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Abstract

The ongoing transition of our energy systems implies a rise of distributed generators, batteries, and new consumers, including electric vehicles and heat pumps. Previous studies have found that distributed flexibility may substantially benefit wholesale electricity markets, but have neglected that these benefits may be subject to distribution grid constraints. Here, we propose using a virtual storage approach to aggregate the net load and flexibility of individual consumers at the distribution grid level, subject to the corresponding grid constraints. We apply our approach to flexible electric vehicle charging scenarios in German distribution grids for the years 2030 and 2045. Our results suggest that distributed flexibility exacerbates distribution grid congestion if it only follows wholesale market prices. However, there may be the potential to alleviate local congestion with stable wholesale market benefits of distributed flexibility. Local coordination of distributed flexibility appears to be able to resolve distribution grid constraints at substantially lower costs than expanding transformer capacity. We conclude that local coordination mechanisms are key to unlocking the wholesale market benefits of distributed flexibility while mitigating hazards in the distribution grids.

Keywords: Electric vehicles, Distribution grids, Energy system modeling, Flexibility, Grid expansion
JEL classification: C61, D47, Q21, Q41, Q48

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1. Introduction

Electricity distribution grids undergo a fundamental transition. While they used to distribute electricity supplied via transmission grids, solar photovoltaic (PV) generators increasingly connect to what may now be better referred to as "distribution and collection grids". Furthermore, new consumption devices like electric vehicles (EVs) and heat pumps are being adopted. Unlike conventional loads, these new technologies and an increasing amount of distributed battery storage may be operated flexibly, actively contributing to balancing the electricity system. The existing research on distributed flexibility takes two distinct perspectives: wholesale markets or distribution grids. So far, these perspectives have been disconnected, with wholesale market studies ignoring distribution grid constraints and distribution grid studies not considering wholesale market implications. This article aims to bridge this divide with an integrated model of electricity wholesale markets and distribution grids. How does considering distribution grid constraints change wholesale market outcomes? And vice versa, how do wholesale market dynamics impact distribution grid constraints?

The electricity wholesale market literature finds that distributed flexibility may offer private benefits to the users of the flexible assets and social benefits to the overall energy system. Table 1 provides an exemplary overview of such studies and the implications of the distributed flexibility they analyze. These studies typically minimize the total costs of interconnected electricity systems, and their results may be interpreted as the outcome of frictionless electricity wholesale markets. [1] The findings of wholesale market studies (as those listed in Table 1) can be summarized as follows: distributed flexibility may lower electricity bills for the users of flexible assets through shifting demand to low-price periods. At the system level, such demand shifting may (1) reduce the residual load peak and the corresponding need for firm generation and storage capacity, and (2) increase load during periods when renewable energy sources (RES) are abundant, reducing corresponding curtailment. As a result, distributed flexibility may lower CO_2 emissions and total system costs. Further studies have shown that distributed flexibility may reduce electricity prices and mitigate price volatility. While most of these studies abstract from electricity grids, a recent article by Sitzmann (2025) finds that distributed flexibility could aggravate transmission grid constraints if those constraints were not reflected in wholesale market prices.

However, none of these wholesale market studies consider distribution grid constraints, which could imply that materializing the identified benefits is physically infeasible. For instance, shifting the charging of an EV

[1] Because such models abstract from real-world market frictions, they are often referred to as system models rather than market models. However, energy system models exist at all system levels, including distribution grids. We hence use the term "wholesale market model" to emphasize that the scope of these models reflects wholesale markets.

could help avoid the curtailment of a PV generator only if there were no binding grid constraints between both assets.

Table 1: Wholesale market studies on the implications of distributed flexibility

Publication	Consumer bills	Residual load peak	RES curtailment	CO_2 emissions	Total system costs	Electricity prices	Price volatility	Transmission grid	Distribution grid
Brown et al. (2018)				✓	✓	✓			
Adelman and Uçkun (2019)	✓				✓	✓			
Ruhnau et al. (2020)		✓	✓		✓	✓			
Powell et al. (2022)		✓		✓	✓				
Kröger et al. (2023)						✓	✓		
Bogdanov and Breyer (2024)	✓		✓	✓	✓				
Emelianova and Namockel (2024)	✓	✓	✓	✓	✓	✓	✓		
Roth et al. (2024)		✓		✓	✓				
Zhang et al. (2024)				✓	✓	✓			
Boehnke et al. (2025)	✓					✓	✓		
Sitzmann (2025)	✓				✓	✓	✓	✓	
Our analysis	✓	✓	✓	✓	✓	✓	✓		✓

On the other hand, the distribution grid literature finds that distributed flexibility responding to wholesale prices may exacerbate local grid congestion (e.g. Muratori, 2018; Daneshzand et al., 2023; Unterluggauer et al., 2023; Stute and Kühnbach, 2023; Li and Jenn, 2024; Lilienkamp and Namockel, 2024; Reibsch et al., 2024). These studies typically investigate distinct distribution grids and compare a case with additional inflexible load from EVs and heat pumps to one in which the additional load flexibly responds to exogenously given wholesale prices. Their results may be interpreted as the outcomes of the central optimization of a flexibility aggregator or the decentralized optimization of home energy management systems. Similar to the wholesale market studies, such distribution grid studies find that shifting load to low-price hours may reduce consumer bills. However, they find that the joint shifting of all flexible loads to the hours with the lowest prices could induce new load peaks—a phenomenon that has been referred to as "herding behavior". While distribution grids may already be congested due to increased inflexible loads, herding behavior may exacerbate this congestion. As a countermeasure and alternative to excessive grid expansion, previous studies suggest the local coordination of flexible loads through load rationing in critical situations (Lilienkamp and Namockel, 2024) or heterogeneous tariff structures that incentivize temporally more distributed aggregate consumption patterns (Daneshzand et al., 2023).[2]

A potential issue with the distribution grid literature is that electricity wholesale prices are assumed to be exogenous. While the impact of individual consumers on wholesale markets is arguably negligible, the collective response of millions of flexible assets could affect market prices. An endogenous determination of prices and quantities could smooth the distribution of flexible load over time and reduce herding behavior relative to the findings of existing distribution grid studies.

[2]Under the term "local flexibility markets", market-based congestion management is also discussed as a solution to distribution grid constraints (e.g. Jin et al., 2020). However, this solution may suffer from adverse gaming incentives and a lack of competition (e.g. Rebenaque et al., 2023).

This article addresses the gap between these two strands of the literature. Specifically, we explore how distribution grid constraints affect the impact of distributed flexibility on wholesale electricity markets and how the simultaneous determination of flexibility dispatch and wholesale prices affects distribution grid constraints. To this end, we develop a novel three-step approach to jointly model wholesale markets and distribution grid constraints. First, we transform individual distributed flexibilities into a virtual electricity storage to enable aggregation with relatively high accuracy (Muessel et al., 2023). Second, we aggregate the individual flexibilities within each distribution grid while accounting for distribution grid constraints. Third, we aggregate the heterogeneous distribution-grid-level flexibilities and integrate the aggregated flexibility into a wholesale market model.

We apply our integrated modeling approach to a case study of flexible EV charging and low-voltage transformers, which are relevant examples of distributed flexibility and distribution grid constraints (IEA, 2022). We calibrate our distribution grid model with scenarios for the German energy system in 2030 and 2045, while considering trade with other European countries in the wholesale market model. To capture heterogeneity at the distribution grid level, we simulate spatially and temporally highly resolved time series of distributed demand and supply, and map these time series with datasets on distribution grid types and low-voltage transformer capacities. On this basis, we analyze the implications of distribution grid constraints for EV charging adjustments and PV curtailment, and for wholesale market outcomes. To demonstrate the effect of our integrated modeling approach, we compare our results to a counterfactual EV charging optimization based on exogenous prices. Finally, we compare the costs of perfectly managed distribution grid congestion (derived from its impact on wholesale market outcomes) to the costs of the distribution grid expansion that would be necessary to relieve all congestion.

Our article contributes to the literature by connecting previously disconnected studies on the impact of distributed flexibility on electricity wholesale markets and distribution grids. Methodically, we contribute a novel approach for the integrated modeling of wholesale markets and distribution grids. Substantially, we contribute insights into how distribution grid constraints may affect the impact of distributed assets on wholesale market outcomes and how the simultaneous determination of market prices and flexibility dispatch may smoothen loads in distribution grids. As our approach builds on the aggregation of distributed flexibility, we also add to the literature on aggregation techniques as a necessary tool to integrate heterogeneous technical details in electricity wholesale market models (e.g. Strobel and Pruckner, 2024; Blanchard and Massol, 2025).

The remainder of this article is structured as follows: Section 2 introduces our model for distributed flexibility in wholesale electricity markets with distribution grid constraints; Section 3 describes the details of our case study of EV flexibility in Germany; Section 4 presents the results; Section 5 compares our results to the literature and discusses limitations and real-world implications; and Section 6 concludes.

2. Methods

This section introduces our approach to integrate distribution grid constraints into electricity wholesale market models using the example of flexible EV charging. This approach entails three steps, as illustrated in Figure 1. First, we derive flexibility profiles for individual EVs (Subsection 2.1). Second, we aggregate these profiles at the distribution grid level while considering constrained transformer capacity and local RES curtailment (Subsection 2.2). Third, we integrate the distribution-grid-specific flexibility profiles into a wholesale market model (Subsection 2.3). As a benchmark for our integrated modeling approach, we also describe a model that optimizes distributed flexibility based on exogenous wholesale prices (Subsection 2.4).

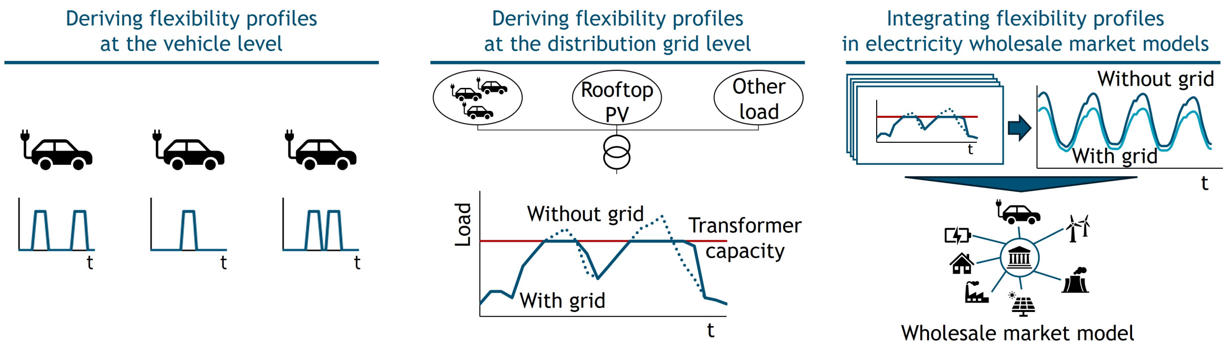

Figure 1: Three-step approach to derive and apply flexibility profiles

2.1. Deriving flexibility profiles at the vehicle level

To derive EV flexibility profiles, we build on the virtual storage approach developed by Muessel et al. (2023). This approach models flexible charging as the combination of an inflexible reference profile and the maximum deviation from this reference profile. Compared to the conventional modeling approach, the virtual storage approach has the advantage of aggregating individual flexibility profiles with higher accuracy (Muessel et al., 2023).[3] We will exploit this characteristic below to aggregate EV flexibility at the

[3]See Appendix A for an evaluation of aggregation accuracy that we conducted based on our case study.

distribution grid and wholesale market levels. Beforehand, we describe how the reference profile and virtual storage constraints are derived from the conventional representation of flexible EV charging.

The conventional representation of flexible EV charging reflects the physical EV battery storage to (3). The decision variables are the physical storage level $LEVEL_{t,e}$ and the physical charging $CHARGE_{t,e}$ in each time step $t \in T$ and for each EV $e \in EV$. The storage level depends on the storage level at the end of the previous period, the charging in the current period, and the electricity consumption during trips $consump_{t,e}$ (Eq. (1)). The charging is defined in energy terms, must be positive[4], and is constrained by an upper bound $charge^{max}_{t,e}$, which reflects whether an EV is connected to the grid and what type of charging infrastructure is available (Eq. (2)). The storage level is limited by a minimum storage level $level^{min}_{t,e}$ and a maximum storage level $level^{max}_{e}$ (Eq. (3)). Here, we set the maximum storage level to the physical capacity of the EV battery capacity, and we use two alternative scenarios for the minimum storage level to reflect uncertainty about user preferences, as explained below.

$$LEVEL_{t,e} = LEVEL_{t-1,e} + CHARGE_{t,e} - consump_{t,e} \quad \forall t \in T, t \neq t_1, e \in EV \tag{1}$$

$$0 \leq CHARGE_{t,e} \leq charge^{max}_{t,e} \quad \forall t \in T, e \in EV \tag{2}$$

$$level^{min}_{t,e} \leq LEVEL_{t,e} \leq level^{max}_{e} \quad \forall t \in T, e \in EV \tag{3}$$

For the virtual storage approach, flexible EV charging is modeled as the deviation from a reference profile. Here, we derive our reference profile from the strategy "charge as early as possible".[5] The deviation from this reference profile can be interpreted as charging and discharging a virtual storage. Put differently, the virtual storage replaces physical charging by the sum of the *early charging* reference profile $charge^{early}_{t,e}$ and the virtual storage charging $CHARGE^{vs}_{t,e}$, which can become negative for discharging:

$$CHARGE_{t,e} = charge^{early}_{t,e} + CHARGE^{vs}_{t,e} \quad \forall t \in T, e \in EV \tag{4}$$

The charging and discharging of the virtual storage is subject to a set of virtual storage constraints. The virtual storage level $LEVEL^{vs}_{t,e}$ equals the virtual storage level at the end of the previous period adjusted by the virtual charging and discharging (Eq. (5)). The virtual charging is restricted by a lower bound $charge^{min,vs}_{t,e}$ and an upper bound $charge^{max,vs}_{t,e}$ (Eq. (6)). The lower bound of the virtual charging power, i.e., the maximum virtual discharging, is equivalent to the negative *early charging* profile. Put differently, the charging in a time step can only be reduced by the physical charging given by the reference profile (Eq.

