Algorithms for Peak Power Reduction in a Battery Electric Bus Depot

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Abstract:

The electrification of public transport introduces significant challenges for battery electric bus (BEB) fleet operators and power grid operators. This paper investigates the potential of two charging optimization strategies to reduce peak power demand in a BEB depot in Vorarlberg, Austria. A heuristic algorithm and Mixed-Integer Linear Programming (MILP) are analyzed and compared to a reference strategy representing uncoordinated charging. The study aims to minimize peak power demand while ensuring efficient use of charging infrastructure. The results demonstrate the effectiveness of intelligent charging management in addressing the challenges posed by BEB operations.

Keywords: battery electric bus depot, peak power reduction, charging management, heuristic, MILP

1 Introduction

The ongoing electrification of public transport presents complex challenges for both battery electric bus (BEB) fleet operators and power grid operators [1]. According to the review paper of Perumal, Lubsy, and Larsen [2], these challenges can be categorized into four main areas:

- investments in BEB fleets and charging infrastructure
- placement of charging stations,
- scheduling of BEBs
- charging planning and optimization.

Charging planning is a complex task due to various interdependent factors. Numerous constraints must be considered, including fleet schedules, BEB consumption patterns, and charging infrastructure availability. Additionally, uncertainties such as fluctuating energy consumption, varying arrival times, and external influences make accurate planning difficult. A key problem when operating BEBs is the occurrence of significant peak powers, especially if the buses are charged immediately upon arriving at the depot without any form of load management. Such charging operation lead to a concentrated demand for electricity, which increases both operational electricity costs and infrastructure investments.

The two primary objectives of charging planning, as identified by the work of Toniato, Mehta, Marinkovic et al. [3], are the minimization of peak power demand and the minimization of costs.

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These target functions are closely interconnected. Regarding operational electricity costs, electricity prices typically consist of an energy charge and a capacity charge. Hence, assuming a constant electricity tariff and unchanged energy requirements for charging processes, also cost minimization is achieved by peak demand reduction.

The power peaks have a direct impact on the power grid, potentially causing capacity issues or the need for costly grid reinforcements. However, in addition to the challenges, there are also opportunities to identify and harness flexibilities in the charging plans through intelligent charging management. This raises the fundamental question of the extent of flexibility in the charging process and the strategies for its optimal utilization.

Various approaches to load management of BEBs have been proposed in the literature. Abdelwahed, Berg, Brandt et al. [4] analyze different dispatching strategies, comparing Discrete Time Optimization (DTO) and Discrete Event Optimization (DEO), as well as priority-based strategies like First-In-First-Serve and Lowest-Charge-Highest-Priority. Jahic et al. [5] explore heuristic and greedy algorithms for peak load reduction, where defined rules are followed to schedule the charging jobs. Regardless of the chosen optimization approach, a fundamental requirement for effective charging management is the availability of reliable data that enables the identification and exploitation of charging flexibilities.

In Vorarlberg, Austria, up to 130 electric buses are expected to be deployed in public transport by 2025 with government funding [6]. To support this transition, two research projects, FreeE-Bus [7] and EBusCharge [8], have been launched to establish charging management and grid simulation. Cooperation with local bus companies and network operators ensures to create a solid data basis for the algorithms.

This paper investigates the potential of two different charging optimization strategies to reduce peak power demand in a real-world BEB depot setting in Vorarlberg. Two charging algorithms, a heuristic-based optimization, and a Mixed-Integer Linear Programming (MILP) optimization are analyzed and compared to a reference strategy representing uncoordinated charging.

2 Data

The data structure developed consists of separate files in a predefined csv format. The minimum data scope includes infrastructure data, vehicle data, and a timetable, as illustrated in Figure 1:

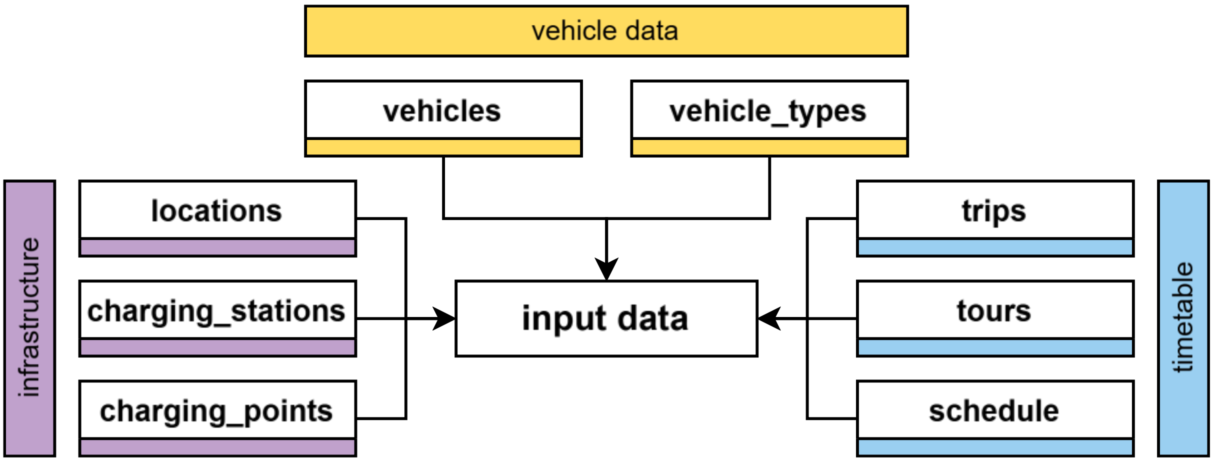

Figure 1: Structure of the necessary input data, including the infrastructure, the vehicle data and the timetable

To compare the three algorithms, a sample dataset was created based on a future BEB depot in Vorarlberg. The dataset distinguishes between two BEB types:

- 20 standard 12-meter BEBs with a usable battery capacity of 312 kWh
- 28 articulated 18-meter BEBs with a usable battery capacity of 416 kWh.

All BEBs support a maximum charging power of 150 kW. The energy consumption rates are assumed to be 1.0 kWh/km for 12-meter BEBs and 1.6 kWh/km for 18-meter BEBs.

Overnight and intermediate charging is possible at the depot which has a grid connection capacity of 2 MW. The charging infrastructure includes nine stations, each with a maximum power output of 600 kW. Every station is equipped with six charging points, each supporting up to 150 kW.

The dataset reflects operational planning data from bus operators, including 48 BEBs operating a total of 48 tours over a single day. Each tour consists of one or more trips throughout the day, as illustrated in Figure 2.

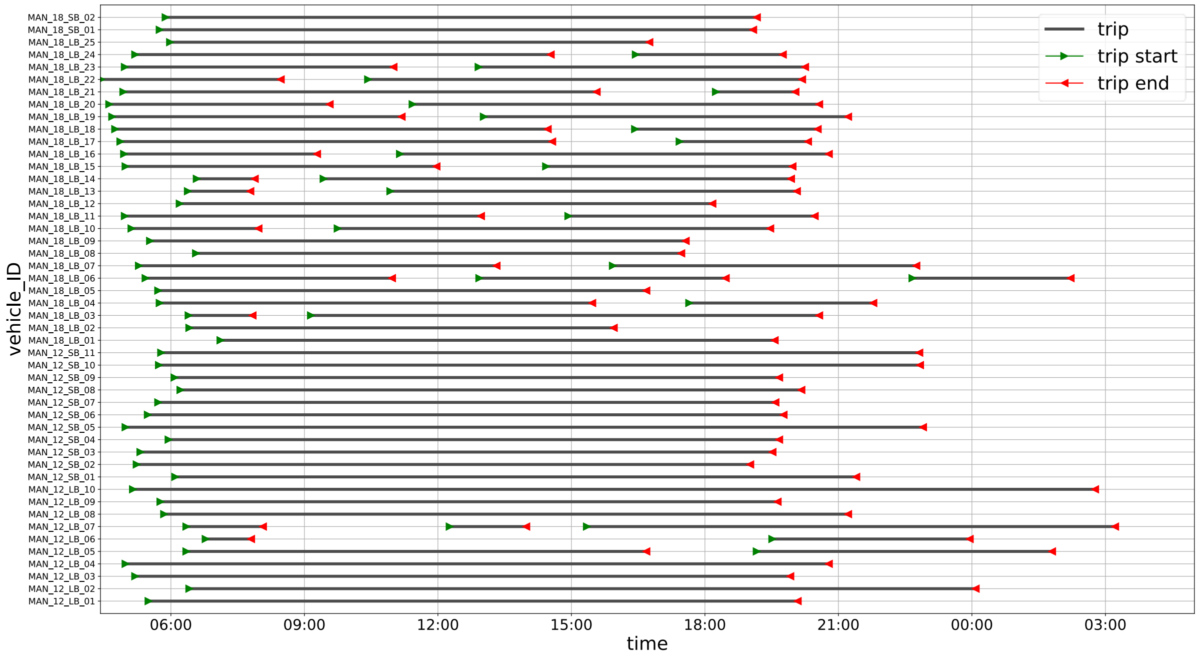

Figure 2: Schedule per BEB over time; a BEB is chargeable at the depot, when it is not on a trip.

