# OPTIMIZATION MODEL FOR SIMULTANEOUS CONTROLLED CHARGING OF ELECTRIC VEHICLES IN DISTRIBUTION GRIDS IN RURAL, SUBURBAN AND URBAN AREAS

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## Abstract

The energy demand of future electromobility poses new challenges for distribution grids due to critical load peaks. Integrating electric vehicles (EVs) into the energy system by controlled charging could offer additional flexibility for the overall system yet may increase the peak loading in the distribution grid. We therefore developed and implemented a modular optimization model representing the simultaneous controlled charging of multiple EVs in one defined branch of a distribution grid from a combined aggregator and grid perspective. The objective consists of minimizing the costs to provide electrical energy to fully recharge all EVs connected to that grid branch during a full year, either in perfect foresight or by applying a rolling horizon with a 36h/24h scheme. The time intervals of connection to the power grid are explicitly modelled as well as the grid limitations.
Using Monte Carlo simulations, a multiplicity of different single grid branches is evaluated. The number of households connected to these grid branches with a defined probability of EV ownership is applied as predictor for the load burden of the future German EV fleet. In the model, a classification of grid branches into fifteen distinct types is used, each defined by specific parameter settings, allowing to capture the diversity of grid branch configurations, e.g. regarding the degree of urbanization. Randomization is employed to create a representative sample of grid configurations based on the predefined clusters and corresponding ranges of grid parameters. This enhances the model's adaptability to reflect the variability of grid configurations. Compared to uncontrolled charging, which is considered as a reference in the model, "smart" optimised controlled charging of multiple EVs is concentrated during periods of the lowest spot prices, which do not coincide with the existing peak load hours in the evening. The impact of grid constraints on the controlled charging patterns is found to depend both on the degree of urbanization and the specificities of the considered grid branches.

## 1 Introduction

The energy demand of future electromobility poses new challenges for distribution grids due to critical load peaks. Integrating electric vehicles (EVs) into the energy system by controlled charging could offer additional flexibility. As part of an applied research project in this field in Germany [1], a modular optimization model was developed and implemented. The novel methodology notably addresses the broad variety of distribution grids and the limited empirical data available for a system-wide analysis of smart charging patterns and impacts.

### *1.1 Low-voltage distribution grids*

There is a high level of heterogeneity in low-voltage (LV) distribution grids. They differ substantially in their topological layout, including the number or branches, their lengths and the configuration of branches with respect to the feeding point of the grid. Urban grids often consist of dense, interconnected networks, while rural grids feature long connection lines with sparse customer distribution. An exemplary illustration is provided in Fig. 1, which depicts a stylized low voltage distribution network featuring a LV transformer (LVT) and two parallel branches.

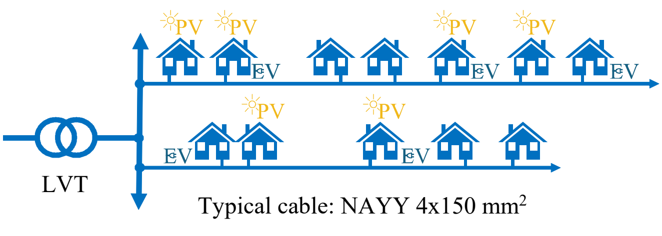


*Fig. 1 Stylized low-voltage distribution network with two parallel branches including households with EV ownership and photovoltaic systems (PV)*

The house symbols represent individual households, but these might also be part of a multi-family dwelling or a high-rise building:
Even the branches of a single municipal distribution grid may differ substantially, e.g., regarding the number of

connected households, the branch lengths, or the cumulative level of PV generation.

Notably the actual number of EVs per grid branch is relevant for the model and determined in dependence of the households per grid branch, as is explained in Section 2.3.