[4]Hence, we do not consider vehicle-to-grid.

[5]This can be obtained by maximizing $\sum_{t}^{T} LEVEL_{t,e}$ for all EVs, subject to the Eqs. (1) to (3).

(8)). The upper limit of the virtual charging power is the delta of the maximum physical charging potential and the physical charging of the reference profile (Eq. (9)). The maximum virtual storage level is zero, and the minimum is defined by $level_{t,e}^{min,vs}$ (Eq. (7)). The negativity constraint results from using *early charging* as the reference. As charging can only be postponed relative to this reference, the deviation in terms of battery level can only be negative. The lower limit of the virtual storage level is the difference of the resulting storage level profiles of *late charging* $level_{t,e}^{late}$ [6] and *early charging* $level_{t,e}^{early}$ (Eq. (10)).

$$LEVEL_{t,e}^{vs} = LEVEL_{t-1,e}^{vs} + CHARGE_{t,e}^{vs} \quad \forall t \in T, t \neq t_1, e \in EV \tag{5}$$

$$charge_{t,e}^{min,vs} \leq CHARGE_{t,e}^{vs} \leq charge_{t,e}^{max,vs} \quad \forall t \in T, e \in EV \tag{6}$$

$$level_{t,e}^{min,vs} \leq LEVEL_{t,e}^{vs} \leq 0 \quad \forall t \in T, e \in EV \tag{7}$$

With:

$$charge_{t,e}^{min,vs} = -charge_{t,e}^{early} \quad \forall t \in T, e \in EV \tag{8}$$

$$charge_{t,e}^{max,vs} = charge_{t,e}^{max} - charge_{t,e}^{early} \quad \forall t \in T, e \in EV \tag{9}$$

$$level_{t,e}^{min,vs} = level_{t,e}^{late} - level_{t,e}^{early} \quad \forall t \in T, e \in EV \tag{10}$$

The two modeling approaches, including the main parameters, are illustrated in Figure 2 for an EV charging process within the time frame between arrival and departure. In the following, we use the term "flexibility profiles" to refer to the time series that define the boundaries of the virtual storage (i.e., $charge_{t,e}^{min,vs}$, $charge_{t,e}^{max,vs}$, and $level_{t,e}^{min,vs}$).

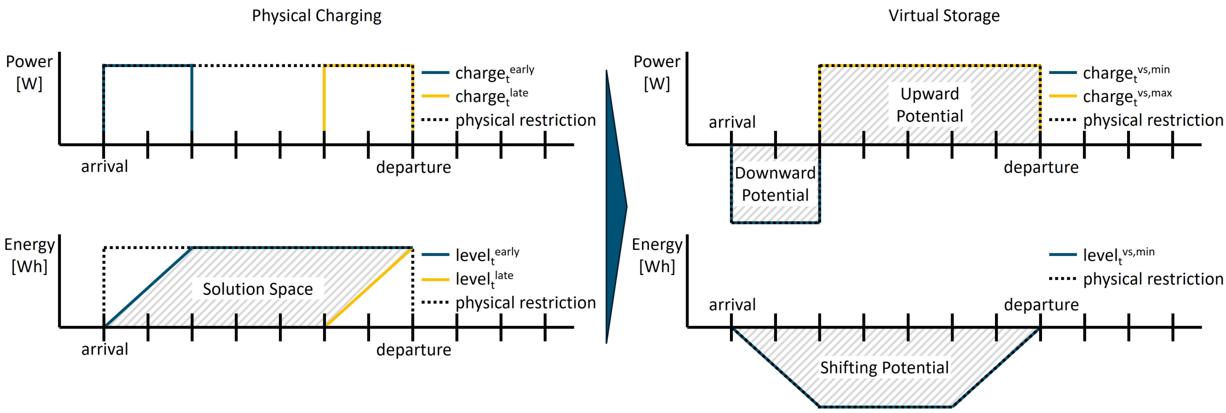

Figure 2: Modeling of EV charging processes

[6]This is the strategy "charge as late as possible", obtained by minimizing $\sum_t^T LEVEL_{t,e}$ for all EVs, subject to the Eqs. (1) to (3).

2.2. Deriving flexibility profiles at the distribution grid level

We further develop the virtual storage approach to derive aggregated flexibility profiles at the distribution grid level while considering physical constraints in these grids. We demonstrate the benefit of our extended approach using the example of limited transformer capacities in low-voltage grids and discuss its applicability to other distribution grid constraints.

First, we aggregate the flexibility of individual EVs at the distribution grid level without considering grid constraints. To this end, we define one virtual storage for each low-voltage grid $g \in G$, aggregating all connected EVs EV_g. This aggregated virtual storage is represented by the decision variables $LEVEL^{vs}_{t,g}$ and $CHARGE^{vs}_{t,g}$ and constrained by the sums of the individual EV constraints, as shown in Eqs. (11) to (13).

$$LEVEL^{vs}_{t,g} = LEVEL^{vs}_{t-1,g} + CHARGE^{vs}_{t,g} \quad \forall t \in T, t \neq t_1, g \in G \tag{11}$$

$$\sum_{e}^{EV_g} charge^{min,vs}_{t,e} \leq CHARGE^{vs}_{t,g} \leq \sum_{e}^{EV_g} charge^{max,vs}_{t,e} \quad \forall t \in T, g \in G \tag{12}$$

$$\sum_{e}^{EV_g} level^{min,vs}_{t,e} \leq LEVEL^{vs}_{t,g} \leq 0 \quad \forall t \in T, g \in G \tag{13}$$

Second, to consider potential distribution grid constraints, Eq. (14) for a transformer is added, including additional inflexible loads $load_{t,g}$ and production by RES $res_{t,g}$ alongside the reference charging profile of the EVs. The transformer load $TXLOAD_{t,g}$ is affected by the (dis-)charging of the virtual storage (i.e., EV charging deviating from the reference profile) and the curtailment of the generation from RES $CURTAIL_{t,g}$. Hence, while we focus on EV charging as the only source of flexibility, renewable generation can be curtailed if necessary. The transformer load is constrained by Eq. (15), where the parameters $txload^{min}_g$ and $txload^{max}_g$ reflect the installed transformer capacity. While the lower limit restricts the peak load from the low- to the medium-voltage grid (defined as negative), the upper limit restricts the generation-driven peak. The curtailment potential is defined with Eq. (16) as non-negative and restricted by the maximum production of RES.

$$TXLOAD_{t,g} = load_{t,g} - res_{t,g} + \sum_{e}^{EV_g} charge^{early}_{t,e} + CHARGE^{vs}_{t,g} + CURTAIL_{t,g} \quad \forall t \in T, g \in G \tag{14}$$

$$txload^{min}_g \leq TXLOAD_{t,g} \leq txload^{max}_g \quad \forall t \in T, g \in G \tag{15}$$

$$0 \leq CURTAIL_{t,g} \leq res_{t,g} \quad \forall t \in T, g \in G \tag{16}$$

Following the virtual storage logic, we model flexibility at the distribution grid level as the deviation from a reference transformer load profile. Here, we derive our reference profile from the strategy "charge as early as possible while considering grid constraints". Put differently, we replace the physical transformer load by the sum of the *early charging under grid constraints* reference profile $txload_{t,g}^{early}$ and the distribution-grid-level virtual storage charging $CHARGE_{t,g}^{vs,tx}$, which can become negative for discharging:

$$TXLOAD_{t,g} = txload_{t,g}^{early} + CHARGE_{t,g}^{vs,tx} \quad \forall t \in T, g \in G \tag{17}$$

Note that the distribution-grid-level virtual storage differs from the aggregated virtual storage of the EVs, i.e., $CHARGE_{t,g}^{vs,tx} \neq CHARGE_{t,g}^{vs}$, as the distribution-grid-level virtual storage considers distribution grid constraints.

The reference transformer load profile for *early charging under grid constraints* is determined by maximizing the virtual storage level as shown in Eq. (18), subject to the constraints Eqs. (11) to (16). In contrast to before, the objective function contains a penalty term for curtailment. The term prioritizes the local utilization of EV flexibility to maximize consumption of otherwise curtailed generation by RES. Hence, the distribution-grid-level virtual storage characterizes the remaining flexibility that is available for the electricity wholesale market after this local optimization. Note that we penalize the *cumulative* curtailment to identify unique solutions, characterized by postponing inevitable curtailment as much as possible, for the maximization (*early charging*) and minimization (*late charging*) of Eq. (18).

$$min/max \sum_{t}^{T} (LEVEL_{t,g}^{vs} \pm bigM * \sum_{\tau=0}^{t} CURTAIL_{\tau,g}) \quad \forall g \in G \tag{18}$$

The flexibility profiles that characterize the distribution-grid-level virtual storage, defined in Eqs. (19) to (21), can be derived from the aggregated EV flexibility profiles. Eq (22) defines the lower bound of the charging of the distribution-grid-level virtual storage $charge_{t,g}^{min,vs,tx}$ as the *early charging under grid constraints* reference profile, which can be derived from the aggregated EV-level early charging profiles and the charging profile of the aggregated virtual storage in the *early charging* run $charge_{t,g}^{early,vs}$. The upper bound $charge_{t,g}^{max,vs,tx}$ is equivalent to the minimum of the aggregated available charging power and the available transformer capacity (see Eq. (23)). The available charging power corresponds to the aggregated EV-level maximum charging power reduced by the *early charging under grid constraints* reference profile. Similarly, the available transformer capacity is the difference between the maximum transformer capacity and the actual transformer load of the reference profile.

The maximum possible energy deviation from the reference profile $level_{t,g}^{min,vs,tx}$ is the aggregated EV-level maximum possible energy deviation adjusted by the difference between the virtual storage levels of the *late charging* (minimization) and the *early charging* (maximization) runs.

$$LEVEL_{t,g}^{vs,tx} = LEVEL_{t-1,g}^{vs,tx} + CHARGE_{t,g}^{vs,tx} \quad \forall t \in T, t \neq t_1, g \in G \tag{19}$$

$$charge_{t,g}^{min,vs,tx} \leq CHARGE_{t,g}^{vs,tx} \leq charge_{t,g}^{max,vs,tx} \quad \forall t \in T, g \in G \tag{20}$$

$$level_{t,g}^{min,vs,tx} \leq LEVEL_{t,g}^{vs,tx} \leq 0 \quad \forall t \in T, g \in G \tag{21}$$

With:

$$charge_{t,g}^{min,vs,tx} = -(\sum_{e}^{EV_g} charge_{t,e}^{early} + charge_{t,g}^{early,vs}) \quad \forall t \in T, g \in G \tag{22}$$

$$charge_{t,g}^{max,vs,tx} = \min(\sum_{e}^{EV_g} charge_{t,e}^{max} + charge_{t,g}^{min,vs,tx}; txload_{g}^{max} - txload_{t,g}^{early}) \quad \forall t \in T, g \in G \tag{23}$$

$$level_{t,g}^{min,vs,tx} = \sum_{e}^{EV_g} level_{t,e}^{min,vs} + level_{t,g}^{late,vs} - level_{t,g}^{early,vs} \quad \forall t \in T, g \in G \tag{24}$$

Our model explicitly focuses on transformer constraints in low-voltage grids. However, further low-voltage-grid constraints may be added to our approach by analogy with Eqs. (14) to (16). Furthermore, it may be extended to account for other grid layers, such as individual low-voltage branches or medium-voltage networks, by iteratively aggregating and adjusting flexibility profiles from lower to higher levels.

2.3. *Integrating flexibility profiles in electricity wholesale market models*

In the final step, we integrate the low-voltage grids' flexibility profiles in aggregated form into an electricity wholesale market model, which is then used to investigate the system effects of low-voltage grid constraints. To this end, we aggregate the grid profiles to a single virtual storage at the system level. We then integrate the aggregated virtual storage into the European electricity wholesale market model DIMENSION. We use DIMENSION to represent the short-term partial equilibrium of the electricity market, which is implemented as a linear program minimizing total system costs. Hence, we optimize the dispatch of various assets with given installed capacities. The model covers one year in an hourly resolution and 28 European countries with one node per country. In addition to electricity generation, central heat generation with combined heat and power plants and heat-only plants, and the production and import of synthetic fuels are optimized. Central model assumptions are presented in Appendix B. Further details about the model capabilities and functionalities have been documented in recent publications, including Richter (2011), Helgeson and Peter (2020), Helgeson (2024), and Emelianova and Namockel (2024).

To integrate low-voltage grids into the optimization model, we add the aggregated reference transformer load profiles ($\sum_{g}^{G} txload_{t,g}^{early}$) and the flexible deviation from these reference profiles ($CHARGE_{t}^{vs,tx}$) to the electricity balance of the model. The other parameters and variables in the electricity balance represent demand, supply, storage, and other flexible technologies connected to higher voltage levels. Hence, the difference between national and low-voltage load and PV supply is considered in the national electricity balance.

