Optimized Smart Charging of Electric Bus Fleets for Greenhouse Gas Emission Minimization

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Abstract—**The EU has set the goal to reduce the greenhouse gas emissions of the transport sector. The electrification of the public transport sector in Europe is underway to contribute to this goal. By 2030, approximately 90 % of new sales of buses have to be zero-emission vehicles, *e. g.*, electric buses. Compared with conventional fossil driven buses, they have the advantage of reducing local noise pollution and avoiding local greenhouse gas emissions. However, when one considers the full lifecycle, the emissions for electricity generation have to be considered. The greenhouse gas emissions stemming from electricity generation fluctuate depending on the share of the different types of generation. As the expansion of renewable energy sources in Europe continues, the overall potential for a reduction of greenhouse gas emissions increases, but so does the volatility of the generation. Therefore, the targeted timing of electricity consumption, *e. g.*, charging processes, can contribute to an overall emission reduction in the electricity and the transport sector. Based on an exact solution approach we identify the greenhouse gas emission minimization potentials for three charging strategies of an electric bus fleet with 80 buses and compare them to an uncontrolled fleet charging strategy. The optimizations run over 3 years of historical price and CO_2 emission factor data for electricity. When minimizing the procurement cost of electricity at the day-ahead and intraday power markets, cumulative greenhouse gas emissions can be reduced by 23.5 % and, when minimizing the emissions directly, up to 31 % can be reduced. A further reduction can be achieved with a holistic scope, if the bus depot feeds electricity back to the grid at suitable times.**

Index Terms—**energy flexibility, electric vehicles, carbon-optimized charging**

I. INTRODUCTION

The Paris Agreement envisages a reduction in greenhouse gas (GHG) emissions to mitigate global temperature increases over the next decades. The goal is to limit the temperature increases to 1.5 °C [1]. The importance of this endeavor is accentuated by developments of the past years. The Intergovernmental Panel on Climate Change has published that extreme weather events are set to take place with increasing frequency and that the climate targets require huge efforts in order to achieve them [2].

Europe is adopting strategies to contribute to these targets. The Renewable Energy Directive sets a target of at least 42.5 % in the share for renewable energies. The power sector has already seen an increase in the share of renewable energies over the past years. If the pace continues and the targets are to be met, this will lead to substantial changes in how the electricity system and market functions [3]. Many studies stress the fact that volatility in electricity generation will increase and, therefore, grid stability become a major issue. Distribution and transmission system operators are taking action on EU- and on local levels to adapt to a more volatile electricity system. The cooperation of transmission system operators is increasing and the market design for, *e. g.*, balancing services is being adapted to increasingly allow electricity generation facilities with a short forecast horizon, such as solar and wind, to participate in it [4].

The transportation sector is a key factor in the overall energy transition. Electrification of powertrains is underway in many transportation modes. In particular, the public transport sector has witnessed an increase in the market share of battery electric buses [5]. Electric buses contribute to local noise and carbon emission reductions [6]. However, despite the increase in renewable energy generation capacity, the production of electricity still generates carbon emissions, which must be considered. Therefore, source-to-wheel analyses investigate the true emission factor for operating electric buses. While they are meticulous and imply a high degree of certainty, these types of analyses are time-consuming and mostly performed on existing systems. A main outcome, however, is that the lifetime carbon footprint of electric vehicles depends on the carbon footprint of the electricity generation [7].

The electricity generation has a time-dependent CO_2-factor or specific emission factor. The different types of electricity generation have different GHG emission factors. On one hand, fossil electricity generation with hard coal, lignite, natural gas, or oil have rather high emission factors. On the other hand, renewable electricity generation has an emission factor close to zero. A more detailed overview of the global warming potential (GWP) that is related to electricity generation is given in Section II-B.

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Due to the time-dependency of the CO_2-factor, electricity consumers can influence the overall GHG emissions, if they adapt their behavior in certain ways. Since marginal costs of renewable energies are relatively low, the day-ahead electricity price for auctions tends to correlate with the CO_2-factor. This is because of the merit-order effect—a market principle according to which demand is covered by supply depending on the specific costs of a certain electricity generation technology. When prices are low, the emission of GHG from electricity generation is also low. Solar and wind generation can—to some degree—be forecast. The overall electricity demand is also subject to patterns and can be forecast to some degree. Together, this leads to repeating patterns in the prices and CO_2-factors that, in turn, can also be forecast. Market participants with available energy flexibility or the willingness to adapt their electricity consumption profile can benefit from this pattern.