*1.2 "Smart" charging versus "dumb" charging*

Two charging strategies are compared: controlled "smart" charging versus uncontrolled "dumb" charging. Conventional "dumb" charging serves as a reference. Here, EVs plugged to the distribution grid are continuously charged to 100% state of charge (SoC) from the moment they are plugged in, without any external control over the charging except for dimming the maximum charging power in case of a line overload. This serves as a baseline to evaluate the benefits of "smart" charging, where the charging process is controlled and optimised to manage energy consumption more efficiently.

## 2 Methodology

To effectively address the aforementioned challenges, a sophisticated yet scalable approach is required. Fig. 2 provides an overview of the components discussed in the following sections of this paper. The method notably involves the utilisation of so-called "meta-clusters" to represent characteristic distribution networks (cf. Section 2.2). Meta-clusters ([2], [3]) in the context of this paper are aggregated groups of LV distribution grids with similar parameter sets. The sampling of multiple representants with cluster-specific random parameters allows to scale the results of the model to the national level and to identify the optimal charging strategies at the national level. Thereby, the modelling of the network constraints using the so-called limiting curve analysis ([4], [5]) is another key element (cf. Section 2.5), providing a simplified description of the capacity limitations in different types of networks. With these input data, the EV charging is optimized for a full year (cf. Section 2.6).

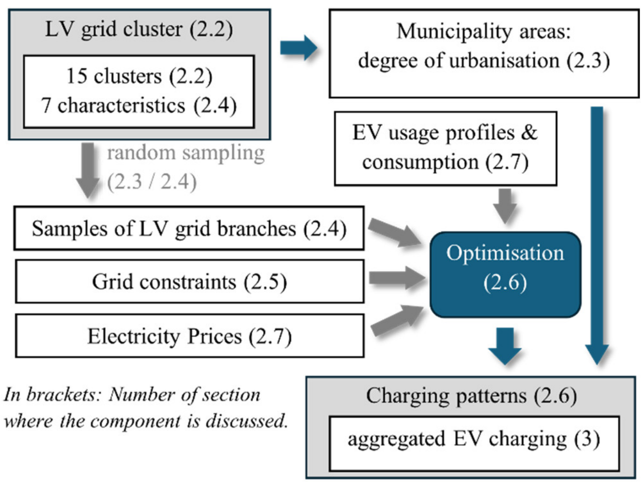


*Fig. 2 Components of the simulation model*

*2.1 Modelling approach*

The core idea of our model setup is to represent the entire German low voltage distribution grid by evaluating multiple single branches ("grid configurations") out of a variety of grid clusters. Each meta-cluster comes along with a parametrization with specific value ranges for the following key parameters:

- Number of house connections to the grid,
- residences per house connection,
- LV transformer power per house connection,
- installed PV power per house connection,
- number of electric vehicles,
- (Effective) length of the distribution network branch,
- Number of branches.

The parameter values are adapted to the settlement characteristics of the area where the corresponding grid configurations are typically found. For the LV grid a radial structure is assumed with several branches connected in parallel to one transformer (cf. Fig. 1).

For every single grid configuration first the grid meta cluster is randomly drawn, with probabilities adjusted to the distribution of different settlement types in Germany (cf. Sections 2.2 and 2.3). The number of households as well as all other grid parameters are then randomly determined based on grid-specific value ranges (cf. Section 2.4). This notably allows to place consistently a random number of EVs in each grid branch, depending on the settlement type, the number of households and other characteristics associated with the grid configuration. The grid parameters are determined based on a simplified approach (cf. Section 2.5) and normalized to one branch. They are then a key element for determining the optimal EV charging schedules in each grid branch in the optimization runs (cf. Section 2.6).

When faced with grid constraints, the "dumb charging" strategy involves a simultaneous "dimming" mechanism for all EVs scheduled for charging within each time step. This means that during periods of high demand or when the network is at risk of overloading, the charging rates of all EVs are reduced uniformly. With smart charging, such a rescheduling is performed in an optimal way taking into account the EV mobility patterns. In this way, a grid-compatible smart charging is ensured.