We integrate the flexibility of low-voltage grids into the wholesale market model as one system-level virtual storage, defined in Eqs. (25) to (27). Recall that the flexibility emerges from adjusting the charging power of EVs connected to the low-voltage grid relative to the reference profile while minimizing local curtailment and respecting the maximum transformer load. The system-level virtual storage is represented by the decision variables $LEVEL_t^{vs,tx}$ and $CHARGE_t^{vs,tx}$ and constrained by the sums of the individual distribution-grid-level flexibility profiles.

$$LEVEL_t^{vs,tx} = LEVEL_{t-1}^{vs,tx} + CHARGE_t^{vs,tx} \quad \forall t \in T, t \neq t_1 \tag{25}$$

$$\sum_g^G charge_{t,g}^{min,vs,tx} \leq CHARGE_t^{vs,tx} \leq \sum_g^G charge_{t,g}^{max,vs,tx} \quad \forall t \in T \tag{26}$$

$$\sum_g^G level_{t,g}^{min,vs,tx} \leq LEVEL_t^{vs,tx} \leq 0 \quad \forall t \in T \tag{27}$$

2.4. Modeling benchmark

To identify the implications of our novel approach for the integrated modeling of distribution grid constraints and wholesale markets, we compare it to the conventional approach of optimizing flexibility utilization in distribution grids with exogenously given wholesale market prices (Daneshzand et al., 2023; Lilienkamp and Namockel, 2024; Reibsch et al., 2024). To this end, we minimize the EV charging costs based on exogenous wholesale electricity price time series, which we derive from an endogenous model run [7]. The optimization is subject to the virtual storage equations (11) to (13).

3. Case study

This section describes our case study of flexible EV charging in Germany, to which we apply the previously introduced modeling approach. Subsection 3.1 focuses on the parametrization of low-voltage grids, before Subsection 3.2 introduces the broader energy system scenarios and the setup of our subsequent evaluation.

[7] More precisely, the EV flexibility deployment for each grid is optimized based on the objective function $min \sum_t^T (\sum_e^{EV_g} (charge_{t,e}^{early} + CHARGE_{t,g}^{vs}) * price_t)$.

3.1. *Low-voltage grid parameters*

To account for the structural and regional heterogeneity of German low-voltage grids, we consider six distinct grid structures with eight different transformer capacities for each of the 402 NUTS-3 regions in Germany. With some grid structures not present in every NUTS-3 region, this results in a dataset of 16,191 unique low-voltage grids. We model these grids individually and scale the results according to their respective share within the German electricity system, before aggregating and integrating them into our wholesale market model.

The individual low-voltage grid parameters are derived in three steps, as illustrated in Figure 3. First, we determine the regional distribution of electricity demand and supply (Subsection 3.1.1). Second, we assign the regionalized demand and supply data to representative low-voltage grids (Subsection 3.1.2). Finally, we build on a real-world grid dataset to parameterize heterogeneous transformer sizes (Subsection 3.1.3).

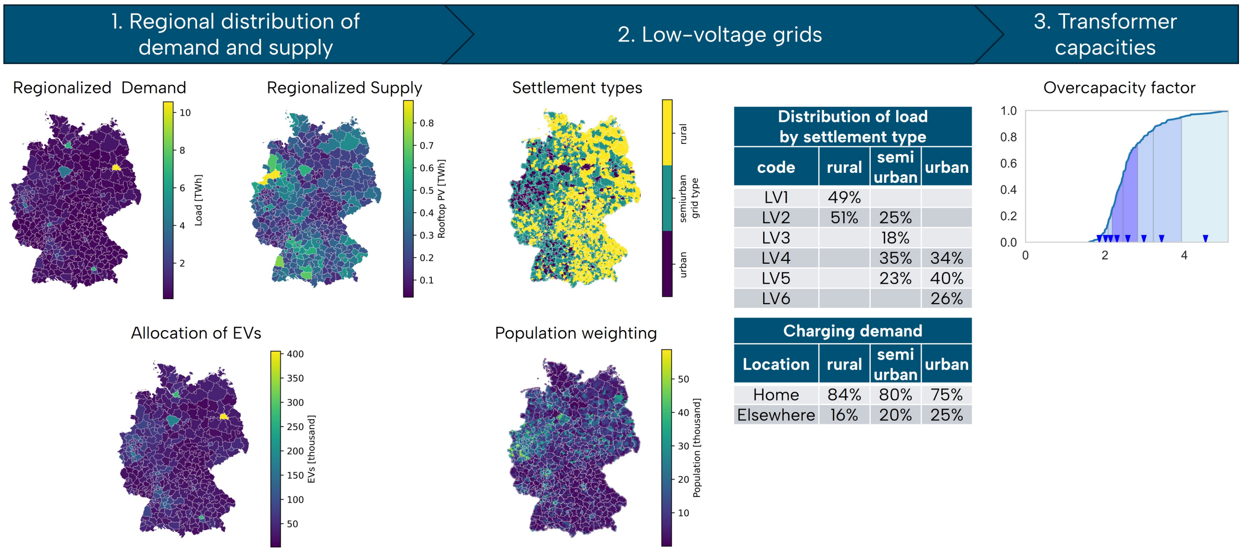

Figure 3: Process for the parameterization of low-voltage grids

3.1.1. *Regional distribution of demand and supply*

To assign the overall electricity demand and supply to the 402 NUTS-3 regions in Germany, we follow the approach outlined by Arnold et al. (2024). We assume that residential and commercial demand is connected to the low-voltage grid level and, therefore, relevant when deriving the distribution-grid-level flexibility profiles (this concerns approximately 52% of Germany's total demand). By contrast, we assume industrial demand to be connected to higher voltage levels and directly consider it in the electricity balance of the wholesale market model. The demand accounts for the expected expansion of heat pumps, which are considered heat-led and hence not flexible in this case study. Regarding RES, we focus on rooftop PV in our distribution-grid-level model while assuming that other renewable generation technologies, such as wind turbines and large-scale PV systems, are connected at higher voltage levels. According to data from the German regulator, approximately 76% of the total rooftop PV capacity is connected to low-voltage grids (BNetzA, 2024a).

The regional distribution of EV penetration and the corresponding demand also follow Arnold et al. (2024). Furthermore, we use the German Mobility Panel (KIT - Institut für Verkehrswesen, 2021) to develop 2,000 individual EV flexibility profiles [8]. These profiles are randomly assigned to individual EVs to reflect variations in user behavior and charging patterns. Furthermore, we assume that EV flexibility is exclusively available at home charging stations. In this context, we account for differences in home charging prevalence across settlement types, which ranges between 75% and 84% of total charging events (see Figure 3)[9].

3.1.2. Low-voltage grid types

The allocation of electricity demand and supply to different low-voltage grid types is based on the classification of municipalities within each NUTS-3 region into settlement types: urban, semi-urban, and rural. Electricity demand and supply are distributed among the municipalities in proportion to population.

The settlement types are matched with representative German medium-voltage grids, as categorized by the Simbench dataset (Meinecke et al., 2020). Each medium-voltage grid is further disaggregated into low-voltage grids, following six distinct topologies (LV1–LV6) derived from the same dataset. A single medium-voltage grid may consist of multiple low-voltage grid types of the same topology. The annual electricity demand within each medium-voltage grid is distributed among the different low-voltage grids based on the original characteristics of the Simbench dataset.

3.1.3. Transformer capacities

Finally, we consider heterogeneity in the capacity of low-voltage grid transformers. This is essential for capturing the phenomenon that some distribution grids will be congested earlier than others. We cannot reproduce this phenomenon with the representative (average) transformer capacities specified in the Simbench dataset and, therefore, make specific assumptions about transformer heterogeneity.

[8]Following Muessel et al. (2023), the amount of 2,000 distinct profiles should adequately represent the heterogeneity of EV charging on a system level.

[9]The values are NUTS-level averages calculated based on Prognos et al. (2020).

To this end, eight different transformer capacities are considered for each low-voltage grid type within a given NUTS-3 region and settlement type. The different transformer capacities are determined by scaling the low-voltage-grid-specific peak load, excluding EV and heat pump demand, with varying overcapacity factors. We exclude EVs and heat pumps here, as we assume the low-voltage grid transformers were dimensioned before the broader adoption of these technologies.

The overcapacity factors are derived from a dataset on low-voltage grid parameters provided by German distribution grid operators for the year 2022 (BNetzA, 2024b). Figure 4 illustrates the distribution of transformer overcapacity factors based on data from 198 distribution grid operators. Note that this distribution reflects variation only across and not within distribution grid operators. This distribution should hence be interpreted as a conservative estimate for the heterogeneity of transformer capacities in German low-voltage grids. In reality, we would expect some transformers within each grid to have even smaller capacities (while others have larger).

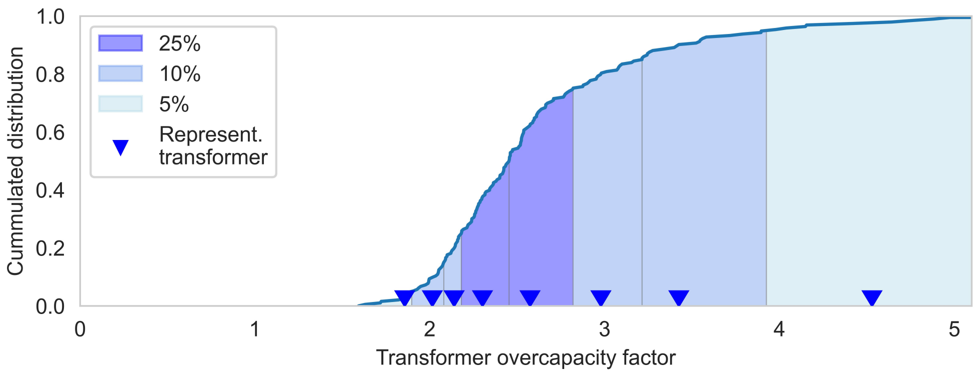

Figure 4: Probability distribution of transformer capacity

On this basis, we divide each modeled low-voltage grid into eight sub-grids. We then assign heterogeneous overcapacity factors and fractions of the load to these sub-grids according to the cumulative distribution function. For example, approximately 10% of the load is assigned to low-voltage sub-grids in which the transformer capacity is about three times the peak load, excluding EVs and heat pumps. Hence, throughout our analysis, the transformer capacities reflect the status quo without considering anticipated future grid expansion.

3.2. Scenario definition and evaluation

This subsection describes the two energy system scenarios to which we apply our model (Subsection 3.2.1). Additionally, we introduce the framework (Subsection 3.2.2) and metrics (Subsection 3.2.3) for evaluating the impact of considering distribution grid constraints in wholesale market models under different assumptions on EV flexibility.

3.2.1. Energy system scenarios

While our case study focuses on Germany, we model the German electricity wholesale market in the European context. To this end, we define two scenarios of the European energy system, for the years 2030 and 2045.

For Germany, our primary data source is one of five prominent German long-term energy scenarios (EWI/ITG/FIW/ef.Ruhr, 2021), which we update to reflect the latest policies and regulations. In particular, we account for recent adjustments regarding the German coal phase-out (BMJ, 2022) and the renewable energy capacity targets (BMWK, 2022a). Details on the assumed installed capacities and on the assumed electricity demand are provided in Appendix B.

For the broader European energy system, we incorporate sector- and fuel-specific energy demand, nuclear capacity trajectories, minimum RES targets, and cross-border net transfer capacities based on data from ENTSO-E and ENTSOG (2024). Regarding coal and natural gas capacities, we complement the capacity trajectories from ENTSO-E and ENTSOG (2024) with further investments resulting from a preceding investment optimization using DIMENSION (Richter, 2011). We use the 2015 weather year and select corresponding RES profiles (wind and solar) from ENTSO-E (2022) and model corresponding sectoral demand profiles following Arnold et al. (2024). Fuel prices are derived from IEA (2024), with additional details provided in Appendix B alongside CO_2 prices.

The primary distinction between the 2030 and 2045 scenarios is the level of decarbonization. In our 2030 scenario, approximately 17 GW of coal capacity will remain operational in Germany, whereas we assume Germany will achieve climate neutrality by 2045. On the other hand, we consider a substantial increase in the installed capacity of RES and the number of EVs between 2030 and 2045. Specifically, we assume 15 million EVs in Germany by 2030 (in line with projections from BMWK (2022b)) and 35 million EVs by 2045. EVs in countries outside Germany are not considered in this analysis.

3.2.2. Evaluation framework

To investigate the impact of distribution grid constraints on distributed flexibility, we compare model configurations that differ in whether EVs are charged flexibly and whether distribution grid constraints are considered, as depicted in Figure 5. Concerning charging flexibility, we contrast the earliest possible charging (*Early*) with flexible charging that responds to wholesale prices (*Flex* and *moreFlex*). For distribution grid constraints, we either consider limited transformer capacity or not. In this regard, *Early-DG* represents the earliest possible charging by EVs, given distribution grid constraints, and *Flex-DG* represents the best possible alignment of EV charging with wholesale prices, given distribution grid constraints. Note that PV curtailment at the distribution grid level is minimized only in the case of flexible charging with grid constraints (the penalty term in Eq. (18)).[10]

The scenarios without distribution grid constraints are hypothetical in the sense that they neglect existing physical constraints. Any divergence from the scenarios with distribution grid constraints implies that the scenarios without constraints are physically infeasible. We calculate the scenarios without distribution grid constraints for two reasons. First, omitting distribution grid constraints represents state-of-the-art wholesale market modeling (i.e., studies in Table 1). Comparing scenarios with and without distribution grid constraints helps us quantify the error in this state-of-the-art modeling and illustrates the added value of our advanced modeling approach. Second, the scenarios without distribution grid constraints serve as counterfactuals for determining the minimally necessary EV charging adjustments and PV curtailment, along with the associated costs as described in Subsection 3.2.3. These minimum volume adjustments and costs may be interpreted as the result of perfectly efficient coordination mechanisms, such as redispatch or temporally and spatially varying grid fees, as discussed further in Subsection 5.4.[11]

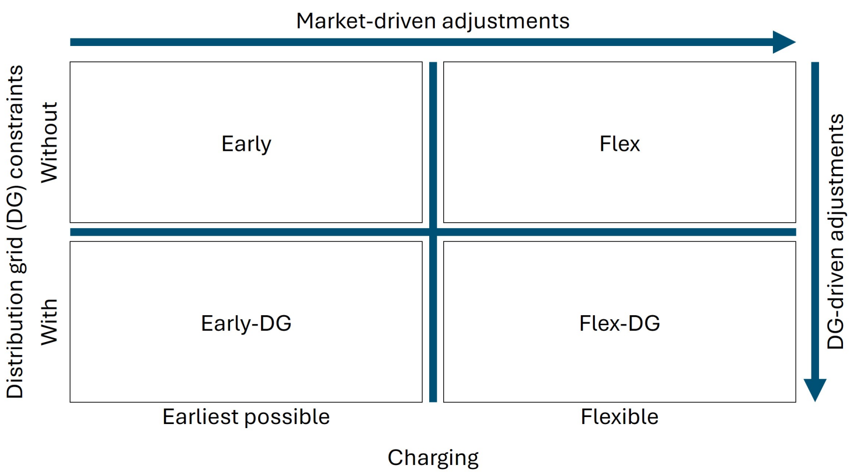

Figure 5: Four different model configurations within the evaluation framework

Early charging without grid constraints (*Early*) marks the starting point for two pairwise comparisons. First, the comparison to early charging with grid constraints (*Early-DG*) yields differences that can be

[10]Without grid constraints, there is no PV curtailment at the distribution grid level. With early charging, there is PV curtailment at the distribution grid level, but it is not minimized.