In this work, we investigate the potential of electric bus fleets to contribute to the energy transition by dynamically adapting their charging behavior based on a smart charging strategy for GHG minimization. We compare an uncontrolled fleet charging strategy where vehicles are charged on arrival at the depot with an economically oriented charging strategy and two smart charging strategies aimed at minimizing GHG emissions during electricity production. It should be noted that this goes beyond tariff options claiming to deliver green electricity. One scenario aims at reducing the overall GHG emissions from other consumers as well. This novel approach lies the groundwork for future trading of GHG emissions, e. g., in the form of CO_2-certificates. Before delving into the methodology in Section III and presenting the results in Section IV, a brief overview of electric bus fleets is given in Section II-A and the global warming effects of electricity generation are outlined in Section II-B.

II. BACKGROUND ON ELECTRIC BUSES AND THE GLOBAL WARMING POTENTIAL OF ELECTRICITY PRODUCTION

A. *Electric bus fleets*

The potential for local noise and pollution reduction is a major driver for the electrification of the public transport sector. The International Council of Clean Transportation describes a new regulation of the European Parliament, according to which 90 % CO_2 emissions from new trucks and buses have to be cut by 2040. To achieve this, 90 % of sales have to be zero-emission by 2030 [8].

Bus fleet operators can choose different types of electric buses. Some are suited for opportunity charging as they combine a smaller battery size with more frequent charging events. Others rely on a bigger battery capacity that allows for the operation of longer trips, without having to recharge. The latter come closer to conventional fossil-driven buses in that they do not need to be refueled (recharged) often to sustain operation. This makes their integration into existing schedules and existing transport infrastructures easier. In 2024, there are electric buses in operation with close to 700 kWh storage capacity [9]. Consequently, some fleet operators choose electric buses with higher battery capacities that are mostly recharged overnight. To assure operational reliability a sufficient number of electric buses has to be procured. This makes scheduling and the management of charging events more flexible—especially in times with lower mobility demand. As the charging and the communication technologies surrounding the charging process advance, fleet operators have the option of deploying more flexible charging strategies. The ISO 15118 and the Open Charge Point Protocol (OCPP) set standards which allow for vehicle-to-grid communication and allow for reverse charging processes so that electric vehicles become electricity sources for the grid [10], [11]. It is worth mentioning that there have been successful cases of the application of OCPP in conjunction with intelligent charging strategies [12].

B. *Global warming potential of electricity consumption*

Life-cycle assessments determine the contribution of different electricity generation technologies to global warming. The CO_2 emissions that occur during the production, operation, and end-of-life of the facilities are taken into account [13], [14]. The GWP is measured in CO_2-equivalents (CO_2-eq.), thereby allowing the comparison of different technologies and different types emissions. In relation to the useful life of products, *i. e.*, electricity generation facilities, specific CO_2-eq.-factors for the amount of electricity generated can be calculated. Table I lists the CO_2-eq.-factors for the types of generation with the highest share of electricity produced for Germany. The Agora platform collects historical data on the CO_2-emissions from electricity production in Germany [16]. In 2020, the average value of CO_2-eq. for the German electricity mix was at 375 g CO_2-eq./kWh [17].

TABLE I
EMISSIONS FACTORS FOR VARIOUS TYPES OF ELECTRICITY GENERATION IN 2030 [15].

Energy Source	**CO_2-eq.-factors** in g CO_2/kWh
Lignite	903.2
Hard coal	747.1
Natural gas	379.5
Solar	84.1
Hydro	37.2
Nuclear	9.0
Wind Onshore	9.5
Wind Offshore	4.9

III. METHODS

The comparison of charging strategies is performed for a time horizon T^{horizon} of three years. From 2021 to 2023, data on day-ahead electricity prices, intraday electricity prices, and the specific CO_2-eq.-factor of the German electricity mix are collected. The comparison is based on a German city with approximately 150 000 inhabitants. The local public transport operator is currently electrifying its bus fleet.

