Analyzing the Impact of Dynamic Tariff Adoption and Regulatory Options on Distribution Grids with an Open-Source Framework

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Abstract

Dynamic tariff adoption is considered to be an important driver of demand response, enabling more sustainable and reliable power systems. However, first studies have shown that a high share of households subscribing to dynamic tariffs can lead to so-called "avalanche effects" on the distribution grid level, wherein load profiles align across households. Avalanche effects can create new demand peaks that necessitate costly grid reinforcement measures. Here, we analyze the impacts of policy options for grid charge and solar photovoltaic (PV) feed-in remuneration on grid reinforcement costs given increasing shares of dynamic tariff adoption. The analysis framework is open-source and uses empirical data from real households. We find that the widely proliferated regulatory scenario with volumetric grid charges and PV feed-in-tariffs leads to heavy reinforcement needs. We show that novel policy options, such as rotating or segmented grid charges, can alleviate grid reinforcement needs.

CCS Concepts

• **Computing methodologies → Modeling and simulation**.

Keywords

Dynamic Tariffs, Distribution Grids, Reinforcement, Grid Charges

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1 Introduction

The introduction of dynamic electricity tariffs is an essential step to reduce peak demand in modern power systems and, thereby, the need to run costly peak power plants [28]. Various types of dynamic tariffs are discussed in the literature, ranging from time-of-use pricing to critical peak pricing, real-time pricing, and other variants. Real-time pricing is considered to be the most direct implementation of dynamic tariffs since it offers customers prices directly linked to the wholesale electricity market [28]. Dynamic tariffs are also increasingly promoted by regulators internationally. In a 2019 directive, the European Union required its member states to enable customers to adapt their consumption to market signals [26]. As a translation into national law, Germany requires utilities with more than 100,000 customers to offer dynamic tariffs from 2025 onwards [12]. Dynamic tariffs offered by German utilities today are mostly based on the wholesale day-ahead market price [81].

Although the roll-out of dynamic tariffs, such as real-time pricing, is already underway, its effects on the power system are still not entirely clear [20, 49]. Studies have shown that when multiple devices are controlled by an automated optimization algorithm that reacts to a given price signal, it might cause new, unprecedented demand peaks. This phenomenon, the avalanche effect, has been discussed for electric vehicles (EVs) [20, 49] and heat pumps (HPs) [60]. However, previous studies on avalanche effects have neglected three important aspects. First, the impact on the distribution grid is mostly modeled by analyzing aggregated loads, thereby neglecting potential issues arising at specific locations within the distribution grid, which could lead to costly reinforcement measures. Second, previous research often considers only standard load profiles, ignoring the interplay of HPs, battery energy storage systems (BESSs), and solar photovoltaic (PV) installations. Third, although studies discuss potential regulatory options to reduce avalanche effects, a thorough comparison is still missing.

This paper addresses these research gaps by analyzing the impact of increasing real-time tariff adoption under different regulatory options. We do this in the scope of a potential 100% electrified future with EVs, HPs, PV, and BESSs installed in every household. We leverage empirical data on HP and household load, battery size, and EV usage to create realistic household profiles. Then, we formulate an optimization problem for the operation of the flexible devices at the household level, exploring different policy options concerning grid charges and PV feed-in compensation. Finally, we connect the individual household loads within various distribution grid topologies to calculate the necessary grid reinforcement costs. We conduct our analysis for different types of days, such as days with the highest household or HP load, or the highest PV feed-in.

In summary, our study has three main contributions. First, the impact of increasing adoption of real-time pricing for residential households on distribution grid reinforcement costs, given different day types and grid topologies, is investigated. Second, the effectiveness of regulatory options for grid charges and PV feed-in remuneration are investigated in light of an increasing share of dynamic tariff adoption. Third, we provide the underlying models and empirical data open-source to enable other researchers to integrate new data sources or test other regulatory options [1].