[11]Note that using dynamic grid fees as a coordination mechanism requires the assumption that EV charging responds to price incentives, which is consistent with flexible charging (*Flex-DG*), but not with early charging (*Early-DG*)

interpreted as the inaccuracy of models that ignore grid constraints or distribution-grid-driven adjustments of EV charging and PV generation. Second, the comparison with flexible charging without grid constraints (*Flex*) yields differences that can be interpreted as wholesale-market-driven adjustments without considering distribution grid constraints. Flexible charging with constraints (*Flex-DG*), in turn, is compared to flexible charging without grid constraints (*Flex*), which reveals the necessary distribution-grid-driven adjustments when EV charging responds to wholesale prices.

Regarding the flexibility of EVs, we consider two different levels. In the *Flex* configuration, we assume that charging can be adjusted only as long as the storage level at departure is as high as possible. To this end, we set the minimum storage level $level^{min}_{t-1,e}$ in Eq. (3) to the storage level of *early charging* at departure $level^{early}_{t_{e,dep}-1,e}$, and to zero for other periods (Eq. (28)). This assumption reflects the observation that some EV users assign a high value to their EVs' storage level (e.g. Lagomarsino et al., 2022).

$$level^{min}_{t-1,e} = \begin{cases} level^{early}_{t-1,e} & \forall t \in T_{e,departures} \\ 0, & \forall t \in T \setminus T_{e,departures} \end{cases} , \forall e \in EV \tag{28}$$

In a sensitivity analysis (*moreFlex*), we allow for more flexibility provided by EVs. We disable Eq. (28) such that EVs must charge only as much electricity as required for the next trip, rather than charging as much as possible. Instead, we force EVs to ensure a minimum level of 30% whenever possible, which is found to be acceptable by Schmalfuß et al. (2015).

3.2.3. Evaluation metrics

We evaluate the effects of the previously introduced model configurations based on the following metrics: used EV flexibility, charging price, peak residual load, curtailment of RES, CO_2 emissions, electricity price, price volatility, and total system costs. All parameters are evaluated for Germany. These metrics are directly derived from the outputs of our electricity wholesale market model. The used EV flexibility is computed as the sum of the positive hourly deviations from the reference charging profile in the *Early* model configuration. The average EV charging price is the average of the hourly electricity prices weighted by the hourly charging load. The peak residual load is calculated by subtracting renewable generation from electricity consumption, including exogenous load time series at all voltage levels and potentially endogenously optimized charging load from EVs. The curtailment of electricity generation from RES is the portion of renewable generation potential that cannot be utilized due to distribution grid constraints (as determined by the low-voltage grid model) and system-wide surpluses (as determined by the wholesale market model). The CO_2 emissions are calculated for all sectors, while only the electricity, central heating, and energy end-use sectors are determined endogenously. The electricity price is the load-weighted average price for the year. Finally, the electricity price volatility equals the standard deviation of the electricity price time series. The total system costs include the variable costs associated with electricity generation, net imports, central heat generation with combined heat and power plants and heat-only plants, and the production and import of synthetic fuels.

In an additional analysis, we compare distribution grid congestion costs with grid expansion costs.[12] For the grid congestion costs, we calculate the difference in system costs between the model configuration that considers grid constraints and the one that does not. Note that this cost difference reflects the costs of grid constraints under the assumption that congestion is perfectly resolved. If congestion is resolved through redispatch, congestion costs may be interpreted as redispatch costs, which are usually paid by system operators and passed on to consumers via grid fees. If congestion is resolved through temporally and spatially varying grid fees, congestion costs may be interpreted as the additional wholesale market costs of EV drivers when responding to the grid fees by shifting charging to times with higher wholesale market prices and the foregone wholesale market revenue of PV owners when responding to the grid fees with curtailment. As the real-world implementation of such mechanisms for resolving distribution grid congestion will always be imperfect, our estimate of distribution grid congestion costs may be interpreted as a lower bound (see Subsection 5.4 for a discussion of potential coordination mechanisms).

To derive grid expansion costs, further assumptions and processing are needed. First, we determine the required capacity expansion to mitigate all distribution grid constraints. To this end, we calculate the residual load before considering grid constraints and compare the maximum absolute residual load with the transformer capacity for each distribution grid. We determine the residual load for the *Early* configuration based on the *early charging* profile. For the *Flex* configuration, we distribute the optimized EV load from the wholesale market model to the individual grids according to the absolute number of EVs. [13] The absolute load peak can be determined by the positive load peak, driven by local consumption (including EVs), or by the negative load peak, driven by local PV surplus. We interpret the maximum difference between the absolute load peak and the transformer capacity as the required grid expansion. However,

[12]As in our analyses, we focus on congestion and expansion costs related to low-voltage transformers. Hence, both our expansion cost estimate and our congestion cost estimate are conservative, as they do not account for grid expansion costs other than low-voltage transformers. They are also both conservative because we assume perfect information (i.e., due to exhaustive measurement technology roll-out). Imperfect information may increase the imperfectness of grid congestion management and require more grid expansion due to extensive safety margins.

[13]Note that we analyze individual distribution grids rather than the aggregated wholesale market profile, as individual load peaks do not necessarily coincide. Thus, considering an aggregated profile would underestimate grid expansion requirements.

we assume that a slight overload of 10%, based on a standard low-voltage transformer with a capacity of 630 kVA, is temporarily acceptable. We translate the required capacity expansion into costs, considering the additional installation of the smallest possible multiple of a 630 kVA standard transformer to cover the expansion requirements.[14] We assume that the additional transformers are controllable and uncontrollable in equal shares and include n-1-redundancy. Last, we annualize the transformer investment costs (including auxiliary costs, i.e., for substations or operational expenses) as explained in Appendix C.

4. Results

The results are structured into four main parts. Subsection 4.1 analyzes the impact of distribution grid constraints on EV charging profiles and PV curtailment. Subsection 4.2 continues with analyzing the impact of distribution grid constraints on the electricity wholesale market. Subsection 4.3 contrasts the results of our approach to jointly model wholesale markets and distribution grid constraints with that of modeling distribution grids with exogenous prices. Finally, Subsection 4.4 quantifies the monetary value of resolving distribution grid constraints, providing insights into the economic and operational benefits of addressing such constraints in the system.

4.1. The impact of distribution grid constraints on EV charging and PV curtailment

We begin by analyzing the temporal patterns in the charging profiles and how they are affected by the distribution grid constraints for the 2030 scenario, as visualized in Figure 6.

[14]We hence ignore potential synergies arising from increasing transformer sizes when age-related replacement is needed anyway. Leveraging such synergies could reduce expansion costs relative to our estimate.

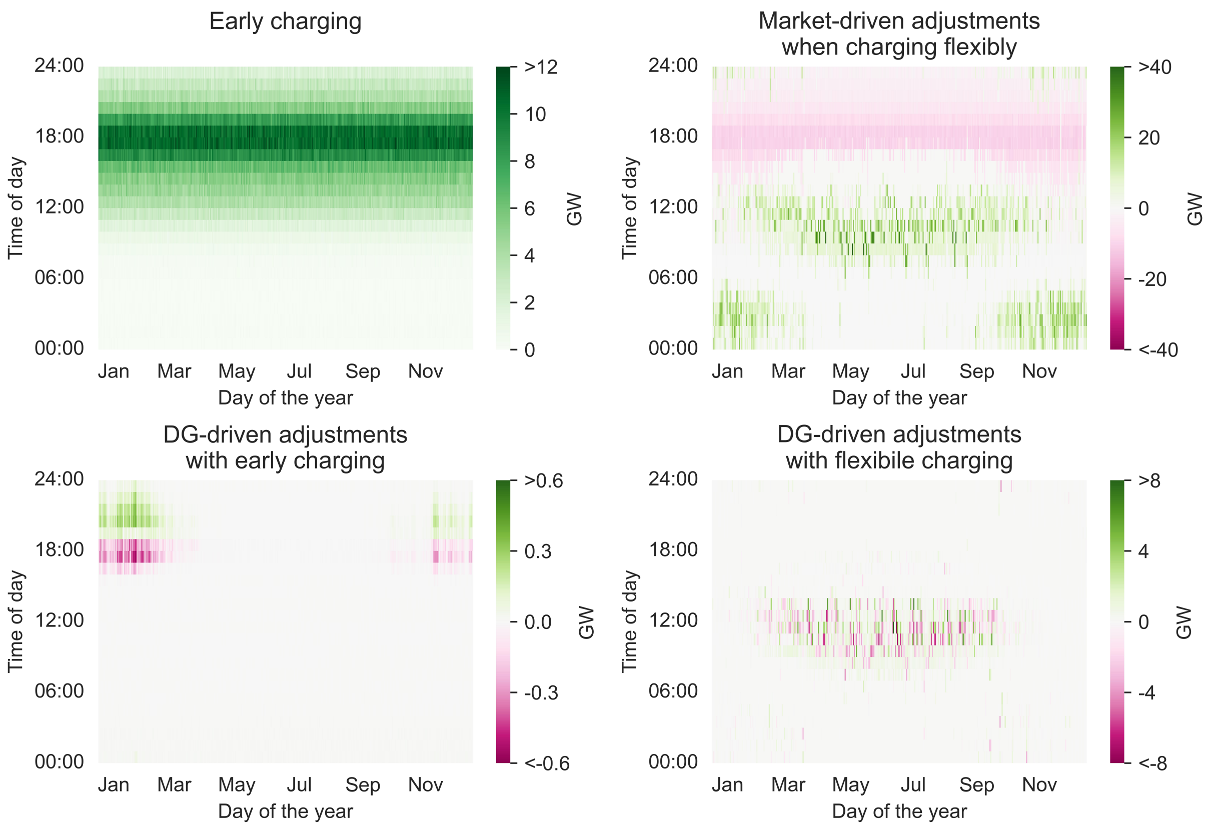

Figure 6: Charging profiles and adjustments across our four model configurations

The top left plot shows the hourly charging profile for the *Early* configuration. The bottom left plot presents the deltas between the *Early-DG* and the *Early* configurations. The top right plot visualizes the deltas between the *Flex* and the *Early* configurations. Finally, the bottom right plot depicts the deltas between the *Flex-DG* and *Flex* configurations.
In the delta plots, the red and green colors indicate a reduction and increase in charging load, respectively.

For the *Early* charging configuration, we observe a distinct daily charging load pattern, which peaks around 6 p.m. and does not exhibit substantial seasonality (top-left plot in Figure 6). The charging load peak is approximately 12 GW, which is substantial compared to the system peak residual load of around 100 GW. This result is consistent with Strobel et al. (2022), who find that the uncontrolled charging of 15 million EVs would increase the national residual peak demand by approximately 8 GW, and with Muessel et al. (2023), who estimate charging load peaks of around 1 kW per EV (i.e., 15 GW for 15 million EVs).

The *Early-DG* configuration reveals that the early charging load needs to be adjusted so as not to violate distribution grid constraints (the adjustments are displayed in the bottom-left plot in Figure 6). Particularly in the winter months, charging demand needs to be reduced between 5 PM and 8 PM, which causes a subsequent increase in demand between 9 PM and 11 PM. Compared to the charging peak load of roughly 12 GW in the *Early* configuration, the maximum charging profile adjustments in the *Early-DG* configuration of approximately 0.6 GW seem minor (5%). These grid issues disappear in the summer months, as the residual load on low-voltage grids is lower due to the absence of electrical heating and the electricity generation of local solar PV systems.

In the *Flex* configuration, the charging load shifts away from the early evening toward times with lower wholesale electricity prices (the adjustments are displayed in the top-right plot in Figure 6). The charging load is shifted to midday hours in summer, when solar PV is available, and to nighttime hours in winter, when other loads are low. We can observe that EVs concentrate their charging load in a few hours, with a maximum load increase of approximately 40 GW. This phenomenon has been observed in earlier publications and is referred to as "herding behavior" (Valogianni et al., 2020; Lilienkamp and Namockel, 2024) or "avalanche effect" (Sperber et al., 2025).

Finally, the *Flex-DG* configuration reveals that, in addition to the wholesale-price-based adjustments in the *Flex* configuration, further charging load adjustments are necessary to align charging load with distribution grid constraints (the adjustments are displayed in the bottom-right plot in Figure 6). These adjustments occur for two reasons. First, the herding behavior in the *Flex* configuration causes distribution grid bottlenecks at specific times. The deltas in winter are undoubtedly caused by herding behavior, and some deltas in summer may be explained by this reason, too. The second reason for charging profile adjustments in summer is minimizing PV curtailment in low-voltage grids.[15] The adjustments reach a maximum of roughly 8 GW, which is 20% of the price-induced adjustments in the *Flex* configuration.