For the scenario of a fully electrified fleet of 80 electric buses, the optimal charging strategy is identified in terms of electricity costs and in terms of cumulative CO_2 emissions. For comparison, we include an *uncontrolled* charging strategy, which means that buses are directly connected to a charging station after arriving at the depot and a charging process is started.

For this purpose, a mathematical optimization is performed for weekly periods with the assumption of perfect foresight regarding electricity prices and specific CO_2-eq.-factor developments for the electricity mix. The problem formulation and solution process are based on mixed-integer linear programming. The problem is formulated with Pyomo and week-periods are solved in parallel on a high-performance computing cluster [18]. The problem structure contains storage units, *i. e.*, electric buses, that have a time-dependent dwelling time at the depot. During this time, a charging strategy can utilize the storage units as regular stationary storage systems. However, the strategy has to make sure that scheduled trips can be served. The problem formulation is outlined in Section III-A and the parametrization of the problem structure shown in Section III-B.

A. Mathematical problem formulation

We choose the indexation of 15-minute intervals, because it is an established resolution in the domain of the electricity market. With a time horizon of three years we declare indices d and t as

$$\begin{aligned} d &\in \mathcal{D}[1:1095] \\ t &\in \mathcal{T}^{15}[1:96] \end{aligned} \tag{1}$$

where $\mathcal{D}$ is the set of days and $\mathcal{T}^{15}$ is the set of daily time-indices. For the optimization, we consider three possible products for the procurement of electricity. We narrow our focus down to the biggest platform for short-termed electricity products—the European Power Exchange (EPEX Spot). The set of products $\mathcal{E}$ comprises day-ahead (DA) and intraday (ID) products. At the ID-market, one of the products is actively traded between two parties. The other two products in $\mathcal{E}$ are subject to a daily auction process, where electricity prices are determined.

$$\mathcal{E} = \{\mathbf{DA60}_{\text{auction}}, \mathbf{ID15}_{\text{auction}}, \mathbf{ID15}_{\text{trading}}\} \tag{2}$$

On the short-term electricity market of EPEX Spot, the smallest tradable unit of energy is 100 kWh. The traded quantity of electrical energy is denoted by the decision variable y. Due to the capacity limit of the bus depot $P_{\text{max}}^{\text{DP}} = 4.2\,\text{MW}$, the traded electricity quantities are

$$y \in \{-4200, -4100, \ldots, 4100, 4200\} \quad \forall\, e \in \mathcal{E}. \tag{3}$$

A charging strategy is flexible in deciding when to charge a bus, if there is sufficient available time where a connection to the charging infrastructure is given. The availability of the buses in the bus depot is determined by the fleet management, which schedules the vehicles. The fleet management is also modeled with a 15-minute time resolution. It is represented for each day d and each time interval t indicator parameter $\mu_{d,t}$. The parameter is binary in nature and, for all buses k in the set of vehicles $\mathcal{V}$, it holds that

$$\mu_{d,t}^{k} = \begin{cases} 1 & \text{if electric bus } k \text{ is at the depot} \\ 0 & \text{if electric bus } k \text{ is not at the depot.} \end{cases} \tag{4}$$

The fleet consists of 80 electric buses $\{1, 2, 3, \ldots, 80\} \in \mathcal{V}$. For each bus k, variable z^k defines the amount of energy transferred during an energy transaction. Further, variable $\tilde{z}$ is declared to account for the losses during the power transfer. It represents the energy before losses during a charging process or the energy after losses during a discharging process. The losses are accounted for by the energetic efficiency η^k. Depending on the direction of power of $\tilde{z}$, it follows that

$$z^k = \begin{cases} \eta^k \cdot \tilde{z}^k & \text{, if } \tilde{z}^k > 0 \\ \frac{1}{\eta^k} \cdot \tilde{z}^k & \text{, if } \tilde{z}^k < 0 \\ 0 & \text{, otherwise.} \end{cases} \tag{5}$$

Power transfer is limited to 150 kW per charging station and there is one charging point per bus. The sum of the storage transactions must correspond to the energy u_t^{DP} absorbed or released by the bus depot within a time interval t.

$$u_t^{\text{DP}} = \sum_{k=0}^{80} \tilde{z}_t^k \quad \forall\, t \in \mathcal{T}^{15} \tag{6}$$