The remainder of this work is structured as follows. In Section 2, we give an overview of existing studies in the field of dynamic tariff adoption and its impact on distribution grids and highlight the resulting research gaps. In Section 3, we describe our overall methodology and simulation framework. Section 4 presents the mathematical formulation of our underlying optimization problem on a household level. Section 5 introduces various policy options for grid charges and PV remuneration. In Section 6, we give an overview of the empirical data used to carry out the evaluations presented in Section 7. We conclude in Section 8.

2 Background

The introduction of dynamic pricing is a promising demand-side management measure that has the potential to flatten load curves, reduce electricity bills, and lower CO_2 emissions [23]. Various forms of dynamic pricing have been suggested. In time-of-use pricing, the electricity price varies between on-peak and off-peak hours and is predetermined for a given period, e.g., per season. In critical peak pricing, a particularly high price is charged when the system-wide load reaches its peak, resulting in a stronger price signal during these times than time-of-use tariffs. The most direct form of dynamic pricing, however, is real-time pricing, where prices change regularly, reflecting wholesale market prices. Although considered the most effective dynamic pricing scheme, real-time pricing requires advanced technology for scheduling distributed devices and communication of price signals, as well as advanced metering infrastructure [23, 28].

However, it has been shown in literature that the required technology to adapt the operation of devices to real-time tariffs with the objective to realize energy cost savings is already available, e.g. for HPs [30, 31, 71], EVs [1, 24] and batteries installed in combination with a PV system [7, 83]. Furthermore, smart metering equipment can provide high-resolution electricity consumption measurements [28]. Proposed operation methods range from online stochastic optimization methods [7] to model predictive control [31] and deep reinforcement learning [84].

Studies have investigated how an increased share of households operated under dynamic tariffs influences the overall power system [67, 80]. It was concluded that an increasing share of load subjected to real-time pricing increases consumers' price elasticity, potentially leading to increased volatility in the overall system. The authors call for assessing the trade-off between economic efficiency and stability of the system. Several studies have investigated this trade-off for specific cases. In [27], optimal real-time pricing curves from a utility perspective have been determined for a 33-bus distribution network with the goal of achieving peak demand reductions. In [69], the potential of real-time tariffs to reduce the required peak generation capacities in the Norwegian power system was demonstrated. In [5], potential cost savings for households with automated heating, ventilation, and air conditioning systems in Texas have been quantified. Switching to real-time pricing led to 30% reductions in peak system load and reduced grid investments. Although these studies underline the relevance and potential benefits of real-time pricing tariffs, they focus on limited grid topologies and certain controllable assets, neglecting the possible effects of their interplay.

A potential issue of high shares of households subscribed to real-time pricing schemes is the aforementioned avalanche effect, which can lead to new peak loads and additional stress on the grid [20]. In [53], a study that simulates the impact of different EV charging strategies in German distribution grids shows that 71% of investigated grids would have to be reinforced to handle new load peaks caused by simultaneous charging of EVs if their charging is optimized for real-time tariffs. While the authors emphasize that signals sent from the wholesale market do not necessarily reflect the local grid situation and acknowledge potential needs for grid reinforcement, they do not discuss potential options to mitigate these effects. Important regulatory options influencing household flexibility utilization are grid charges [38] and feed-in remuneration [58]. A first discussion on policy design in light of the increasing adoption of dynamic tariffs was presented by [80]. However, the work is focused on a few low-voltage grid topologies and lacks a detailed discussion of potential grid charges.

We close this research gap by analyzing a future 100% electrified grid scenario in light of potential avalanche effects connected to increasing real-time pricing adoption rates of households. Based on that, we analyze and discuss the effects of regulatory options on grid reinforcement costs on the low- and medium-voltage grid level. We publish our work open-source with an easy-to-use workflow, enabling an analysis of alternative regulation and flexibility patterns in future studies.