By comparing the second row in Figure 6, we observe different patterns of distribution-grid-induced charging profile adjustments. With early charging, the adjustments occur in the winter evening hours. By contrast, flexible charging mitigates adjustments in the evening because the charging load at this time has already been reduced based on wholesale prices. However, adjustments now occur during sunny summer hours and a few nighttime hours in winter. Interestingly, the charging load in the *Flex-DG* configuration in summer is mainly shifted to adjacent hours. It can be expected that PV generation is similarly abundant, and electricity prices are similarly low in these adjacent hours, albeit to a somewhat lesser extent than the first-best charging hour.

In addition to the previously analyzed temporal patterns of charging adjustments, Figure 7 compares the duration curves of charging adjustments caused by distribution grid constraints.

[15] As noted in Subsection 2.2, there are multiple solutions to minimizing PV curtailment in low-voltage grids, and we identify the solution that postpones inevitable curtailment as much as possible. There may be other solutions that minimize PV curtailment in low-voltage grids but require smaller charging load adjustments relative to the *Flex* configuration.

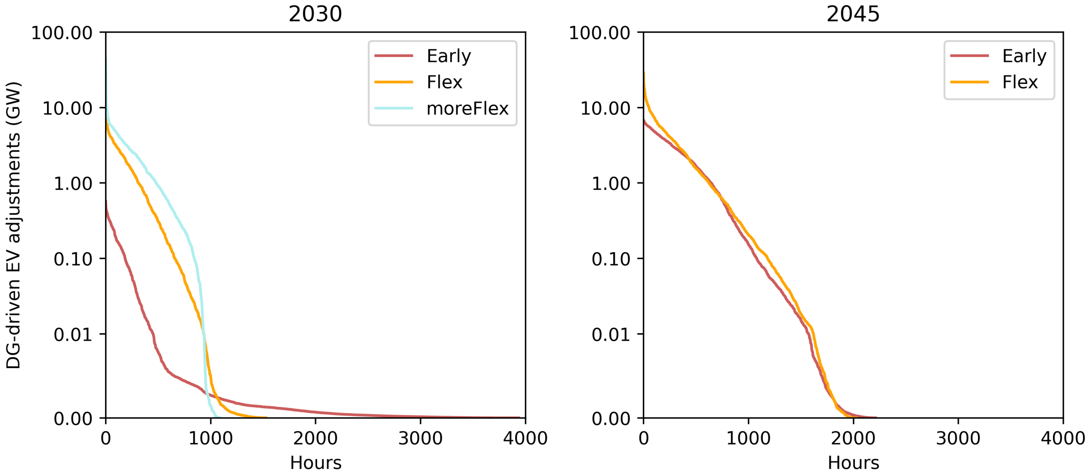

Figure 7: Duration curves of distribution-grid-driven EV charging adjustments

The duration curves show the delta between configurations with and without considering distribution grid constraints. For example, the line labeled with “Early" shows the delta between the *Early-DG* and the *Early* configurations, i.e., the same data as in the bottom left plot in Figure 6.

For the 2030 scenario, we observe distinct patterns for different assumptions on EV charging flexibility (left plot in Figure 7). If we assume *Early* charging, i.e., no EV flexibility, distribution-grid-driven EV charging adjustments are necessary in almost every second hour of the year. However, the size of the adjustments is relatively small, with a maximum of 560 MW. In total, 60 GWh of charging demand needs to be shifted to avoid distribution grid congestion. Flexible charging, in contrast, results in fewer hours with distribution-grid-driven EV charging adjustments (1,000 to 1,500 hours per year), but the magnitude of these adjustments is substantially larger, reaching up to 7.8 GW in the *Flex* and 41.2 GW in the *moreFlex* configurations. The total amount of shifted EV charging increases to 1 TWh and 1.8 TWh, respectively. Notably, these shifting events do not only occur to avoid EV-related grid congestion but also to reduce the curtailment of local PV generation.

In the 2045 scenario, with *Early* charging, the number of hours with charging profile adjustments decreases compared to the 2030 scenario, but the magnitude of adjustments increases significantly to a maximum of 6.8 GW. Although adjustments occur less frequently, the total energy shifted increases to around 2.2 TWh. This suggests that, without expansion, an increasing EV penetration exacerbates the grid's challenges in accommodating the load even without charging flexibility. This trend of a decreasing number of hours with adjustments and a growing magnitude of adjustments intensifies in the *Flex* configuration. The maximum deviation reaches 28.8 GW, and the total energy shifted rises to 3 TWh. Recall that these adjustments are not only due to EV-induced grid congestion, but also to avoid curtailing local PV production.

Interestingly, the relative differences between the *Flex* and *Early* configurations become smaller in the 2045 scenario, relative to the 2030 scenario. This indicates that the total amount of grid-induced EV charging adjustments becomes less dependent on the assumed flexibility of EV charging.

The real-world interpretation of charging adjustments depends on the mechanisms implemented for resolving distribution grid congestion. If congestion is resolved through redispatch, charging adjustments may be interpreted as redispatch volumes. If temporally and spatially varying grid fees are implemented, the adjustments may be interpreted as the response of EV charging to these grid fees. Note that we abstract from the imperfection of real-world mechanisms for resolving congestion, as discussed further in Subsection 5.4.

Distribution-grid-driven PV curtailment

We now turn toward analyzing distribution-grid-driven PV curtailment, an important driver of flexible EV charging adjustments (as discussed above) with relevant implications for energy market outcomes (as discussed below). Figure 8 displays the duration curves of distribution-grid-driven PV curtailment for the different energy system scenarios and model configurations.

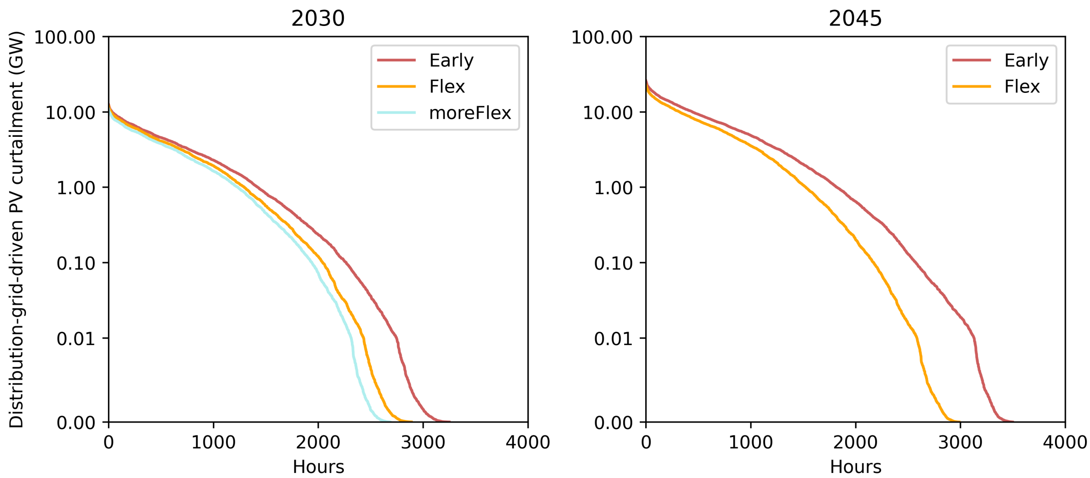

Figure 8: Duration curves of distribution-grid-driven PV curtailment

The amount of distribution-grid-driven PV curtailment decreases when EV charging becomes more flexible, which is a direct result of our assumption that EV flexibility is used to avoid local curtailment. In the 2030 scenario, grid-driven curtailment is reduced from 6.17 TWh in the *Early* configuration to 5.44 TWh in the *Flex* and 4.84 TWh in the *moreFlex* configuration. While the maximum constrained feed-in in terms of power remains constant at approximately 10 GW across all configurations, increased flexibility in EV charging behavior notably reduces the frequency of congestion events. In the 2045 scenario, grid-driven PV curtailment rises to 12.92 TWh in the *Early* configuration and decreases to 10.11 TWh with flexible charging in the *Flex* configuration. These elevated levels reflect the higher penetration of distributed PV generation, increasing the likelihood of grid congestion. Again, flexible charging reduces the number of hours with congestion, while the maximum curtailment decreases only slightly, from 25.8 GW to 22.8 GW.

Similar to the interpretation of EV charging adjustments, PV curtailment may be interpreted as redispatch volumes or the response to temporally and spatially varying (generation) grid fees, depending on the mechanisms implemented for resolving distribution grid congestion.

Comparing our results on PV curtailment with those on charging adjustments suggests that decentralized PV may present a greater challenge to distribution grids than EVs in terms of both energy and frequency. Regarding peak power, charging adjustments appear relatively small in the *Early* configuration compared to grid-driven PV curtailment, but they increase as more flexibility is utilized. In the *moreFlex* configuration, the peak charging profile deviation exceeds the maximum PV curtailment.

4.2. The impact of distribution grid constraints on electricity wholesale markets

This subsection analyzes the implications of distribution grid constraints on electricity wholesale markets for varying assumptions on EV flexibility. Such implications may result from the redispatch of distributed EV consumption and PV generation, which requires equivalent volumes to be redispatched at the wholesale market level. Alternatively, these implications may be interpreted as the result of distributed assets responding to temporally and spatially varying grid fees and, therefore, self-adjusting bids on wholesale markets. Figure 9 presents the absolute values and changes for our evaluation metrics across the different model configurations.

		Early charging			Flexible charging		
	Parameter	**absolute**	**absolute delta**	**relative delta**	**absolute**	**absolute delta**	**relative delta**
With distribution grid constraints	EV adjustments [TWh]	0.06	0.06	-	18.71	0.03	0.16%
	Charging price [€/MWh]	67.68	0.27	0.40%	46.15	0.90	1.99%
	Peak residual load [GW]	100.84	-0.32	-0.32%	91.63	0.00	0.00%
	RES curtailment [TWh]	27.66	2.82	11.35%	24.08	2.82	13.26%
	CO_2 emissions [Mio. t. CO_2 Eq.]	401.55	0.22	0.05%	399.63	0.20	0.05%
	Weighted electricity price [€/MWh]	61.16	0.01	0.02%	60.46	0.03	0.05%
	Electricity price volatility [€/MWh]	30.24	-0.31	-1.01%	29.37	-0.26	-0.89%
	Total system costs [bn. €]	10.07	0.05	0.49%	9.47	0.06	0.64%
	Parameter	**absolute**			**absolute**	**absolute delta**	**relative delta**
Without distribution grid constraints	EV adjustments [TWh]	0.00			18.68	18.68	-
	Charging price [€/MWh]	67.41			45.25	-22.16	-32.87%
	Peak residual load [GW]	101.16			91.63	-9.53	-9.42%
	RES curtailment [TWh]	24.84			21.26	-3.58	-14.41%
	CO_2 emissions [Mio. t. CO_2 Eq.]	401.33			399.43	-1.90	-0.47%
	Weighted electricity price [€/MWh]	61.15			60.43	-0.72	-1.18%
	Electricity price volatility [€/MWh]	30.55			29.63	-0.92	-3.01%
	Total system costs [bn. €]	10.02			9.41	-0.61	-6.13%

Figure 9: Energy system effects of flexibility and distribution grid constraints

The bottom-left corner shows the reference configuration — early charging without distribution grid constraints. The top left presents the absolute values in the configuration as well as the deltas compared to the reference. In the bottom right, we examine the configuration where flexible charging is allowed. Again, the presented deltas refer to the reference. In the top right plot we observe the deltas between flexible charging with distribution grid constraints and the flexible charging case without constraints (bottom right).

The *Early* configuration serves as the baseline configuration for the 2030 scenario (lower-left corner in Figure 9). In this setup, charging occurs according to a fixed profile, which determines the evaluation metrics, including average charging price, peak residual load, curtailment of RES, CO_2 emissions, the average electricity price (weighted by total load), price volatility, and total German system costs.

When we introduce distribution grid constraints (top-left corner in Figure 9), the most significant implication is an increase in RES curtailment. The observed increase of about 2.8 TWh (11.35%) is the net effect of an increase in distribution-grid-driven PV curtailment of about 6.2 TWh (see Subsection 4.1) and a decrease in market-driven curtailment of about 3.4 TWh. Hence, some PV generation that is curtailed at the distribution-grid level would have been curtailed at the wholesale market level anyway. These curtailment effects partly influence the other evaluation metrics, though their changes are less significant. The higher RES curtailment results in increased electricity production from conventional power plants, leading to higher CO_2 emissions and an increase in total system costs. Perhaps, this also partially explains reduced price volatility. Additionally, about 60 GWh of charging is postponed to meet grid limits. This reduces peak residual demand and may also contribute to lower electricity price volatility. EV owners do not benefit from adjusted charging in terms of a lower charging price. Apparently, the slightly postponed charging still coincides with relatively high electricity prices. As a result of these changes, total system costs increase by 49 million euros (less than 1%), and the change in the average electricity price is negligible. [16]

When we allow for flexible charging (bottom-right corner in Figure 9), system efficiency increases significantly. By shifting about 19 TWh of EV charging (65% of total home charging), all evaluation metrics improve in the *Flex* configuration compared to the *Early* configuration. This is in line with previous studies quantifying welfare gains from decentralized flexibility deployment (e.g., Ruhnau et al., 2020; Emelianova and Namockel, 2024). Flexible charging significantly reduces both peak load and renewable energy curtailment by shifting EV demand away from high-demand periods and toward times of abundant renewable generation. As a result, CO_2 emissions, average prices, price volatility, and system costs decrease.

When distribution grid constraints are introduced in combination with flexible charging (*Flex-DG* configuration in the top-right corner in Figure 9), the most notable impact is an increase in RES curtailment. As in the *Early-DG* configuration, this is the net effect of an increase in distribution-grid-driven curtailment and a decrease in market-based curtailment. The other evaluation metrics are barely affected by considering distribution grid constraints (changing less than 1%, except for charging prices increasing by around 2%).[17] Comparing the *Flex-DG* and *Early-DG* configurations, the benefits of flexible charging are almost independent of considering distribution grid constraints: charging prices, peak residual load, RES curtailment, CO2 emissions, electricity prices, their volatility, and total system costs also reduced in the presence of distribution grid constraints.