In addition to the power limitation at the storage level, there is an additional constraint at the depot level. Sufficient electric buses must be connected at the depot during the time interval t, so that the power v^{DP} at the bus depot level can be absorbed or released. For the power v_t^{DP} in t, it holds that

$$\left|v_t^{\text{DP}}\right| \leq \sum_{k=0}^{80} (\hat{\gamma}^k \cdot \mu_t^k) \quad \forall\, t \in \mathcal{T}^{15}, \tag{7}$$

where $\hat{\gamma}^k$ is the nominal charging power of bus k depending on where it is connected. In terms of energy, the transactions z^k for bidirectionally charging buses are limited by γ, as described in (8).

$$-\hat{\gamma}^k \cdot 15\,\text{min} \leq z_t^k \leq \hat{\gamma}^k \cdot 15\,\text{min} \tag{8}$$

If only unidirectional charging is allowed, the left side in (8) becomes zero. The State of Charge (SoC) φ_t^k of each electric bus depends on the respective SoC at the previous time-step, the energy transactions z, and the electric consumption of the vehicles β (see (9)). The latter is computed *a priori* on a 15-minute basis and reflects route-specific energy consumption per bus depending on the bus schedule.

$$\varphi_t^k = \varphi_{t-1}^k + z_{t-1}^k - \beta_{t-1}^k \tag{9}$$

Apart from linking the time-steps, φ_t^k has to be bound in order to remain within the allowed SoC-corridor. The limits are set to 5 % and 95 %, in order to mitigate battery degradation due to extreme SoC. In their publication on energy arbitrage with batteries, Kumtepeli *et al.* also define a usable SoC-range of 90 % [19].

Table II shows an overview of the main parameters of the bus depot model.

TABLE II
MAIN PARAMETERS OF THE BUS DEPOT MODEL.

Parameter	Description	Value
φ_{min}	Lower SoC-limit of vehicles	5
φ_{max}	Upper SoC-limit of vehicles	95
v^{DP}_{max}	Depot power limit	4200 kW
$\hat{\gamma}$	Nominal charging station power	150 kW

In the Results Section, we will compare the following charging strategies:

1) **Uncontrolled** Buses are fully charged upon arrival at the depot.
2) **Smart-EUR** Buses are charged in order to minimize costs at the day-ahead electricity market.
3) **Smart-GHG-1** Buses are charged in order to minimize GHG emissions.
4) **Smart-GHG-2** Buses are charged in order to minimize GHG emissions and discharged in order to replace CO_2 intense electricity production.

For the comparison of the four charging strategies, we define three objective functions. The first one, in the scenario of an uncontrolled strategy, maximizes the sum over all SoC values over the whole optimization time horizon, as this will be achieved by charging the buses as soon as possible. The second one represents the total electricity costs for the operation of the electric buses. The amount of purchased energy y^e is multiplied with the corresponding price π^e of the product in all time-steps (see (10)).

$$\min_y f^{\mathrm{EUR}} = \min_y \sum_{t=1}^{96} \sum_{e \in \mathcal{E}}^{3} y_t^e \cdot \pi_t^e \tag{10}$$

The third objective function minimizes the cumulative GHG emissions. In the case of charging strategy *Smart-GHG-1*, electricity cannot be fed back to the grid. In the second case, *Smart-GHG-2*, the buses—and the bus depot—can feed electricity back to the grid, which allows them to act as an energy buffer for the electricity grid. Electric energy can be stored during periods of low specific CO_2 emissions and later be fed back to the grid, so that other consumers can consume it. This will only make sense, if the transmission losses incurred are small in comparison to the GHG-savings potential of the transaction. We assume that, when feeding electricity back to the grid in times of high specific CO_2 emissions, a share of conventional electricity generation is replaced by the bus depot. Therefore, we assume that the amount of electricity fed back to the grid multiplied by the specific CO_2-eq.-factor ψ at that time corresponds to the amount of CO_2 saved thanks to the charging strategy. Equation (11) shows the objective function for ecological optimization.

$$\min_y f^{\mathrm{GHG}} = \min_y \sum_{d=1}^{1095} \sum_{t=1}^{96} \sum_{e=1}^{3} \psi_{d,t} \cdot y_{d,t}^e \tag{11}$$

where $y \geq 0$ in the case of charging strategy Smart-GHG-1.