*2.2 Clustering of low-voltage grids*

The first main step to cope with the heterogeneity of LV grid configurations consists of a suitable clustering. In [2], the meta-clusters shown in Table 1 and a qualitative categorization of settlement type and a categorization according to the "degree of urbanization" (DoU) are given, e.g. "low-density mixed-use area" is labelled as "rural to suburban". In the absence of more detailed knowledge, we apply the Laplace principle [6] and assume that each category is equally likely, therefore allocating 50% to both categories.

*Table 1 Clustering of LV grids by settlement type with categorization of these areas according to their degree of urbanisation: rural (), sub-urban () and urban () [2].*

| *Cluster* | *DoU* | |
|---|---|---|
| Scattered settlement mixed-use area | 100 % | |
| Low-density residential area A | 100 % | |
| Low-density residential area B | 100 % | |
| Low-density mixed-use area | 50 % | 50 % |
| Medium-density residential area A | 100 % | |
| Medium-density residential area B | 100 % | |
| Medium-density mixed-use area | 50 % | 50 % |
| High-density residential area | 50 % | 50 % |
| High-density mixed-use area | 50 % | 50 % |
| Low-density multifamily r. a. | 50 % | 50 % |
| Medium-density multifamily r. a. A | 50 % | 50 % |
| Medium-density multifamily r. a. B | 50 % | 50 % |
| High-density multifamily r. a. | 100 % | |
| Urban multifamily residential r. a. | 100 % | |
| High rise area | 100 % | |

(r. a. = residential area)

Three typical commercial settlement types also proposed by [2] were not considered in our data setup, as they are not directly corresponding to specific DoUs and the charging-relevant mobility patterns in these areas would be quite different.

### *2.3 Degree of urbanisation and number of households*

A data set from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development [7] categorizes 10,990 German municipalities according to their DoU. Out of the total German population of 84.36 million in 2022, 19.01 million reside in rural areas, 34.86 million in suburban areas, and 30.50 million in urban areas.

As the population size of each municipality is also given, it is possible to subdivide them into a data matrix in dependence of the size classes and the DoU. For instance, 1337 municipalities with a population between 5,000 and 20,000 are part of a sub-urban area.

Another official data set [8] provides information on the number of households for all municipality size classes in dependence on the number of persons living in the household (HH), ranging from 1 to 5 or more persons per household. The combination of both data sets allows for calculating the mean number of persons per household for every DoU area (Table 2) and to link settlement types, DoUs and number of households. The total number of German households in 2022 amounts to 41.5 million.

*Table 2 Computed population parameters in dependence on the degree of urbanisation (DoU).*

| *DoU:* | *rural* | *sub-urban* | *urban* |
|---|---|---|---|
| Inhabitants GER*) | 19.01 | 34.86 | 30.50 |
| % population | 22.53% | 41.32% | 36.15% |
| Persons per HH | 2.16 | 2.12 | 1.88 |
| HH total*) | 8.81 | 16.48 | 16.20 |
| % total HH | 21.23% | 39.72% | 39.05% |

*) values are to be expressed in millions, HH=household(s).

### *2.4 Stochastic parameterization*

With an EV stock of 15 million EVs as projected by the German government [9], the average probability for a household to own an EV in 2030 is roughly 15/41. Compared to recent official projections estimating between 41.7 million and 42.3 million households in 2030 [10], this probability is slightly upward biased resulting in somewhat more congestion issues in the analysed grid branches.

For determining the number of EVs in each simulated branch, it is assumed that each building connected to the grid is either a single-family dwelling or a multi-family dwelling, where each dwelling is occupied by one household owning a maximum of one electric vehicle (EV). Correspondingly, the parameter "Number of house connections" represents the total count of such buildings on the grid and together with the average number of households per building the number of households is determined. For the households, then a binomial distribution is then applied to determine the number of EVs per grid branch.