Overall, accounting for distribution grid constraints reveals that RES curtailment is somewhat higher than estimated by distribution-grid-unaware wholesale market models, although the impact on emissions, prices, and overall system costs is relatively small. Crucially, the benefits of flexible EV charging—such as lower charging prices, reduced peak residual load, and decreased curtailment—remain substantial even when considering distribution grid constraints.

[16] Recall that we only estimate the effects of distributed flexibility and distribution grid constraints in Germany and neglect potential spillovers that distributed flexibility and distribution grid constraints in other countries may have on the German market.

[17] Note that the 30 GWh increase in the overall EV adjustments is relatively small compared to the 1 TWh increase in the distribution-grid-driven EV adjustments observed in Subsection 4.1. This can be explained by the fact that most of the distribution-grid-driven adjustments affect charging volumes that have already been adjusted on a market basis in the *Flex* configuration.

How different model assumptions drive results

We now assess how our results change with more optimistic assumptions on EV flexibility (the *moreFlex* configuration) and in our 2045 scenario. Figure 10 visualizes selected evaluation metrics across all scenarios and configurations. Table D.1 provides numbers for the complete set of evaluation metrics.

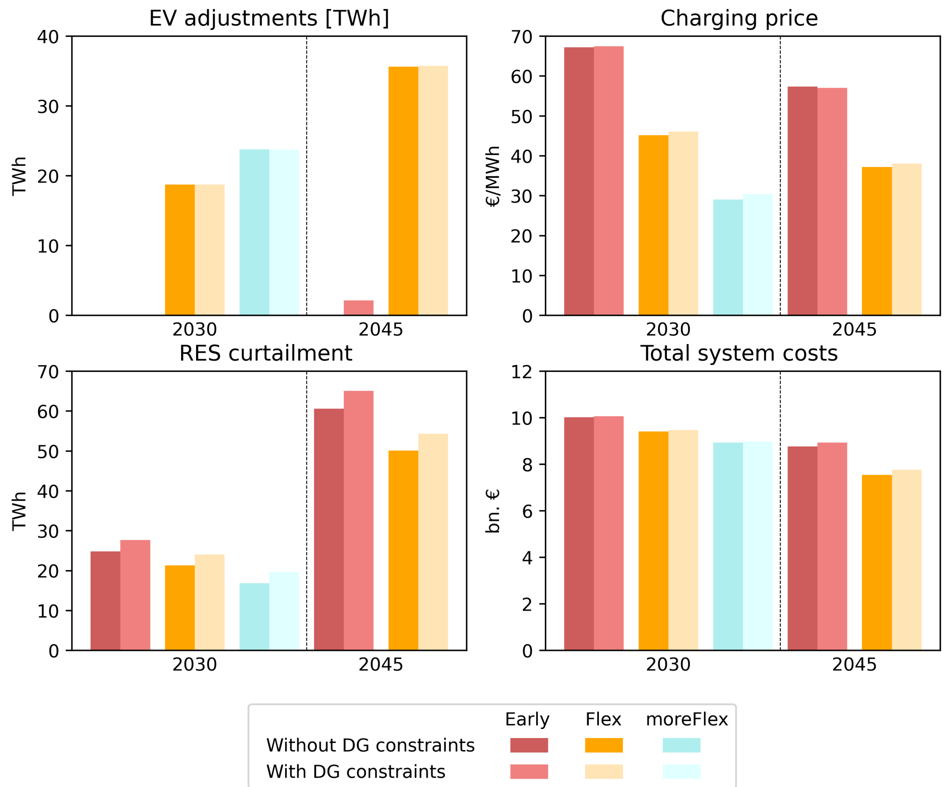

Figure 10: Scenario comparison system effects

Each subplot of the figure focuses on a specific parameter, displaying the absolute values for the different system configurations. The different configurations are grouped for the 2030 and 2045 scenarios.

In general, while the level of certain evaluation metrics changes substantially across scenarios and model configurations, the impact of distribution grid constraints remains virtually unchanged. In particular, the deployment of flexibility reduces charging prices, RES curtailment, and total system cost even when accounting for distribution grid constraints.

Focusing on the *moreFlex* configuration, in which we replace the requirement for EVs to be fully charged upon departure by a minimum state-of-charge, leads to an increase in EV flexibility by about 5 TWh. EV charging can now be adjusted even better to coincide with periods of low electricity prices and high RES availability. This further reduces RES curtailment and total system costs. Moreover, EV owners benefit from further decreased charging prices. Nevertheless, compared to the *Flex* configuration, distribution grid constraints still add 2.82 TWh of curtailment, and increase charging prices even more significantly (+1.26 EUR/MWh with *moreFlex-DG* compared to +0.9 EUR/MWh with *Flex-DG*).

In the 2045 scenario, which entails a climate-neutral German energy system, the higher number of EVs comes with greater flexibility but also leads to increased EV-driven distribution grid congestion in the *Early* configuration. While the level of charging prices decreases in the 2045 scenario, distribution grid constraints continue to slightly increase charging prices in the *Flex-DG* configuration relative to the *Flex* configuration. As expected, RES curtailment increases due to the growing share of RES in the 2045 scenario. Interestingly, the relative impact of distribution grid constraints becomes smaller (e.g., +7.4% in the 2045 scenario versus +11.4% in the 2030 scenario for the *Early-DG* configuration). Furthermore, total system costs rise due to the increased reliance on synthetic fuels. The relative impact of distribution grid constraints on total system costs increases slightly from 0.1% in the 2030 scenario to 0.2% in the 2045 scenario.

4.3. Comparing integrated modeling with using exogenous wholesale prices

In our integrated modeling approach, electricity wholesale prices are endogenously determined and thus directly influenced by distribution grid constraints. This contrasts with previous distribution grid studies that optimize EV charging under distribution grid constraints based on exogenous wholesale prices (Daneshzand et al., 2023; Stute and Kühnbach, 2023; Lilienkamp and Namockel, 2024; Reibsch et al., 2024). Exogenous prices would be justified if EV charging did not impact wholesale price formation. While this assumption may hold for adjusting EV charging within a single distribution grid, the aggregate impact of adjusting EV charging across all distribution grids could be substantial. Assuming prices are exogenous to EV charging seems particularly questionable given that previous studies find that EVs concentrate their charging in the hour with the lowest price. In contrast, we expect such herding behavior to weaken with integrated modeling: as EVs shift consumption to the lowest-priced hour within a specific period, the increase in EV consumption raises the price until it is not the lowest price within that period anymore; further EV consumption will then be shifted to other hours, resulting in a more balanced distribution of EV consumption over time.

To illustrate the effect of integrated modeling on herding behavior, Figure 11 compares our results from the *Flex* configuration to an additional model run in which prices are fixed exogenously to the levels that endogenously emerge from our integrated modeling. Overall, this comparison confirms our hypothesis of integrated modeling leading to smoother load patterns.

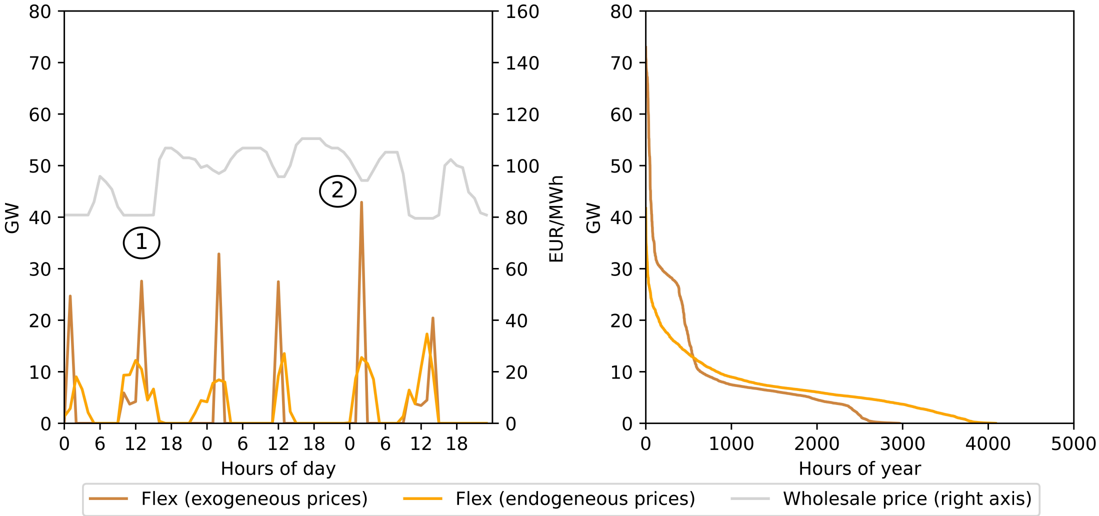

Figure 11: Integrated modeling vs. exogenous prices

The left plot shows the price time series (gray line) and the corresponding aggregated EV loads when prices are determined endogenously (orange line) or given exogenously (brown line) for three days in the 2030 scenario and the *Flex* configuration. The right plot presents the corresponding yearly EV load duration curves.

The left plot in Figure 11 displays EV load patterns and prices for three exemplary days. Under exogenous pricing, herding behavior leads to more pronounced peaks when prices are lowest at night (when load is low) or around midday (when PV production is high). Note that we frequently observe situations in which the same low price occurs for several subsequent hours, and the resulting EV load peak can be considered arbitrary, as other load patterns exist that are equally attractive under exogenous pricing (1). In contrast, endogenous prices introduce a more even distribution of charging loads, as prices adjust in response to increased demand until an intertemporal equilibrium is reached. This also applies to situations when there is a single cheapest hour within a specific period. While load concentrates in this hour under exogenous prices, load is also shifted to adjacent hours with higher prices with endogenous prices (2).

This pattern is further reflected in the comparison of the load duration curves, as shown in the right plot in Figure 11. Under exogenous prices, the load profile is significantly more concentrated, with a step-wise structure and a 75% higher peak load. By contrast, the curve under endogenous prices shows a more continuous and balanced shape.

The contrasting modeling approaches lead to considerably different load profiles, directly affecting the derived conclusions. This includes potentially necessary distribution-grid-driven EV charging adjustments, as examined above, or grid expansion, as analyzed below. We discuss the real-world interpretation of endogenous and exogenous in Section 5.

4.4. Comparing distribution grid congestion costs with grid expansion costs

We conclude our analysis by quantifying the costs required to resolve all distribution grid constraints and comparing them with the costs of distribution grid congestion. To this end, we first calculate the aggregated expansion requirements for each model configuration (with endogenously calculated prices). The results are presented in the left plot of Figure 12, with distinctions between whether PV or EV primarily drives the expansion.

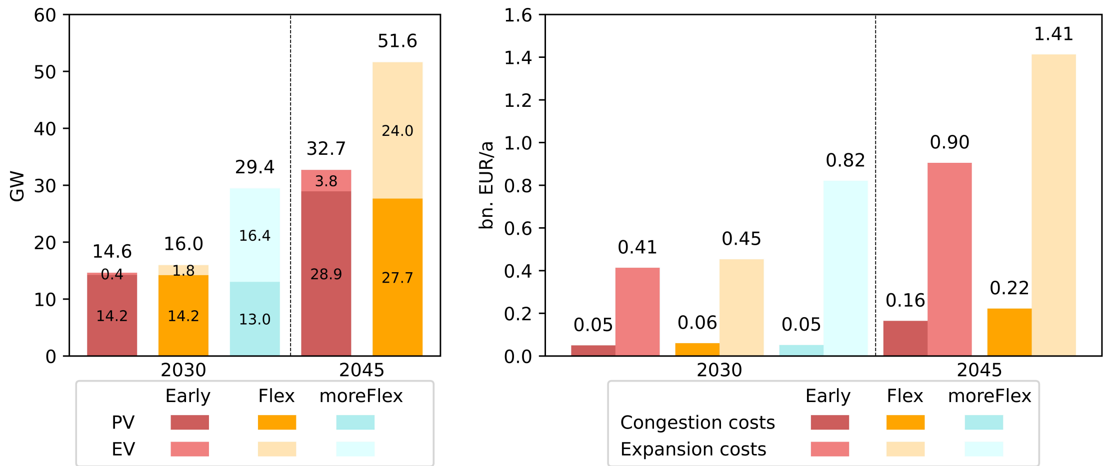

Figure 12: Cumulated grid expansion requirements and cost comparison

The left plot shows the cumulated grid expansion requirements by the primary driver. For each grid we check, whether PV or EV causes more significant grid constraints and, therefore, defines the overall grid expansion.
The right plot presents the comparison of the annualized congestion costs and expansion costs.

The results indicate that the expansion requirements increase over time, reflecting the ramp-up of EVs and PV systems, and with the assumed EV flexibility. In the 2030 scenario, approximately 15 GW of expansion is needed, mainly due to PV installations in both the *Early* and *Flex* configurations. Only under a substantial increase in EV flexibility, as in the *moreFlex* configuration, do EVs become the dominant driver of expansion. In the 2045 scenario, with roughly double the PV capacity and more than twice the number of EVs, grid limits are exceeded more frequently and to a greater extent. Total expansion requirements rise to approximately 33 GW and 52 GW across configurations. While PV-driven expansion doubles in the *Early* and *Flex* cases compared to 2030, EV-driven expansion increases tenfold and thirteenfold, respectively. In the *Flex* configuration, EV-driven expansion becomes nearly as relevant as PV-driven expansion. It is worth noting that expansion requirements exceed the aggregated load-shifting and PV curtailment volumes presented in Figure 7 and Figure 8. Aggregated profiles conceal the heterogeneous and diverging peaks across individual distribution grids.

We also evaluated the spatial distribution of expansion and found that it reflects the two drivers: while PV-driven expansion is concentrated in rural areas, EV-driven expansion primarily occurs in urban load centers; accordingly, as EVs become a more relevant driver of distribution grid constraints over time, expansion needs in urban areas grow disproportionately (see Appendix E).