3 Methodology

This section provides an overview of the charging algorithms analyzed in this study. First, the reference case is introduced, representing a simulation without any charging management. To optimize charging, two approaches are examined: a heuristic algorithm and MILP. Both methods have access to all relevant data as specified before and aim to reduce peak power demand.

3.1 Reference

The reference case represents a simulation without charging management or optimization. Upon arrival, each BEB is assigned to an available charging point at the charging station with the most available capacity. Charging starts immediately at connection of the BEB to the charging point at the maximum power available. If the total charging capacity of the location or charging station is exceeded, the power available is evenly distributed among all charging points to prevent overload.

3.2 Heuristic

A heuristic algorithm was developed as part of this master's thesis [9], extending an existing approach by Jahic et al. [5]. The algorithm aims to reduce peak power demand by optimizing the scheduling of charging intervals. The extension introduced in the master’s thesis [9] includes an event-based approach to reduce the number of possibilities that need to be considered during computation. Instead of evaluating all possible start times minute by minute, the algorithm focuses only on relevant start times where a change in charging power occurs due to previously scheduled charging sessions. This significantly decreases computational effort.

The procedure of the algorithm is illustrated in Figure 3. First, the minimum required energy for each charging window is determined to ensure the BEB can complete its next trip. Next, all relevant charging windows are sorted in ascending order based on their temporal flexibility. To determine the optimal charging start time, the algorithm evaluates only event-based charging intervals within the charging window. For each of these intervals the resulting peak power is calculated. If multiple options lead to the same minimum peak power, the charging interval with the least overlap with other charging intervals is selected. In case of further ties, the earliest possible charging start time is chosen.

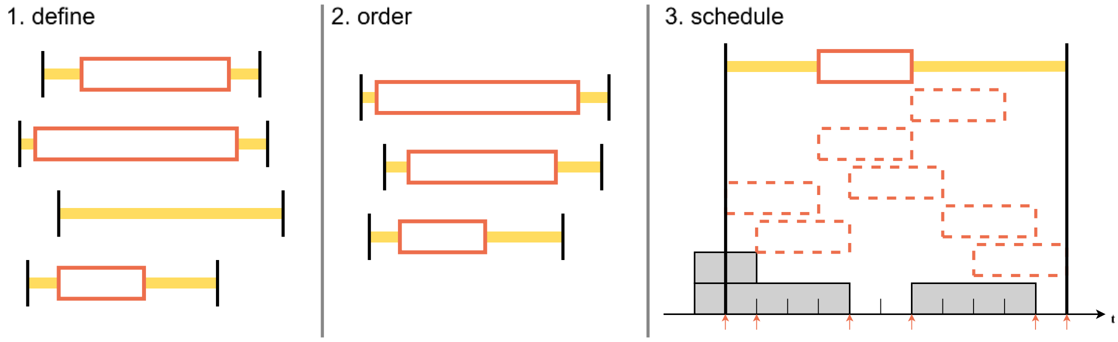

Figure 3: Graphical representation of the heuristic steps including definition of all charging windows, organizing them in ascending order and schedule the charging interval based on defined rules

3.3 MILP

MILP is used to minimize peak load. All BEB, schedule, and charging infrastructure data are modeled as linear equations and inequalities. Continuous variables represent charging power and state of charge (SoC), while binary variables determine charging point-to-bus assignments. As the extended heuristics introduced in Section 3.2, also the MILP formulation employs event-based time discretization, where events correspond to bus arrivals and departures.

The objective function of the optimization is to minimize the aggregated charging power at the depot. This is achieved through a set of constraints. For instance, the charging power during the intervals and for each bus is constrained, considering the availability of charging. Battery capacity limits and minimum and maximum charging powers are applied to the BEBs. The charging infrastructure is also limited by maximum location power, charging station power limits, and the maximum and minimum charging power of individual charging points.

