)	81 %	44 %
Ambient temperature (worst-case)	0 %	20 %
Battery degradation (worst-case)	0 %	21 %
Delays (worst-case)	0 %	20 %
Charging power at HPC (worst-case)	69 %	19 %

KPI 1 as indicator for the feasibility of the rotations shows similar results as in Case 1. The charging power at HPC charging stations has the greatest influence for the feasibility of opportunity charging rotations. This is shown in the *worst-case (all parameters)* scenario as well as in the *charging power at HPC (worst-case)* scenario. The evaluation of KPI 3 gives additional information. The values for *worst-case (all parameters)* scenario are much higher than for the *charging power at HPC (worst-case)* scenario (44% in comparison to

19%). The main difference between both scenarios is the number of available HPC charging stations. The *worst-case (all parameters)* scenario limits this number to a maximum of one HPC available whereas the system for *charging power at HPC (worst-case)* scenario is designed with theoretically unlimited number of available charging stations. The limitation to one available HPC results in more necessary charging events with maximum available power which increases the value of the average daily charging power at the stations and therefore KPI 3(opp).

3.3 Case 3

This case focuses on depot charging. The simulations were done with maximum/minimum values of the different interference parameters, to see the system response for extreme (worst-case) scenarios. Each simulation had one value changed while the others stayed the same. This way the effects of individual parameters were analysed. One worst-case simulation was done with all parameters being at their extreme values.

The results for the KPI 1 and KPI 4 are shown in Table 3.

Table 3: KPI evaluation for Case 3 scenarios

Scenario	KPI 1	KPI 4
Wort-case (all parameters)	44 %	100 %
Ambient temperature (worst-case)	0 %	100 %
Battery degradation (worst-case)	44 %	100 %
Delays (worst-case)	0 %	100 %
Charging power at depot (worst-case)	0 %	83 %

The analysed line has a quite easy profile with an average daily mileage of 170 km per bus. The assumed maximum battery capacity of 400 kWh allows the system to compensate all interferences with the exception of a reduced battery capacity because of battery degradation. This parameter decreases KPI 1 to 44% in the *worst-case (all parameters)* and in the *battery degradation (worst-case)* scenario. As KPI 4 describes the ability of the system to reach fully charged buses at the end of the standing time at the depot, the value of 83% in the *charging power at depot (worst-case)* scenario shows the difficulties a disruption in available charging power at depot charging stations can cause. The value of 100% of KPI 4 in the *worst-case (all parameters)* scenario is a result of the calculation methodology, as rotations with negative SOC (not feasible) are not taken into account for this KPI. That means, that all remaining rotations/buses in this scenario are able to get a full charge during their time at the depot.

4 Conclusing and outlook

In this paper, we identified the interference parameters ambient temperature, charging power, number of charging stations, battery degradation and delays for the operation of electric bus fleets and their energy system. We analysed the effects of these parameters using a Monte Carlo simulation in three case studys: a complete electric bus depot, one bus line with opportunity charging buses and one bus line with depot charging buses.

The results of Case 1 show that the charging power at HPC charging stations at end stops in the bus network has the greatest influence on the feasibility of the electrification. The other interference parameters can mostly be compensated by the system.

Worst-case analyses for opportunity and depot charging lines show that the charging power is the most important interference parameter when there are HPC charging stations in the system. This parameter can decide whether an electrification is feasible and how good the system can react to disruptions. The combination of a degrading battery and decreased charging power at the depot shows the biggest uncertainty for feasible rotations in depot charging bus networks.

With these results we recommend bus operators to lay particular focus on the planning and design of HPC charging stations in the network. A well designed electrical system (reliable charging power) at these stations can offer the necessary flexibility to compensate for disturbances in the operation. On the other hand, a reduction in charging power caused by disruptions can increase problems even further. As expected, available battery capacity should be the main focus for electric bus system with mostly depot charging.

Detailed calculations and planning is required for each individual bus operator and bus network, to identifiy specific interference parameters and their effects on the operation because every bus network shows unique challenges and attributes towards a successful electrification.

Acknowledgments

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Presenter Biography

Wiebke Labudde works as a researcher for mobility with renewable energies at the Reiner Lemoine Institut Berlin. She currently works on the use of climate-friendly commercial vehicles, especially trucks and busses. She did her master and bachelor studies in industrial engineering with the focus on logistics at the Otto-von-Guericke University Magdeburg.