Finally, the right plot of Figure 12 compares the resulting annualized grid expansion costs for the different model configurations with the cost of grid congestion, which we derive from the difference in system costs between the model configurations with and without consideration of grid constraints. Recall that the congestion costs may be interpreted as the costs of perfect redispatch or changes in wholesale market costs and revenues of EV and PV owners when responding to temporally and spatially varying grid fees (see Subsection 3.2.3).

Across all configurations, full grid expansion costs exceed congestion costs by roughly one order of magnitude. In the 2030 scenario, congestion costs are in the double-digit million range for all model configurations, while grid expansion costs vary with the level of EV flexibility. For instance, the *Early* configuration requires grid investments of 410 mn. EUR per year, increasing by about 10% in the *Flex* configuration and doubling in the *moreFlex* configuration. For the 2045 scenario, all numbers rise, though the relative increase is larger for congestion costs. While congestion costs triple in the *Early* configuration, expansion costs only double. In the *Flex* configuration, congestion costs increase even more significantly, while expansion costs reach approximately 1.4 bn. EUR per year.

As expected, our estimated expansion costs are somewhat smaller than the total distribution grid expansion costs estimated in prior studies. For instance, ef.Ruhr and EWI (2024) project total low-voltage and medium-voltage grid expansion costs of 67 bn. EUR by 2045, which corresponds to an annuity of about 4.2 bn. EUR per year when applying the same annuity factor used in our analysis. The deviation between our estimate and theirs can be attributed to differences in modeling approach (ef.Ruhr and EWI (2024) assumes higher simultaneity factors than we observe in our data) and scope (ef.Ruhr and EWI (2024) considers multiple voltage levels and grid elements, while we focus on low-voltage transformers).

[17] The cost basis for this analysis is given in Appendix C.

5. Discussion

This section discusses the implications of our findings for the literature on EV flexibility in electricity wholesale markets and distribution grids. Furthermore, we discuss our article's limitations and takeaways for coordinating wholesale markets and distribution grids in the real world.

5.1. EV flexibility in electricity wholesale markets

Our results suggest that distribution grid constraints have a limited impact on the potential role of EV flexibility in electricity wholesale markets. Previous wholesale market studies have found—without considering distribution grid constraints—that distributed flexibility can improve market results. Namely, distributed flexibility can reduce the system peak residual load, renewable curtailment, power sector emissions, average electricity prices, their volatility, and system costs (see Table 1). While the results of our model configuration without distribution grid constraints confirm these findings, our main contribution is the joint modeling of wholesale markets and distribution grid constraints. For the example of low-voltage transformer capacities in Germany, we find that considering grid constraints significantly increases the curtailment of distributed solar PV and partially necessitates shifting EV charging processes. However, the simulated wholesale market results and the corresponding EV charging price are hardly affected. This suggests that distributed flexibility can deliver benefits to electricity wholesale markets despite distribution grid constraints.

5.2. EV flexibility in distribution grids

Our results suggest that flexible EV charging can both exacerbate and resolve distribution grid congestion. Previous studies have found that EV charging that flexibly aligns with national wholesale prices can induce local grid bottlenecks (e.g. Daneshzand et al., 2023; Li and Jenn, 2024; Lilienkamp and Namockel, 2024). Our model results confirm that such herding behavior potentially threatens the distribution grid. However, our integrated modeling of wholesale markets and distribution grids suggests that herding behavior may be less pronounced than estimated by previous studies that use exogenous wholesale prices. On the other hand, we find that EV flexibility can help resolve distribution grid constraints, which would also occur if EVs did not respond to national wholesale prices. This includes the congestion caused by inflexible EV charging and local excess PV generation, both of which we find become more prevalent with the increasing penetration of EVs and PV. By shifting EV charging away from periods with EV-driven congestion and toward periods of PV-driven congestion, flexibility helps alleviate the strain on transformers and reduce local PV curtailment.

Furthermore, our findings indicate that using some EV flexibility and accepting some local PV curtailment to resolve distribution grid constraints is one order of magnitude cheaper than expanding transformer capacity to the extent that resolves all distribution grid constraints. This is in line with previous studies finding that flexible load management can reduce grid expansion costs (e.g. Stute and Kühnbach, 2023) and implies that the cost-optimal expansion costs may be lower than estimated by previous studies that aim for distribution grids without bottlenecks (e.g. BNetzA, 2023; Agora Energiewende, 2024; IMK, 2024; Fraunhofer ISI, 2024; ef.Ruhr and EWI, 2024).

5.3. Limitations

Our results are idiosyncratic to the assumed flexibility of EV charging, which is naturally uncertain. First, we assume that all EV drivers participate in providing flexibility services in response to wholesale price fluctuation and distribution grid constraints, which should be interpreted as an upper limit. Other studies assume lower participation rates (e.g., 56% in Agora Energiewende (2023)) and identified various drivers of participation rates (Vey et al., 2025). Similarly, we assume that EVs are always plugged in at home, which may also be optimistic (Gonzalez Venegas et al., 2021; Gschwendtner et al., 2023). Lower participation and plug-in rates would attenuate both benefits and threats that EVs imply for wholesale markets and distribution grids. Second, in our *Flex* configuration, we assume that the state-of-charge of EVs is maximized at departure, which may be somewhat conservative. Our *moreFlex* configuration highlights the substantial effect of increasing flexibility, but it does not capture the full range of possible assumptions. A lower minimum state-of-charge or considering vehicle-to-grid could increase flexibility beyond what we model.

Furthermore, our article focuses solely on the flexibility provided by EVs. Other potential flexibility options in distribution grids, such as home storage systems and the flexible operation of heat pumps, may have similar implications as EV flexibility (Ruhnau et al., 2020; Restel and Say, 2025). For instance, home storage systems could absorb local surplus during midday hours, reducing local grid congestion and related PV curtailment. On the other hand, home storage responding to wholesale prices may also be prone to herding behavior.

Lastly, our results capture only a fraction of real-world distribution grid constraints, and we ignore transmission grids. We focus on the limit that low-voltage transformer capacity imposes on *active* power. While this approach provides valuable illustrative insights, it remains stylized. In reality, transformer capacity limits *apparent* power, i.e., the superposition of active and reactive power. As reactive power is generally not zero, low-voltage transformers will be congested more than our results suggest. Beyond transformer capacity, line capacity and voltage limits can imply low-voltage grid constraints. Further congestion may occur due to medium- and high-voltage constraints in the distribution and transmission grids, from which we abstract in our case study. To the extent that these constraints are not reflected in wholesale markets, they would further increase congestion, and flexibility benefits may be smaller in the wholesale markets and larger in the grids, relative to our results.[18]

5.4. Real-world implications

We employ a deterministic techno-economic optimization model, which implies that the results of our model should be interpreted as techno-economic potentials under perfect foresight: EVs are charged either as early as possible (*Early*) or aligned as much as possible with low wholesale prices (*Flex*); and the consideration of grid constraints results in minimal adjustments of these results. Techno-economic models are frequently used to represent short-term electricity wholesale markets (e.g. Ruhnau et al., 2022). Real-world wholesale market results can be expected to deviate from modeling results due to imperfect foresight and market imperfections such as market power. In our case, imperfect foresight may lead to a suboptimal scheduling of EV flexibility and, hence, reduced associated benefits. However, EV flexibility could also yield additional benefits not covered in our model. For instance, EV flexibility could help balance forecast errors of renewable energy sources (through intraday or balancing markets) and reduce opportunities for suppliers to exercise market power (through increasing the price elasticity of electricity demand).

The results of our model runs with distribution grid constraints may be interpreted as a representation of wholesale electricity markets with perfectly efficient local coordination mechanisms. These local coordination mechanisms could be redispatch or spatially and temporally varying grid fees. Redispatch refers to the locational rescheduling of generation and controllable load within a bidding zone by system operators. Hence, system operators would need to adjust EV charging and PV generation behind the distribution grid constraint relative to the schedules resulting from wholesale market trading and also change the schedules of assets in front of the constraint to keep the overall system balance. As an alternative to redispatch, spatially and temporally varying grid fees could incentivize the desired dispatch of distributed assets, implying that they would also adjust their wholesale market bidding accordingly. This requires the assumption that EV charging responds to price incentives, which is consistent with flexible charging (*Flex-DG*) but not with early charging (*Early-DG*). To incentivize adjustments of both load and generation, dynamic grid fees would be required for both usage and export.

[18] Sitzmann (2025) analyzes this phenomenon at the transmission grid level.

In the real world, one could expect both types of locational coordination mechanisms to be highly imperfect and, therefore, deviate from the techno-economic optimum we identify. Redispatch requires extensive information about the state of the grid and the connected flexible assets, as well as the technical possibility to control these assets centrally. On the other hand, setting efficient dynamic grid fees would require information about wholesale market prices, which the grid fees would need to counteract, as well as the responsiveness of producers and consumers to prices (wholesale prices and grid fees). As a result of imperfect locational coordination, the real-world distribution-grid-driven charging and PV adjustments, as well as the related costs, may be larger than estimated by our model. The implementation of coordination mechanisms may also imply expenses that are not considered in our analysis.

To illustrate the imperfections of real-world coordination mechanisms, consider the example of Germany. German distribution system operators (DSOs) have recently introduced time-of-use grid fees. Such deterministically varying local price signals may, on average, incentivize grid-friendly EV charging. However, they cannot coordinate EV charging with stochastic variations in the local residual load as captured in our model. Furthermore, German grid fees are homogeneous within each DSO and, therefore, cannot address heterogeneity between low-voltage transformers as in our model. As a measure of last resort, German DSOs can mandate a locally specific but otherwise non-discriminatory reduction in EV charging power. Unlike with redispatch, these reductions are not compensated for by the DSOs but must be balanced by the affected balancing responsible parties (suppliers or aggregators). While this may help address stochastic variations and within-DSO heterogeneity, the non-discriminatory nature of the charging power reduction may not as efficiently coordinate between different EVs behind one transformer as we model it. While price and volume signals may improve in Germany and elsewhere, the fragmented nature of distribution grids may imply that coordination at this grid level may remain highly imperfect for the foreseeable future (Lilienkamp and Namockel, 2024).

Finally, our modeling results with endogenous and exogenous prices have implications for the real-world integration of EVs in electricity wholesale markets. We show that the integrated modeling of wholesale prices and EV flexibility reduces peak demand compared to fixed price signals. In the real world, dynamic tariffs are often fixed to wholesale prices from the day-ahead auction. As a result, consumers may choose to concentrate the load in hours with the lowest day-ahead wholesale prices, as in our modeling with exogenous wholesale prices. Suppliers must balance such concentrations in intraday markets or pay imbalance prices. Once the EV load is large enough to affect prices, this will lead to additional costs for the supplier and the overall system. Such wholesale costs of herding behavior may be reduced through a better integration of

EVs in wholesale electricity markets. For instance, aggregators could submit price-dependent bids to the day-ahead and intraday markets and coordinate the fulfillment of continuously optimized schedules among the EVs in their portfolio.

6. Conclusion

Previous studies have found that distributed flexibility may significantly benefit future electricity wholesale markets, but they did not account for distribution grid constraints. We address this gap with a wholesale market model that captures distribution grid constraints through an enhanced virtual storage approach.

Applying our novel model to a case study of EV flexibility in Germany, we find that distribution grid constraints limit not only EV flexibility but also inflexible EV charging and PV in-feed. While distribution grid constraints may significantly increase the curtailment of distributed PV, the effect on EV flexibility seems minor. Optimizing flexible EV charging only based on wholesale prices may induce load peaks when wholesale prices are low (herding behavior). Relative to previous distribution grid studies that use wholesale prices as an exogenous input, herding behavior is reduced in our integrated model. This is because we capture that shifting the EV charging to the hour with the lowest wholesale price increases the price until it is no longer the lowest, and further charging is moved to other hours, which then feature equally low prices. Still, even with endogenous pricing, EV charging load may need to be adjusted to respect local grid constraints. Our results suggest that these adjustments are substantial in magnitude and frequency but have minor effects on wholesale markets, as EV charging can be shifted to adjacent hours with similarly high shifting benefits. As a result, the implied costs of distribution grid congestion are one order of magnitude lower than our estimated costs of expanding distribution grids until there are no more bottlenecks.

This suggests that distributed flexibility has the potential to be a more cost-effective solution to distribution grid constraints than large-scale grid expansion. For this potential to materialize, local coordination mechanisms are essential. Such mechanisms must address both generation- and load-related constraints and may use price or volume signals. Regardless of the type of signal used, local coordination mechanisms need to consider not only the demand and supply situation in the local grid but also the wholesale market result, as this may substantially impact the use of distributed flexibility. For instance, wholesale market prices may incentivize an increase in EV charging to reduce market-wide PV curtailment, which may aggravate local grid congestion. Efficient coordination mechanisms may enable the wholesale market to benefit from distributed flexibility while avoiding hazards in the distribution grids.

We identify several areas for further research that could build on our article. First, the uncertainty around our parametrization of EV flexibility may be resolved based on extended empirical research on the users' willingness to participate. Second, our analysis may be extended to other flexibility options, such as heat pumps or home storage systems, to gain a more complete view of the aggregate effect of various kinds of distributed flexibility. Likewise, our approach may be extended to capture grid constraints beyond low-voltage transformers. Finally, the efficient design of local coordination mechanisms, which help align wholesale market incentives with grid constraints, is a relevant direction for further research.