Additionally, there are specific conditions regarding the assignment of buses to charging points. These include ensuring charging availability during defined charging windows, with each BEB assigned to exactly one charging point, and each charging point assigned to exactly one BEB. Furthermore, a constant assignment of buses to charging points is maintained throughout a charging window.

To solve the MILP, the solver by Gurobi [10] has been used.

4 Results

The aggregated charging power profiles obtained by application of the different algorithms to the charge scheduling problem are shown in Figures 4 and 5. These profiles represent the total power demand including all charging points. Since the analysis only considers a single charging location, the aggregated power corresponds to the total power demand of all BEBs.

Figure 4 presents the aggregated charging power profile obtained for the reference scenario and the heuristic algorithm. The available charging infrastructure capacity is fully utilized, reaching the 2 MW limit for several hours during the evening. It can be observed that trough the heuristic algorithm the peak power from the reference case is reduced by 350 kW and the load is being redistributed over the night. Additionally, there is potential for a more efficient utilization of intermediate charging windows during the day.

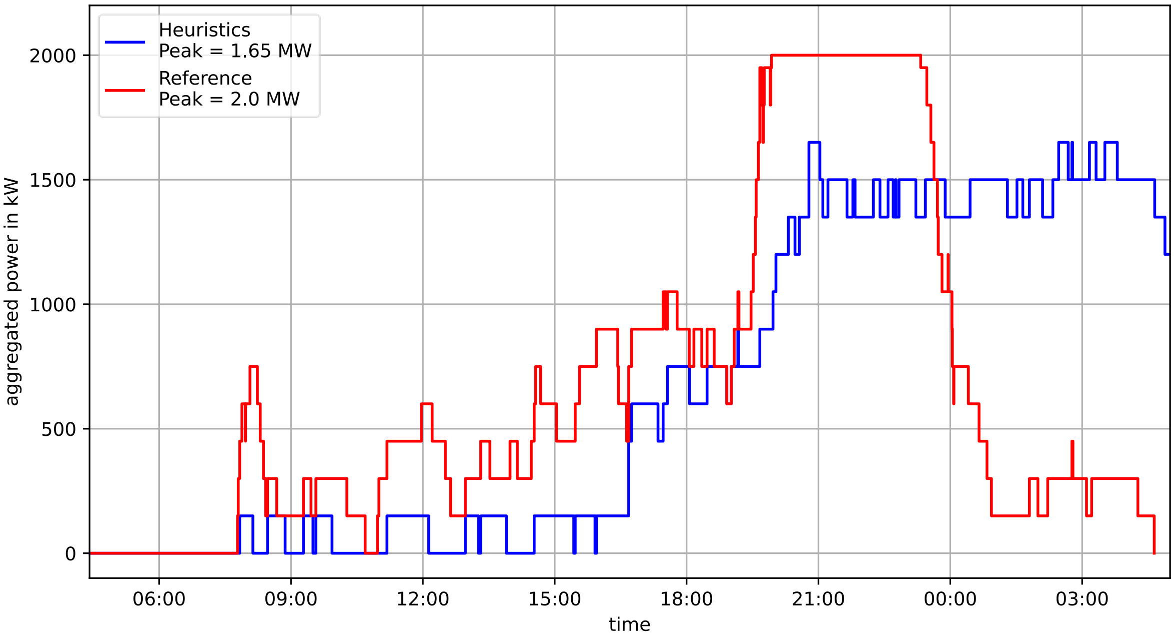

Figure 4: aggregated power in kW over time obtained by the reference case and the heuristics; reference peak power = 2 MW; heuristics peak power = 1.65 MW

Figure 5 presents the aggregated power profile resulting from the application of the MILP. MILP achieves the global optimum, and compared to the heuristic further reduces the peak power. Compared to the reference case, it nearly reaches a peak power reduction of 50%.