For the aforementioned parameters as well as the others listed in Section 2.1, parameter values for each grid meta-cluster are provided in [3]. For each of the parameters, a deterministic scalar value $v$ is given. To reflect the heterogeneity of grid branches within a cluster, a different random value for every single run of the Monte Carlo simulation is determined. Unless other information is available, we assume that the lower bound $x_{lb}$ for the random values corresponds to half of the given value $v$. Conversely, the upper bound $x_{ub}$ is set to twice the value of $v$. The resulting interval then defines the range of a triangular probability density function [11] where probabilities are bigger than zero (cf. Fig. 3).

The triangular distribution enables a parsimonious modelling of uncertainty. Minimum, modal and maximum value fully describe the distribution function. This enhances its applicability compared to other distributions such as the normal distribution, especially when a skewed distribution is likely, upper and lower bounds exist and the true distribution is unknown. [12]

The modal value $m$ of the asymmetric triangle is set equal to the given grid parameter $v$, which is then positioned a third of the way between $x_{lb}$ and $x_{ub}$, as shown in Fig. 3.

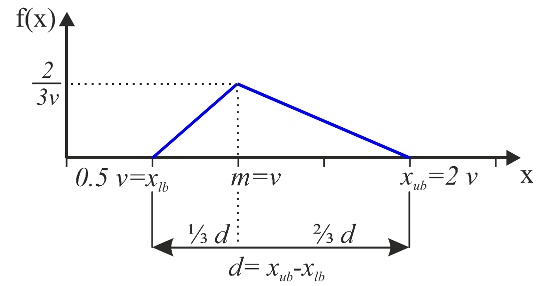


*Fig. 3 Parameters of an asymmetric triangular probability density function.*

*2.5 Limitation of power flows*

Real power cables used in LV distribution grids like the NAYY 4x150 (mm$^2$) [13] show resistive impedance and frequency-dependent self-inductance. The code "NAYY" represents a standardized cable type ("N") with aluminium conductors ("A") and insulation made of PVC ("YY"). The NAYY 4x150 power cable with four conductors has a maximum current-carrying capacity of 246 A when installed in free air and 275 A when buried underground [14].

Both resistance and self-inductance of the cables contribute to voltage drops which are proportional to the length of the cable. Therefore, the absolute voltage drop becomes more pronounced over longer branch lengths, potentially reducing the maximum power that can be transmitted without exceeding the permissible voltage drop limits. Equivalent circuit representations of real power cables ([15], [16]) allow to calculate these voltage drops. The resulting limit power curves as function of the line length are explained in detail in [4] and [5]. To apply the limiting curve analysis properly, we assume that all households connected to the grid branch are accumulated at the terminal point of an equivalent branch. This branch shows an effective length of 70% of the physical length.

*2.6 Optimization model formulation*

The aggregators focus on minimizing energy system costs through charging scheduling, all while meeting the demands of EV users. For this purpose, an optimization model was implemented, following largely the structure proposed by [17]. It consists of three groups of constraints:

- Battery SoC equations: For every EV, the SoC in time step *t* equals the SoC of timestep *t-1* plus any difference of the SoC in *t* caused by energy consumption or battery charging.
- The total charging power per time step *t* must not exceed the transmittable power as discussed in Section 2.5.
- As default setting, each EV battery is recharged to 100% within each charging cycle.

To make sure that the optimization problem is a linear program (LP), no Boolean variables were used. Instead, a binary parameter matrix was introduced indicating the connection status to the distribution grid for each of the EVs for every timestep of the test period, as shown in Fig. 4. For every "idle" timestep, where an EV is not connected, the upper bound of the corresponding optimization variable was dynamically set equal to zero, which is also the value of the lower bound.

Fig. 4 contains a stylized scenario of seven EVs which are connected to the same grid branch for substantially parallel charging over a given period with fifteen discrete time steps.