3 Methodology

This section describes our overall methodology, which consists of four steps: household preprocessing, household optimization, grid power flow, and reinforcement simulation, as depicted in Figure 1. Given different regulatory contexts, we aim to simulate the impact of increasing shares of households with dynamic tariffs on grid reinforcement costs. We conduct our study in a future scenario with 100% electrified heating, EVs, distributed PV generation, and home batteries. This scenario resembles the case investigated by [53]. Given the current political development that many European countries, for instance, Germany [16], incentivize the installation of large numbers of HPs over the coming years and the fact that already a large fleet of PV and battery storage systems are installed

[1] Our open-source framework and underlying data is published open-source on Github, see: https://github.com/leloq/dynamic-tariffs-in-distribution-grids.

in households [61], we consider this as a realistic scenario. However, our flexible open-source model allows the analysis of different scenarios, for instance, with lower shares of EVs, PV, or battery systems, thereby reflecting alternative scenarios in future studies.

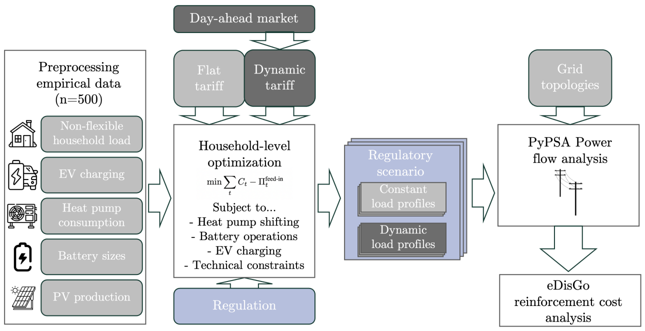

Figure 1: Overview of simulation steps and overall methodology.

3.1 Household preprocessing

In this step, we generate N residential profiles consisting of regular household loads, HP loads, PV generation, and EV profiles. Furthermore, sizing decisions for the BESS are made. The regular household and HP load profiles are based on a German dataset [73], extended using the methodology described in [74]. For the EV load, we use empirically observed EV usage data from Norway [77, 78], considering charging events and plug-in and plug-out times. The household BESS are sized according to an empirical sample from 947 German households [75]. We match households with larger HP and household consumption with larger batteries to make the scenario more realistic. We generate the PV output power profiles based on the widely proliferated approach introduced by [63]. Overall, our household preprocessing is designed to constitute a realistic sample of households based on empirical data while still exhibiting variance between households through randomly drawing HP, household, and EV profiles as well as sizes of PV and BESS installations. Section 6 describes our data source in further detail.

3.2 Household optimization

We study two different cases with regard to the operation of flexible devices in households. The first case assumes that EV and HP consumption are equal to the empirical profiles, neglecting their flexibility potential. Only the BESS is operated to increase the self-consumption of the households, thereby leading to reduced electricity drawn from the grid, as illustrated in [53]. Since a constant electricity tariff is present in this case, charging and discharging decisions solely depend on whether there is surplus PV generation.

In the second case, by contrast, the operation of EVs and HPs is flexible, i.e., consumption can be shifted to reduce costs further and exploit cost benefits when subscribing to pricing schemes other than a constant volumetric charge [31, 57]. We model the HP flexibility potential based on two real-world projects [45, 50]. We ensure that the daily HP consumption from the empirical observations is satisfied. However, we assume that based on [50], the HP can be blocked during high price periods three times per day and at most for two consecutive hours without losses of comfort for inhabitants. After being unblocked, the HP has to be operated for at least two hours to maintain thermal comfort. Regarding EV charging, the energy demand, arrival time, and departure time are given for each charging session. Charging can be shifted within the specified time window of the parking event, considering also the power constraints of the underlying technical equipment. The exact mathematical formulation of the optimization model on a household level is described in Section 4.

Given the large share of additional demand constituted by HPs and EVs, we restrict the household flexibility potential to these loads, assuming the remaining household load to be inflexible in all scenarios [37]. We note that in future studies, also the flexibility of additional loads from appliances like dishwashers could be considered [3].