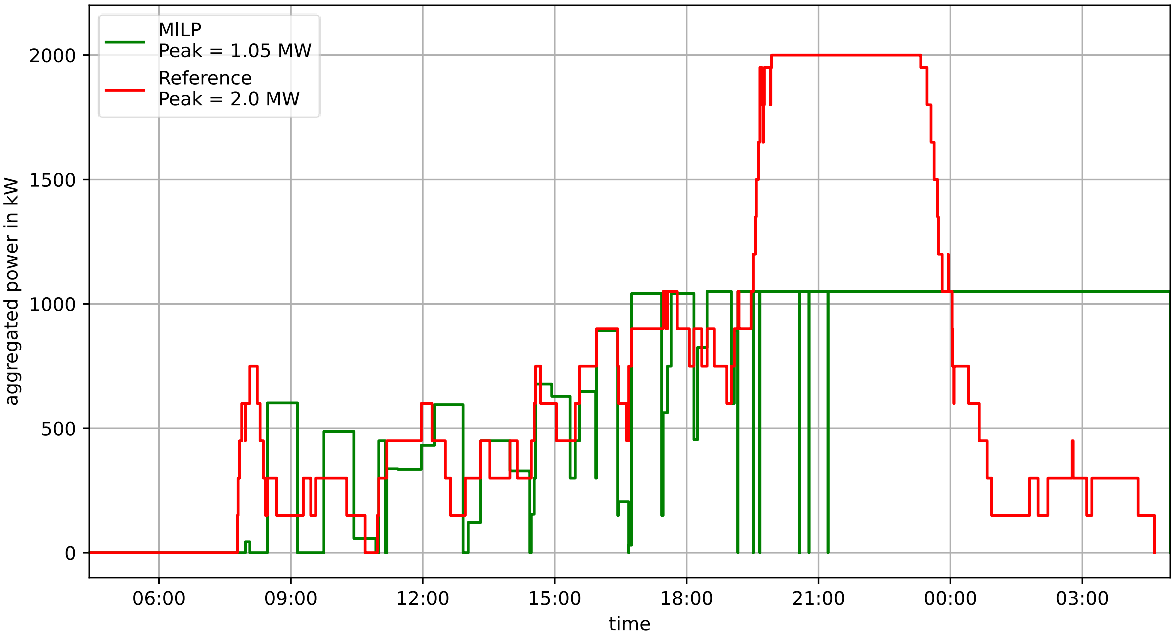

Figure 5: aggregated power in kW over time obtained by the reference case and MILP; reference peak power = 2 MW; MILP peak power = 1.05 MW

Figure 6 shows the cumulative energies obtained by the reference case, the heuristic and the MILP. When operating at the optimum, the cumulative energy increases linearly. All approaches achieve the same total energy over the course of the day. However, the heuristic demonstrates its potential, performing close to the optimum at night while leaving significant potential unutilized during the day.

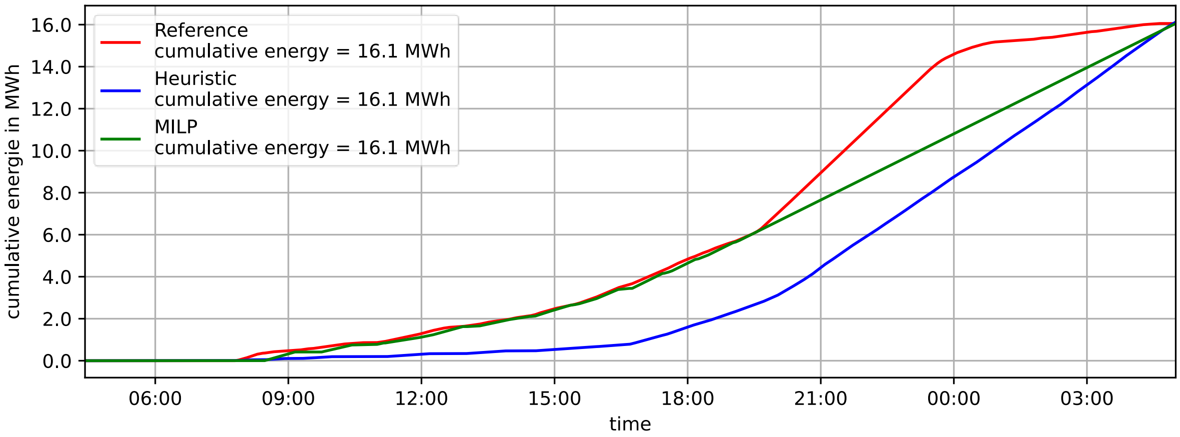

Figure 6: cumulative energy charged in MWh over time obtained by the reference case, the heuristic and the MILP

5 Conclusions

We investigated the peak power reduction potential in a real world BEB depot setting. Both algorithms considered, a heuristic and a MILP formulation used an event-based time discretization to reduce the computational costs. The results show that both algorithms achieve significant peak power reductions in comparison to the reference case.