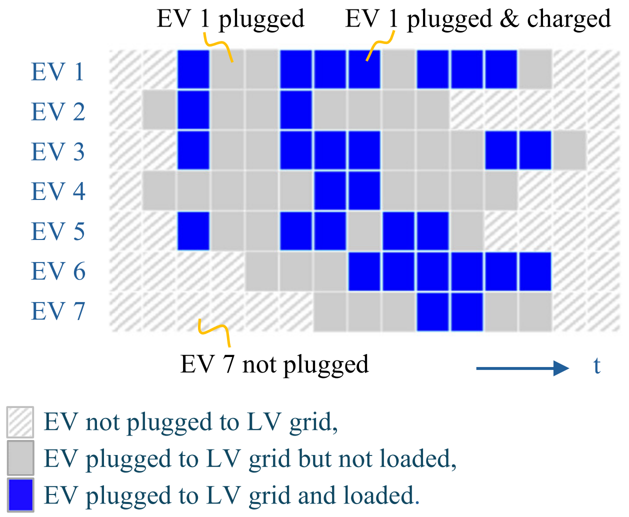


*Fig. 4 Representation of parallel controlled charging of seven EV connected to the same LV grid branch over a given period with fifteen discrete time steps, status after optimization.*

As the charging is controlled and optimized by the aggregator, the timesteps with solid grey filling represent timesteps where the EV is plugged to the grid branch but not charged due to the level of the electrical spot price.

*2.7 Modular model setup and real-world time series*

To ensure maximum flexibility, the simulation model is composed of multiple files written in Python. Fig. 5 shows the modular functional components of the simulation framework. The Monte Carlo simulation is applied by a single loop file where either the model file with smart charging and perfect foresight optimization or the model file with smart charging and optimization based on a rolling horizon can be used. Both model files can also be applied as "stand-alone" files to run a full-year optimization for a single branch with deterministic parameters.

Central parameter of the optimization is the spot price for electrical energy. The hourly EPEX day-ahead price for Germany and Luxemburg of 2021 [18] has been chosen as baseline timeseries to model future scenarios of up to 8760 h in hourly or quarter-hourly resolution.
The simulation model framework can be executed using either synthetic time series to investigate e.g. future scenarios and highlight specific effects within the model or real-world data. The latter include the following datasets:

- Household consumption [19],
- PV generation [20],
- EV driving profiles and consumption [21].

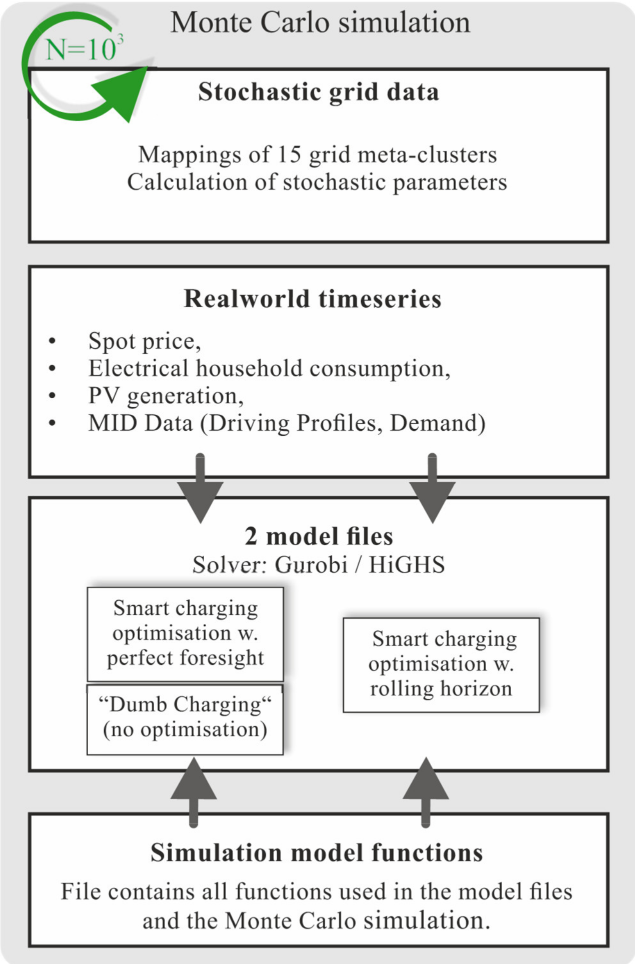


*Fig. 5 Simulation model framework.*

## 3 Results and discussion

A full Monte Carlo simulation with hourly resolution and $10^3$ loops over a full year based on real world data timeseries as listed in Section 2.7 takes less than 45 min on a PC with the following system specifications:

- Processor: Intel® Core™ i7-1165G7 at 2.80 GHz,
- Installed RAM: 32.0 GB,
- Operating system: Windows 11 Pro 64-bit (23H2).

Therefore, an average single simulation takes 2.4 seconds. This value is yet dependent on the actual number of EVs.

One main finding is illustrated across all subsequent figures: When the charging for all EVs in a grid branch is optimised, the charging of multiple EVs is concentrated during periods of the lowest spot prices. This behaviour is consistently visible in all figures. It highlights the key role of spot prices in cost-effective charging strategies for the aggregators and how this is taken up by the model.

*3.1 Total charging in the grid branch*

Fig. 6 shows the total power consumption to charge ten EVs in controlled and uncontrolled mode per timestep (a) for a week in winter and (b) for a week in summer. To emphasise visually the effect of congestion, the power flow limit in the grid branch was set to a low value to 50 kW. These results were obtained using the stand-alone simulation model.

In addition, synthetic time series were applied both for the EV driving profiles and the consumption. To create a stress scenario with respect to the already existing evening peak, all EVs arrive between 4:45 p.m. and 6:45 p.m. with a remaining SOC of 65% (26 kWh) and leave fully charged between 5:00 a.m. and 8:45 a.m. on each day of the test period.

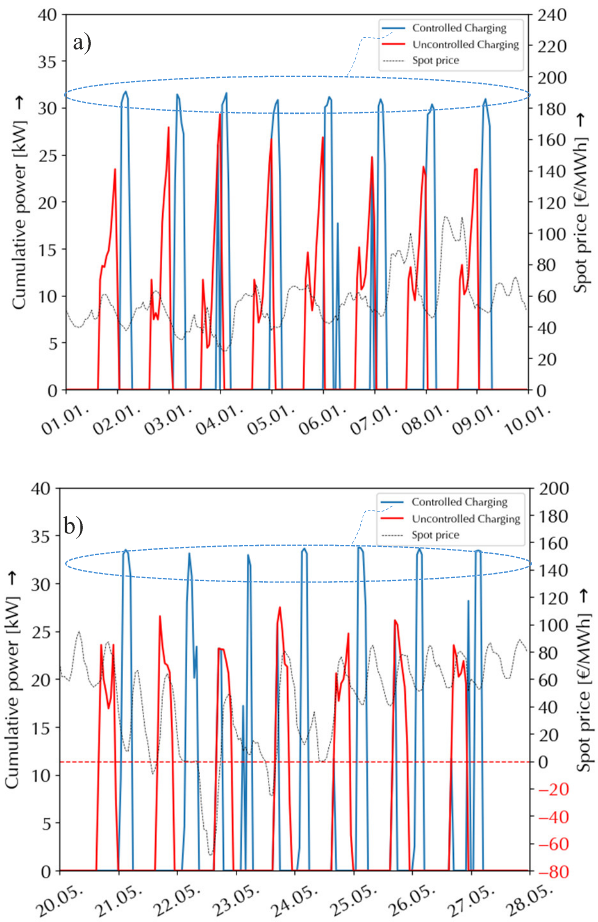


*Fig. 6 Total controlled and uncontrolled charging of all EVs per timestep (a) for a week in winter and (b) for a week in summer.*

The week in summer was specifically chosen because the spot price for electrical energy was close to zero, or even negative, during the central hours of the day, indicating a period with high solar energy generation. This situation highlights the model's ability to take advantage of favourable price conditions when an EV is connected to the grid branch, thereby maximising charging during these low-cost periods. Yet at the same time these effects are limited by the connection of the EVs to the grid – correspondingly no charging occurs during the hours around noon and charging only starts when the EVs come back at home in the afternoon.