We assume that each household has a home energy management system, which schedules the flexible loads based on an optimization problem. We analyze the impact of an increasing share of households subscribing to dynamic tariffs by gradually increasing the number of households that use a dynamic price signal as input to the optimization. This dynamic household tariff is based on the day-ahead price [34] as this pricing scheme is already implemented in practice [81]. Furthermore, the optimization is subject to varying regulatory scenarios, i.e., different combinations of PV feed-in remuneration (e.g., flat feed-in tariff, market-price oriented) and grid charge designs (e.g., volumetric, peak demand, etc.) [4], as described in Section 5. The resulting load profiles are then used as input to the power flow computations.

3.3 Grid power flow and reinforcement simulation

Every investigated low-voltage grid topology has M nodes where households are connected. Due to the computational complexity of the previously introduced household-level optimization problem, only N households are simulated. To scale to a number of M households in every investigated grid topology, M households are randomly sampled with replacement from the set of N simulated households. For comparability purposes, we keep the same households connected to the same nodes for each investigated regulatory framework and dynamic tariff penetration rate.

For each scenario and investigated grid topology, the AC power flow computation is carried out in PyPSA [10, 39, 76]. PyPSA is an open-source tool that uses power supply and demand time series to calculate voltages and power flows on lines and transformers. PyPSA uses the Newton-Raphson algorithm to numerically solve the nonlinear algebraic equations that govern AC power flow.

In a consecutive step, required grid reinforcement measures and their costs are calculated through the open-source framework eDisGo [39]. The resulting branch currents and bus voltages from the PyPSA simulation are compared to predefined limits, i.e. 100 % for component loading and ±10 %[2] deviation from the nominal voltage. If any of these bounds are violated, eDisGo iteratively installs new components or splits feeders until all grid issues are resolved. As a last step, the total cost of grid reinforcement is calculated using

[2]There are additional voltage-level-specific bounds for the voltage drops and rises. These are further detailed in [65].

standard costs for the installed components. We run five simulations per grid topology to account for statistical deviations in the placement of different household loads.

3.4 Assumptions

The modeling framework described above entails five key assumptions, which we explain below.

Modeling households as price takers: We assume the households to be price takers, i.e., their consumption does not impact wholesale market electricity prices. This is a strong assumption, especially in the case that 100% of households are subscribed to a real-time price. However, given that households do not directly participate in wholesale electricity markets, this is a reasonable assumption if the real-time prices incorporate the potential shift of the loads or if the inflexible load is still the dominant part of the load. Furthermore, our flexible open-source model could be integrated with a power system model that evaluates the impact of household decisions on wholesale price curves.

Same operation strategies for every household: Although we model a wide variety of households following distinct empirical electricity consumption patterns, the optimization strategy that schedules flexible load is the same for each household. We note that in practice, there might be a variety of home energy management systems following different strategies, which would ultimately lead to different household load profiles. However, we argue that our proposed optimization algorithm yields a good approximation for the best possible scheduling of flexible devices, following the formulations in [4, 53, 54], and hence delivers a realistic approximation of household behavior under real-time pricing.

Focus on a 100% electrified household scenario: While we analyze the impact of varying HP, EV, PV, and BESS adoption rates on peak loads in a sensitivity analysis, our primary focus is on a fully electrified scenario where 100% of households are equipped with HPs, EVs, PV, and BESS installations. Given the rapidly increasing installation numbers of these technologies [43, 49, 75], we see this as a potential future scenario. In addition, several related studies investigate a comparable scenario with full or high electrification of heating and transportation [53, 66, 68]. Moreover, we focus on residential households, neglecting potential dynamic tariffs and regulatory perspectives for industrial and commercial customers. We model industrial and commercial customers in the distribution grids with constant consumption not influenced by dynamic tariffs. Our framework theoretically could also implement these customer types' dynamic behavior and scheduling. However, this would go beyond the scope of this study.