B. Parametrization of the Bus-related Data

The fully electrified bus fleet comprises standard length and articulated buses. Thanks to technological advancements, the battery capacity of newer buses is higher than in previous generations. Table III shows an overview of the bus fleet. Since none of the buses have electric heating, their electricity consumption does not increase during cold winter months. The consumption of standard electric buses is 1 kWh/km and that of standard articulated buses is 1.5 kWh/km. The fleet schedule determines which trips have to be served by the electric buses. In general, bus schedules are characterized by a weekly pattern. Table IV provides an overview of daily mileage and the number of trips that are served by the buses. The time horizon spans 157 weeks.

TABLE III
OVERVIEW OF THE ELECTRIC BUS FLEET COMPOSITION [9], [20], [21].

Description	Type	Battery Capacity in kWh	Number of buses
Daimler eCitaro	Standard	288	6
Daimler eCitaro	Standard	396	11
Daimler eCitaro	Articulated	396	13
MAN Lion's City	Articulated	640	9
Daimler eCitaro	Articulated	694	41

TABLE IV
OVERVIEW OF THE FOUR REPRESENTATIVE DAYS REGARDING THE FLEET MANAGEMENT OF THE BUS DEPOT.

Weekday	T^{Horizon} days	Mileage km per day	Trips per day
Mon. to Thu.	624	16 630	92
Fri.	157	16 979	92
Sat.	157	9476	32
Sun.	157	6965	25

C. Solution procedure

After the model has been parameterized, it is solved with the help of the optimization software Gurobi for finding an optimal solution for the given model. Due to the length of the time horizon, it is split into single optimization intervals on a weekly basis and solved separately. For the solving process itself, computing units with 16 processing cores and 64 GB of memory are allocated to each interval.

IV. RESULTS

Over the course of the optimization horizon, 18.59 GWh electric energy are procured at the electricity market. For the ecological assessment of the four charging strategies, we compare the cumulative GHG emissions that are generated over the optimization horizon. Note that only the electricity-related GHG emissions which occur during the operation of electric buses are considered. Market mechanisms such as CO_2-certificates or *green* energy tariffs are not taken into account.

Figure 1 shows the sum of GHG emissions caused by the operation of the electric bus fleet during the optimization horizon. The indirectly emitted CO_2-eq. emissions are shown with black bars. The GHG emissions that can be replaced by feeding back to the grid are displayed in blue. The ecological optimum for the regular case in which only unidirectional charging is possible is marked with a green dotted line. The GHG emissions of the uncontrolled charging strategy are marked with a red dashed line. With that charging strategy, electricity is effectively procured with a specific CO_2-eq.-factor of 357.5 g CO_2/kWh which is roughly 6 % below the CO_2-eq.-factor of natural gas. It is remarkable that solely via the economic optimization for the *Smart-EUR* charging strategy, 23.5 % of GHG emissions can be saved compared to the uncontrolled charging strategy. This corresponds to a specific CO_2-eq.-factor of 273.6 g CO_2/kWh. Through the ecological optimization with *Smart-GHG-1* charging, 31 % GHG emissions savings can be achieved leading to an effective CO_2-eq.-factor of 246.8 g CO_2/kWh. In the case of *Smart-GHG-2* charging, if the amount of avoided CO_2 emissions due to the displacement effect of the electricity fed back to the grid is attributed to the bus depot, the specific CO_2-eq.-factor gets down to 175.8 g CO_2/kWh. Figure 2 displays a heatmap showing a typical pattern that emerges for buying and selling electricity in summer months. The illustration unequivocally shows that the depot is able to leverage its energy flexibility and procure electricity during the periods in which photovoltaic production is high. Then, during the night hours and when overall electricity demand starts rising during the morning hours, it is fed back to the grid. Especially when there is low mobility demand on weekends or during the holiday season, the energy flexibility potential increases. Human-made patterns, such as summer holidays, lead to a higher availability of energy flexibility during that time, which is convenient because, during that time of the year, photovoltaic generation is the highest. Note that the effect of the holiday season is not considered in this paper, as we only have performed optimizations for the four most common representative weekdays.