During the winter week, the power flow limit for charging the EVs is slightly lower than in summer. This is likely due to the generally higher demand for heating and lighting during winter, which reduces the surplus power available for EV charging. At the same time, no negative prices arise, and intraday price spreads are rather low during the first days. Consequently, the model still effectively optimises charging times to align with the lowest available spot prices, although the opportunities are less abundant compared to the summer scenario.

### *3.2 Monte Carlo simulation*

Monte Carlo simulations are used to evaluate different configurations of LV grid branches to represent the entire German distribution grid. Each of the runs can be seen as a computational experiment based on a specific set of random parameter values [22] to evaluate the electricity consumption induced by EVs in a future scenario. Fig. 7 depicts the total charging consumption per timestep for all $10^3$ runs during the first week of the test period. Despite the differing parameter setups, the optimising process behind controlled charging causes the time steps with the lowest spot price to be preferably selected – leading to a higher simultaneity of charging under controlled charging compared to the uncontrolled case.

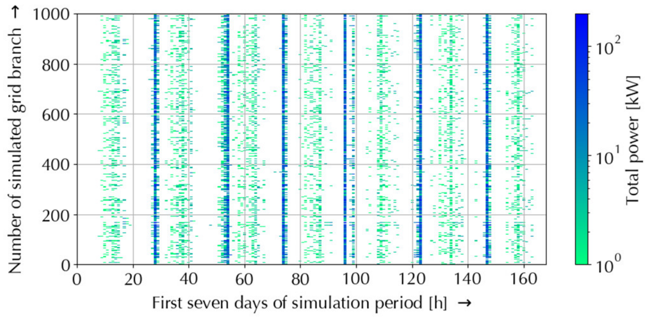


*Fig. 7 Heat map of total charging per time step and grid branch for the case of smart charging with perfect foresight (log scale).*

Fig. 8 illustrates the variation in charging behaviour throughout the day on Thursdays as example of a working day with mean values and 10th and 90th percentiles shown. The controlled charging plot (Fig. 8a) depicts how the optimisation model shifts charging to periods with lower spot prices in the early morning, inducing a rather high peak load and aligning with the most cost-effective times as far as possible under the grid constraints. The uncontrolled charging plot (Fig. 8b) reflects typical, unoptimised charging patterns, with peaks corresponding to times when EVs are plugged in with the highest likelihood.

Note that the mean can be higher than the 90th percentile in time steps with little charging activity. Notably this occurs if there is no charging at all in more than 90 % of all observations (days), yet there are strictly positive values in the other 10 % which drive up the mean value. Also, other constellations may occur with some very high but rare values – e.g. on Thursdays at 11 p.m. in Fig. 8a.