Perfect foresight: We assume perfect foresight of prices and energy demand in the household optimization model. Given our grid and policy analysis focus, we argue that this is a fair assumption, which is also common in related studies [4, 49]. In reality, the scheduling of devices and the utilization of flexibility potentials would need to be implemented through dedicated control algorithms, which do not have the luxury of perfect foresight [31, 42].

Time-series-based grid reinforcement analysis: We use time-series-based simulations to estimate the grid reinforcement costs. Traditionally, estimating grid reinforcement needs follows a more conservative approach, namely calculating only worst-case snapshots (see e.g. [36]). For these, values for the simultaneity of different load and feed-in technologies are assumed, and calculations are run for worst-case situations with high load and high feed-in. Compared to a time-series-based analysis, the worst-case simulations result in higher costs and more robust grids since they indirectly assume that all peaks occur simultaneously even though, in reality, the peaks likely occur at different times and, therefore, may require less reinforcement. In our investigations, we only assess strictly necessary grid reinforcement and investigate the influence of dynamic tariffs on these requirements. Furthermore, we assume that with increasing observability in the grids, time-series-based reinforcement calculations will become more realistic, and future grid planning will move more in this direction. Moreover, policymakers have begun advocating for time-series-based grid reinforcement analysis [25]. Therefore, time-series-based grid reinforcement is used in the following investigations. Although conducting a worst-case snapshot reinforcement analysis lies beyond the scope of this study, we consider it a valuable avenue for future research.

4 Mathematical formulation

This section presents the mathematical formulation of the optimization problem for scheduling HPs, EV charging, and battery storage systems in the investigated households. This optimization problem is separately applied to every household within the set of all simulated N households. We base our optimization model and the necessary constraints on several studies covering operation strategies in households with batteries, PV installations, EVs, and HPs, namely [4, 32, 54]. From a household perspective, the energy costs C_t minus the feed-in revenues $\Pi_t^{\text{feed-in}}$ are to be minimized over the simulation period with T time steps, resulting in the following objective function:

$$\min \sum_{t=1}^{T} \left(C_t - \Pi_t^{\text{feed-in}} \right) \tag{1}$$

The components in this expression can be computed by

$$C_t = E_t^{\text{total}} \cdot p_t^{\text{tariff}}, \qquad \forall t \tag{2}$$

$$\Pi_t^{\text{feed-in}} = E_t^{\text{PV,feed-in}} \cdot p_t^{\text{feed-in}}, \qquad \forall t \tag{3}$$

$$E_t^{\text{PV}} = E_t^{\text{PV,feed-in}} + E_t^{\text{PV,Internal}}, \qquad \forall t \tag{4}$$

$$E_t^{\text{total}} = E_t^{\text{HH}} + E_t^{\text{EV}} + E_t^{\text{HP}} + E_t^{\text{BESS,Charge}} - E_t^{\text{BESS,Discharge}} - E_t^{\text{PV,Internal}}, \qquad \forall t \tag{5}$$

$$E_t^{\text{total}} \cdot E_t^{\text{PV,feed-in}} = 0, \qquad \forall t \tag{6}$$

$$E_t^{\text{total}}, E_t^{\text{PV,feed-in}}, E_t^{\text{PV,Internal}}, E_t^{\text{EV}}, E_t^{\text{HP}}, E_t^{\text{BESS,Charge}}, E_t^{\text{BESS,Discharge}} \geq 0, \qquad \forall t \tag{7}$$

where the costs C_t are calculated by multiplying the respective net household consumption E_t^{total} with the electricity tariff p_t^{tariff} at time t, while the feed-in revenues $\Pi_t^{\text{feed-in}}$ are the product of the feed-in energy $E_t^{\text{PV,feed-in}}$ and the feed-in remuneration $p_t^{\text{feed-in}}$ at time t. The values for p_t^{tariff} and $p_t^{\text{feed-in}}$ are time-variable or constant, depending on the respective policies in place. In (4), the PV production E_t^{PV} is split up into two components, namely $E_t^{\text{PV,Internal}}$