Several aspects remain to be addressed in future research. Factors such as setup time and charging power steps have not yet been incorporated into the model. Moreover, while this study focused on a single BEB depot, future work should extend the analysis to multiple depots, including intermediate charging at different locations.

The current heuristic algorithm also shows potential for further improvement, particularly in better utilizing intermediate charging opportunities throughout the day. This would require revising the energy allocation strategy to ensure that buses charge beyond the immediate needs of the next trip when beneficial. While the heuristic has the advantage of short computation times and easily interpretable rules, it is designed only for peak power reduction and does not guarantee a global optimum. In contrast, the MILP approach delivers the global optimum, however, with outputs that are often more difficult to interpret. Furthermore, it has a high computational effort, especially due to the numerous binary variables involved. In the considered BEB depot setting, the difference in computation time between the heuristic and MILP approaches is approximately a factor of 50.

As outlined in the introduction, the two main objective functions, peak power reduction and cost reduction, are strongly interconnected in this setting. If the constant electricity price changes to time-dependent tariffs or if bus operators can cost-effectively utilize self-generated energy, e.g. photovoltaics, it becomes necessary to distinguish between the two objective functions. While the MILP approach can be adapted to these conditions with minimal effort, the heuristic method would require new rule definitions to optimize for cost reduction accordingly. In conclusion, we could demonstrate that aggregate charging flexibility allows a significant reduction in peak power in a real world BEB depot setting.

Acknowledgements

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Literature

[1] E. Union, “Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC,” *Official Journal of the European Union*, vol. 5, 2009.

[2] S. S. G. Perumal, R. M. Lusby, and J. Larsen, “Electric bus planning & scheduling: A review of related problems and methodologies,” *European Journal of Operational Research*, vol. 301, no. 2, pp. 395–413, Sep. 2022, doi: 10.1016/j.ejor.2021.10.058.

[3] E. Toniato, P. Mehta, S. Marinkovic, and V. Tiefenbeck, “Peak load minimization of an e-bus depot: impacts of user-set conditions in optimization algorithms,” *Energy Inform*, vol. 4, no. S3, p. 23, Sep. 2021, doi: 10.1186/s42162-021-00174-4.

[4] A. Abdelwahed, P. L. van den Berg, T. Brandt, J. Collins, and W. Ketter, “Evaluating and Optimizing Opportunity Fast-Charging Schedules in Transit Battery Electric Bus Networks,” *Transportation Science*, vol. 54, no. 6, pp. 1601–1615, Nov. 2020, doi: 10.1287/trsc.2020.0982.

[5] A. Jahic, M. Eskander, and D. Schulz, “Charging Schedule for Load Peak Minimization on Large-Scale Electric Bus Depots,” *Applied Sciences*, vol. 9, p. 1748, Apr. 2019, doi: 10.3390/app9091748.

[6] “Vorarlberg wird größtes E-Bus-Bundesland Österreichs | VMOBIL.AT.” Accessed: May 13, 2024. [Online]. Available: https://www.vmobil.at/ueber-vmobil/pressecorner/vorarlberg-wird-groesstes-e-bus-bundesland-oesterreichs

[7] “FreeE-Bus - flexible, responsive, erneuerbare, effiziente E-Busse,” FHV, program: Interreg Alpenrhein-Bodensee-Hochrhein. Accessed: Jun. 19, 2024. [Online]. Available: https://www.fhv.at/forschung/energie/projekte/laufende-projekte/freee-bus

[8] “EBusCharge - Flexible E-Bus Fleet Charge Management,” FHV. program: Klima und Energiefonds Programm Leuchttürme eMobilität, FFG Programm Zero Emission Mobility und Zero Emission Mobility 2202/01, Accessed: Jun. 19, 2024. [Online]. Available: https://www.fhv.at/forschung/energie/projekte/laufende-projekte/e-bus-charge

[9] D. Bauer, “Entwicklung und Evaluation eines heuristischen Ladelastmanagement-Algorithmus für Elektro-Bus-Betriebshöfe in Vorarlberg,” FH Vorarlberg (Fachhochschule Vorarlberg). doi: 10.25924/opus-5459.

[10] “Gurobi Optimization,” Gurobi Optimization. Accessed: Feb. 20, 2025. [Online]. Available: https://www.gurobi.com/