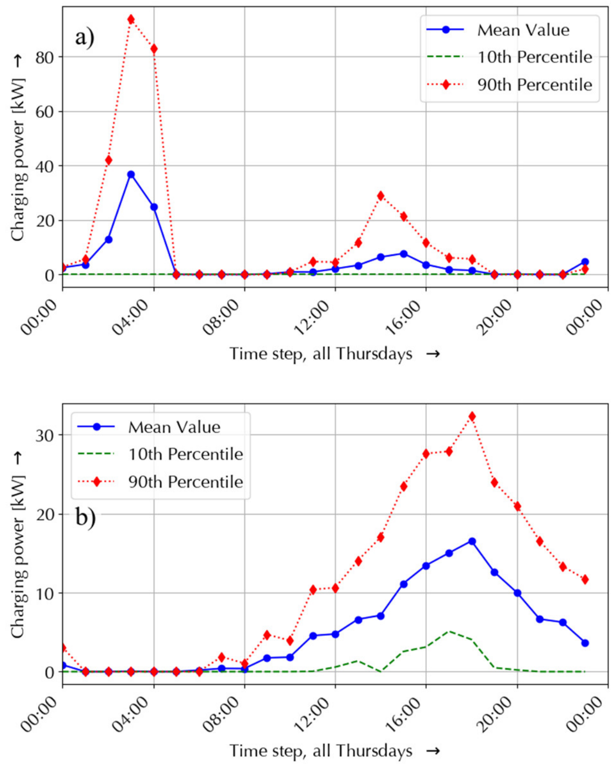


*Fig. 8 Daily patterns of total charging power in the grid branch over all Thursdays of the scenario year 2030 (a) for smart charging and (b) for dumb charging.*

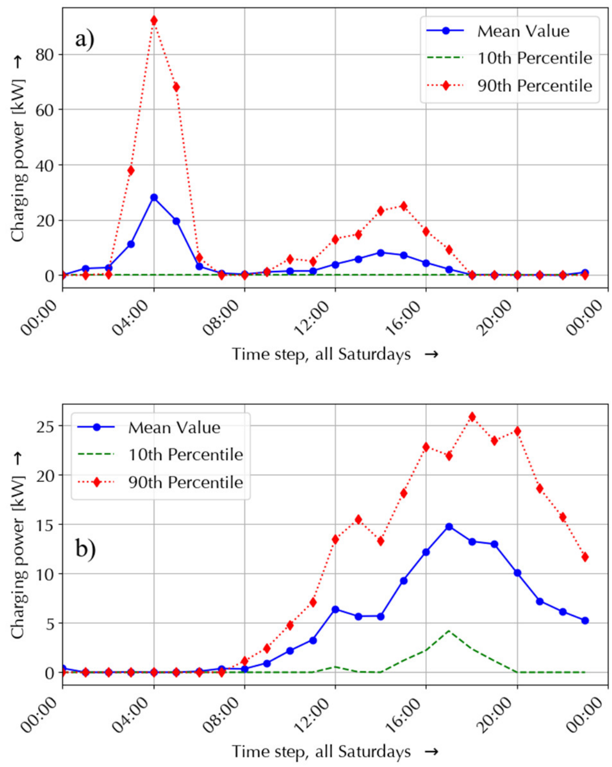


*Fig. 9 Daily patterns of total charging power in the grid branch over all Saturdays of the scenario year 2030 (a) for smart charging and (b) for dumb charging.*

Another pair of figures (Fig. 9) shows the charging patterns for Saturdays in the scenario year. Fig. 9a depicts controlled charging over all Saturdays, whereas Fig. 9b shows uncontrolled charging is averaged over all Saturdays, with corresponding mean and percentile ranges.

These figures reveal that, while the qualitative behaviour of charging on Saturdays is similar to that on Thursdays, the peak levels are generally slightly lower. The controlled charging plot (Fig 9b) demonstrates how the optimisation model adjusts to these lower peaks, concentrating charging during times of lower spot prices and smoothing out demand even more effectively than on weekdays.

## 4 Conclusion

The proposed model setup offers a flexible and efficient approach to analyse the role of the German low voltage distribution grid for EV charging by leveraging Monte Carlo simulations. By modelling the grid branches through fifteen distinct clusters, each characterized by a specific parameter set, the model can capture diverse configurations of the grid branches. The randomization process, which selects clusters and grid parameters based on predefined value ranges, enhances the model's adaptability to different grid scenarios. Making use of the concepts of limiting curve analysis and "meta-clusters" enables the rapid computation of multiple cases of grid utilization. Notably, the computational efficiency of the setup allows for completing the entire Monte Carlo simulation with $10^3$ branches in hourly resolution over a full year in less than 45 minutes. This demonstrates its practical applicability for large-scale grid analysis and indicates significant potential for evaluating the value of flexibility by controlled charging of EVs.

## 5 Acknowledgements

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