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Nomenclature

Sets, parameters and decision variables

Table 2: Sets

Set	Unit	Description
$e \in EV$	-	Electric vehicle
$e \in EV_g$	-	Electric vehicle located in low-voltage grid g
$g \in G$	-	Low-voltage grid
$t \in T$	-	Time step

Table 3: Decision variables

Variable	Unit	Description
$CHARGE_{t,e}$	MWh	Physical charging of electric vehicle e at time step t
$CHARGE^{vs}_{t,e}$	MWh	Virtual charging of electric vehicle e at time step t
$CHARGE^{vs}_{t,g}$	MWh	Aggregated virtual charging of electric vehicles in low-voltage grid g at time step t
$CHARGE^{vs,tx}_{t,g}$	MWh	Aggregated virtual charging of electric vehicles in low-voltage grid g at time step t, taking distribution grid constraints into account
$CURTAIL_{t,g}$	MWh	Curtailment of the production from renewables in low-voltage grid g at time step t
$LEVEL_{t,e}$	MWh	Physical storage level of electric vehicle e at time step t
$LEVEL^{vs}_{t,e}$	MWh	Virtual storage level of electric vehicle e at time step t
$LEVEL^{vs}_{t,g}$	MWh	Aggregated virtual storage level of electric vehicles in low-voltage grid g at time step t
$LEVEL^{vs,tx}_{t,g}$	MWh	Aggregated virtual storage level of electric vehicles in low-voltage grid g at time step t, taking distribution grid constraints into account
$TXLOAD_{t,g}$	MWh	Transformer load in low-voltage grid g at time step t

Table 4: Parameters

Parameter	**Unit**	**Description**
$charge_{t,e}^{early}$	MWh	Early charging reference demand for electric vehicle e at time step t
$charge_{t,g}^{early,vs}$	MWh	Charging demand of the aggregated virtual storage in the *earlycharging* run for low-voltage grid g at time step t
$charge_{t,e}^{max}$	MWh	Upper bound for charging for electric vehicle e at time step t
$charge_{t,e}^{max,vs}$	MWh	Upper bound for virtual charging for electric vehicle e at time step t
$charge_{t,g}^{max,vs,tx}$	MWh	Aggregated upper bound for virtual charging of electric vehicles in low-voltage grid g at time step t, taking distribution grid constraints into account
$charge_{t,e}^{min,vs}$	MWh	Lower bound for virtual charging for electric vehicle e at time step t
$charge_{t,g}^{min,vs,tx}$	MWh	Aggregated lower bound for virtual charging of electric vehicles in low-voltage grid g at time step t, taking distribution grid constraints into account
$consump_{t,e}$	MWh	Electricity consumption during a drip for electric vehicle e at time step t
$level_{t,e}^{early}$	MWh	Early charging reference storage level for electric vehicle e at time step t
$level_{t,g}^{early,vs}$	MWh	Aggregated virtual storage levels of the *earlycharging* (minimization) runs for electric vehicles in low-voltage grid g at time step t
$level_{t,e}^{late}$	MWh	Late charging reference storage level for electric vehicle e at time step t
$level_{t,g}^{late,vs}$	MWh	Aggregated virtual storage levels of the *latecharging* (minimization) runs for electric vehicles in low-voltage grid g at time step t
$level_{t,e}^{max}$	MWh	Maximum storage level for electric vehicle e at time step t
$level_{t,e}^{min}$	MWh	Minimum storage level for electric vehicle e at time step t
$level_{t,e}^{min,vs}$	MWh	Minimum virtual storage level for electric vehicle e at time step t
$level_{t,g}^{min,vs,tx}$	MWh	Aggregated minimum virtual storage level of electric vehicles in distribution grid g at time step t, taking distribution grid constraints into account (Maximum possible energy deviation from the reference profile)
$load_{t,g}$	MWh	Inflexible load in low-voltage grid g at time step t
$res_{t,g}$	MWh	Renewable energy production in low-voltage grid g at time step t
$txload_{t,g}^{early}$	MWh	Sum of the *earlychargingundergridconstraints* reference load in low-voltage grid g at time step t
$txload_{g}^{max}$	MWh	Maximum capacity of the transformer in low-voltage grid g in situations with negative residual load
$txload_{g}^{min}$	MWh	Maximum capacity of the transformer in low-voltage grid g in situations with positive residual load

Appendices

A. Evaluation of aggregation accuracy

To assess the accuracy of our virtual storage approach, we benchmark the resulting charging costs for an aggregated optimization of the EV charging processes in a representative distribution grid with a run, in which the respective charging processes are optimized individually for each EV.

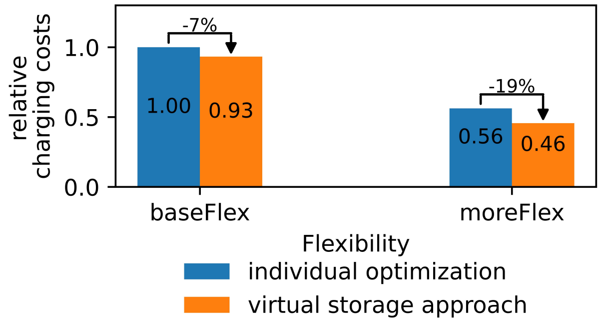

Figure A.1: Evaluation of virtual storage approach

B. Assumptions related to the energy system model

Table B.1: Exogenous electricity demand in TWh

Voltage level	Application	2030	2045
LV	EVs (Home)	28.8	67.2
	EVs (Public)	6.9	16.0
	Residential buildings	153.2	171.0
MV/HV	Industry Processes	263.1	310.7
	Commercial / industrial buildings	168.0	177.7
	Non-road transport	19.6	24.4

The demand in the end-use sectors is based on the dena pilot study (EWI/ITG/FIW/ef.Ruhr, 2021). Additionally, endogenous demand in the conversion, PtX and decentral heating sector build the total net demand in Germany. The endogenous demand varies between the different system configurations.

Table B.2: Commodity prices and EU Carbon Permits in 2030 and 2045

Year	Oil	Coal	Lignite	Gas	CO_2
2030	43.6 EUR/MWh	10.0 EUR/MWh	5.5 EUR/MWh	22.3 EUR/MWh	88 EUR/t
2045	41.4 EUR/MWh	9.4 EUR/MWh	5.5 EUR/MWh	26.3 EUR/MWh	Cap

Note that prices for oil, coal, and gas are based on the "Stated Policies" scenario in IEA (2024), while the lignite price follows ENTSO-E and ENTSOG (2024). The assumed price of emission allowances for 2030 refers to the ICIS Modeling group, with its results visualized in Pahle et al. (2022). In 2045, we model a CO_2 cap to achieve climate neutrality in Germany.

Table B.3: Installed capacities in Germany per generation group and corresponding efficiencies

Technology group	**Efficiency in %**	**Capacity in GW 2030**	**Capacity in GW 2045**
Waste	17	0.8	0.0
Lignite	32-41	8.7	0.0
Coal	37-46	8.0	0.0
Gas	28-60	32.7	61.2
H_2	40-56	7.0	50.0
Wind Offshore	100	30.0	70.0
Wind Onshore	100	115.0	175.0
Photovoltaic	100	215.0	400.0
Biomass	31-49	8.0	8.0
Hydropower	100	5.3	5.3
DSM (Industry)	100	1.8	4.7
Battery	90	13.1	30.0
PHS	76	9.9	9.9
Electrolysis	68	10.0	92.0

The capacities of lignite and coal are determined based on the coal phase-out trajectory outlined in BMJ (2022). Targets for Wind Onshore, Wind Offshore, and PV capacities align with the objectives defined in the Easter Package (Bundesrat, 2022). Initial capacities for gas-fired power plants are sourced from the list of power stations as of November 21st, 2024, as published by the BNetzA (BNetzA, 2024c). Subsequently, an additional amount of backup power plants are assumed, as outlined in The Federal Government (2024).

C. Assumptions related to grid expansion costs

The cost basis for the calculation of the grid expansion costs in Subsection 4.4 is based on Wintzek et al. (2021). The assumed weighted average costs of capital (WACC) of 5.5% is based on Probst et al. (2024). The total costs of a transformer include the costs for the transformer itself and auxiliary costs. The auxiliary costs include fix costs for the groundwork and the substation, as well as for operational expenses.

Table C.4: Transformer data

	rONT	ONT
Transformer costs (630 kVA) [EUR]	21,000	10,000
Fix costs [EUR]	80,000	
Operational expenses	2.5% of CAPEX per year	
Lifetime [years]	40	
WACC	5.5%	

D. Additional results on wholesale markets

Table D.1: Scenario comparison system effects

Year	Parameter	Early	Early-DG	Flex	Flex-DG	moreFlex	moreFlex-DG
2030	EV flexibility [TWh]	0.00	0.06	18.68	18.71	23.80	23.74
	Charging price [€/MWh]	67.41	67.68	45.25	46.15	29.07	30.33
	Peak residual load [GW]	101.16	100.84	91.63	91.63	91.63	91.63
	RES curtailment [TWh]	24.84	27.66	21.26	24.08	16.83	19.65
	CO_2 emissions [Mio. t. CO_2 Eq.]	401.33	401.55	399.43	399.63	397.96	398.15
	Weighted electricity price [€/MWh]	61.15	61.16	60.43	60.46	59.67	59.77
	Electricity price volatility [€/MWh]	30.55	30.24	29.63	29.37	29.19	28.83
	Total system costs [Mio. €]	10.02	10.07	9.41	9.47	8.93	8.98
2045	EV flexibility [TWh]	0.00	2.17	35.63	35.75	-	-
	Charging price [€/MWh]	57.35	57.07	37.22	38.08	-	-
	Peak residual load [GW]	125.41	119.48	121.24	119.00	-	-
	RES curtailment [TWh]	60.58	65.08	50.10	54.33	-	-
	CO_2 emissions [Mio. t. CO_2 Eq.]	0.00	2.33	2.33	2.33	-	-
	Weighted electricity price [€/MWh]	47.14	47.05	45.36	45.48	-	-
	Electricity price volatility [€/MWh]	28.53	28.01	26.00	25.76	-	-
	Total system costs [Mio. €]	8.77	8.94	7.54	7.77	-	-

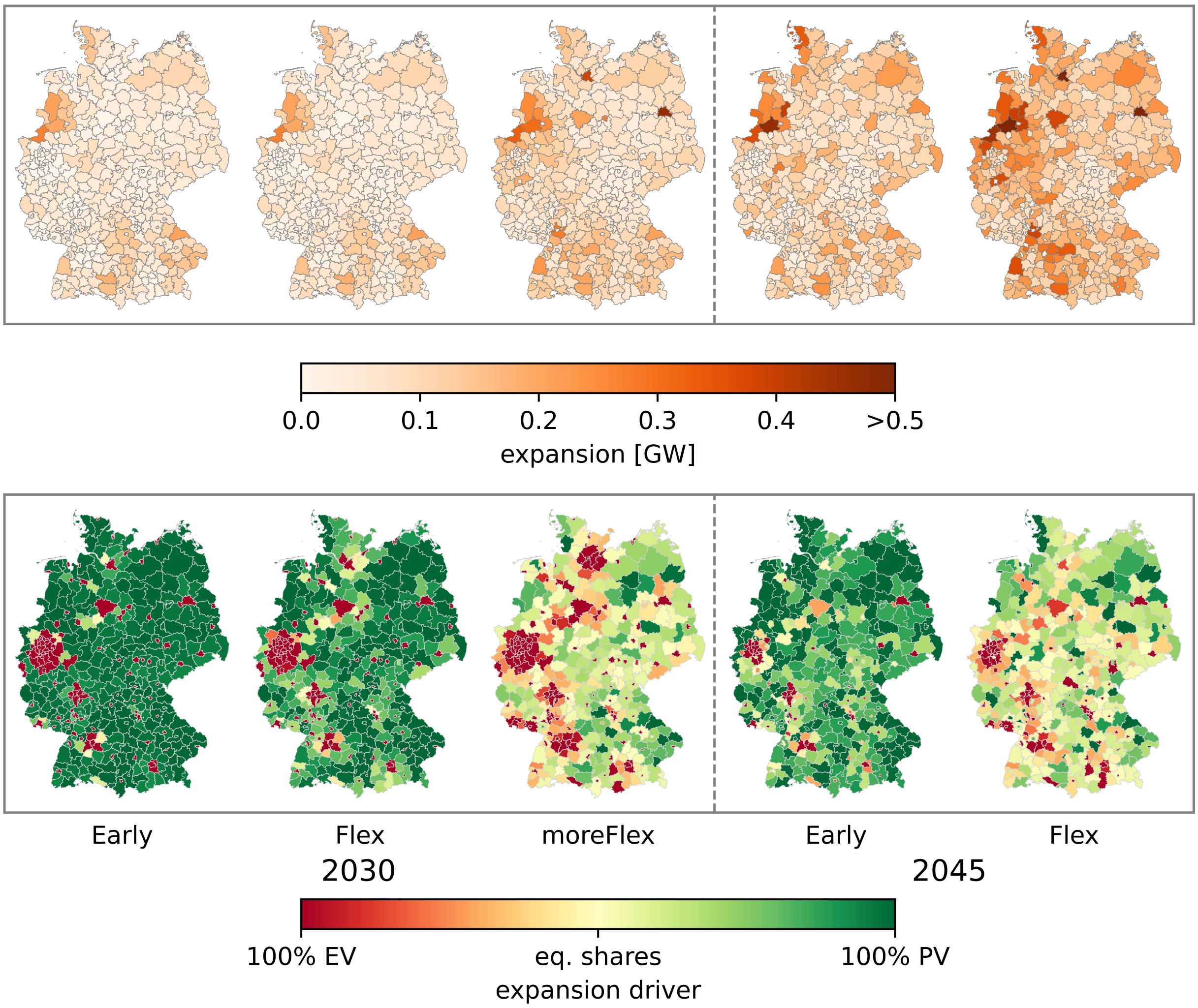

Figure E.1: Regional distribution of expansion requirements and expansion drivers

Note: The top row shows the distribution of the absolute expansion requirements for the individual NUTS and the various model configurations. The bottom row shows the drivers of the expansion for the individual NUTS accordingly. The scale ranges from 100% EV-driven to equal shares of EV and PV to 100% PV-driven.