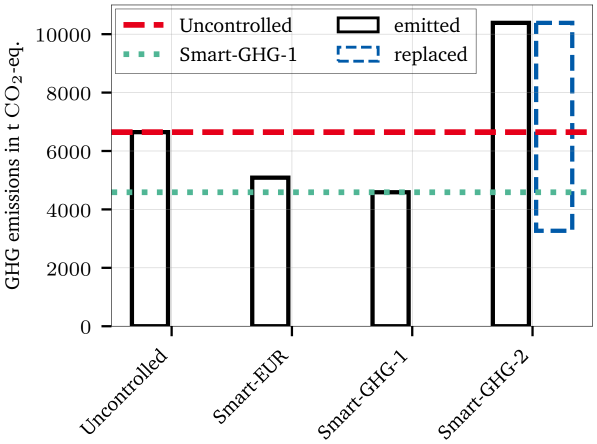

Fig. 1. Comparison of uncontrolled and economically oriented charging strategies as well as charging strategies with the goal of greenhouse gas minimization with and without the possibility to feed electricity back to the grid.

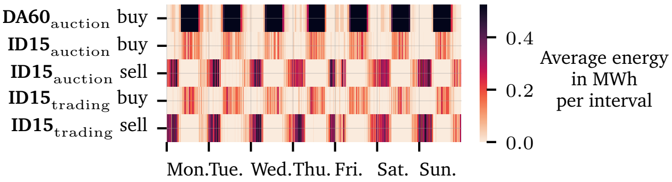

Fig. 2. Heatmap of the average electricity bought and sold per time-step during the summer months of 2022 for the *Smart-GHG-2* charging strategy.

V. CONCLUSION

We have performed four fleet charging strategy optimizations with a mixed-integer linear programming approach over a time horizon of three years. The fleet schedule was based on four representative days designed for a city with approximately 150 000 inhabitants. Periods with lower mobility demand, *e. g.*, holidays, have not been explicitly considered. They would further increase the energy flexibility. The results demonstrate that if a bus fleet operator decides for a smart charging strategy, a reduction of GHG emissions from electricity generation can be achieved. In the case of a smart charging strategy that optimizes the procurement at the EPEX Spot in the bidding zone of Germany and Luxembourg with a minimal cost approach, GHG emission are reduced by 23.5 % when compared to an uncontrolled charging strategy. If a charging strategy has the objective of GHG emission minimization, a bus fleet operator is able to achieve a reduction of 31 %. In the case of buses with bidirectional charging capabilities and the option of feeding electricity back to the grid, CO_2 arbitrage can take place. Other electricity consumers can then consume the electricity, that has been stored by the bus depot while the specific CO_2-eq.-factor of the electricity generation was low. If the CO_2 savings of other consumers are attributed to the charging strategy of the fleet, a further reduction of the carbon footprint of the electric bus fleet is achieved. It should be noted that feeding electricity back to the grid comes at the costs of additional battery degradation which has not been taken into account. Further, a realization of this additional CO_2 savings potential through bidirectional charging capabilities requires incentives for fleet operators. Without incentives to stimulate the *Smart-GHG-2* charging strategy, fleet operators will likely not pursue it.

Smart-GHG charging can be realized with ease as there are open-source tools forecasting the specific CO_2-eq.-factor for the German electricity grid [22]. In general, the forecasting of weather events and day-ahead market prices—which are correlated to each other—has improved over the past years [23].

We finally conclude that fleet operators have a great potential for reducing overall GHG emissions in society. For this, actors have to be willing to contribute which means that there need to be incentives that outweigh the additional costs related to these charging strategies. This is especially relevant with regards to battery degradation in the scenario *Smart-GHG-2*. Therefore, future research in this area should focus on integrating battery degradation effects and increasing the time resolution in order to do so. Models with reduced complexity, *e. g.*, a reduced time-horizon, can accomplish this.

ABBREVIATIONS AND SYMBOLS

CO_2-eq.	CO_2-equivalents
EPEX Spot	European Power Exchange
GHG	greenhouse gas
GWP	global warming potential
$\mathcal{D}$	Set of days in the optimization horizon
$\mathcal{T}^{15}$	Set of time indices in a day
$\pi_{d,t}$	Price for electricity
$y_{d,t}$	Electricity purchased
$z_{d,t}$	Electricity charged to storage systems
$\beta_{d,t}$	Consumption of vehicles
γ	Charging power capacity
$\mu_{d,t}$	Fleet management (vehicle availability)
$\psi_{d,t}$	Specific greenhouse gas emissions of the electricity mix

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