directly consumed by the household and $E_t^{\text{PV,feed-in}}$ fed into the grid. Constraint (5) defines the overall net energy demand of the household E_t^{total} as the sum of the non-flexible component E_t^{HH}, the consumption for EV charging E_t^{EV}, the HP consumption E_t^{HP}, and the energy charged to the BESS $E_t^{\text{BESS,Charge}}$, minus the energy discharged from the BESS $E_t^{\text{BESS,Discharge}}$ and the internally used PV production $E_t^{\text{PV,Internal}}$. Constraint (6) prevents simultaneous PV feed-in and power draw from the grid, and (7) enforces positive energy values.

BESS: The necessary constraints for the BESS are given as follows:

$$E_t^{\text{BESS,Charge}} \leq P^{\text{BESS,Max}} \cdot \Delta t, \qquad \forall t \tag{8}$$

$$E_t^{\text{BESS,Discharge}} \leq P^{\text{BESS,Max}} \cdot \Delta t, \qquad \forall t \tag{9}$$

$$E_t^{\text{BESS,Charge}} \leq E_t^{\text{PV,Internal}}, \qquad \forall t \tag{10}$$

$$E_t^{\text{BESS,Charge}} \cdot E_t^{\text{BESS,Discharge}} = 0, \qquad \forall t \tag{11}$$

$$E_t^{\text{BESS,SOE}} = E_{t-1}^{\text{BESS,SOE}} + \eta \cdot E_t^{\text{BESS,Charge}} - \frac{1}{\eta} \cdot E_t^{\text{BESS,Discharge}}, \qquad \forall t \tag{12}$$

$$E_0^{\text{BESS,SOE}} = E^{\text{BESS,min}} \tag{13}$$

$$E^{\text{BESS,min}} \leq E_t^{\text{BESS,SOE}} \leq E^{\text{BESS,max}}, \qquad \forall t \tag{14}$$

$$\sum_t^T \left(E_t^{\text{BESS,Charge}} + E_t^{\text{BESS,Discharge}}\right) \leq 2 \cdot E^{\text{BESS,max}} \cdot G^{\text{cycles}} \tag{15}$$

The maximum charging/discharging rate $P^{\text{BESS,Max}}$ limits the energy that can be charged and discharged during one time step with duration Δt, as captured in (8) and (9). We note that in practice, the rated power could vary for the charging and discharging case. However, we choose the same value for simplicity. Furthermore, the battery charge $E_t^{\text{BESS,Charge}}$ is bounded by the internally used PV production $E_t^{\text{PV,Internal}}$, as defined in (10). Thereby, charging the BESS from the grid is prohibited, as is the case in Germany [11], as well as indicated in related literature analyzing dynamic tariff impacts [59]. In (11), we enforce mutual exclusivity of charging and discharging operations. The state of energy of the battery $E_t^{\text{BESS,SOE}}$ is tracked in (12) by integrating the charging/discharging decisions and accounting for the BESS efficiency η. Constraint (13) specifies that the initial state of energy of the battery $E_0^{\text{BESS,SOE}}$ at $t = 0$ is set to the minimum allowed charge level $E^{\text{BESS,min}}$. Finally, (14) keeps the BESS state of energy within the capacity limits $E^{\text{BESS,min}}$ and $E^{\text{BESS,max}}$. To account for battery degradation without explicitly modeling complex physical processes, Equation (15) limits the cumulative energy throughput—that is, the total amount of energy charged and discharged over the simulation horizon—to a maximum number of full cycles, defined by the product of the maximum BESS energy capacity and the number of guaranteed cycles per year G^{cycles}, as commonly specified in manufacturer warranties [47], thus avoiding excessive degradation.

Heat pump: We model the flexibility potential of the HP by assuming that it can be blocked for some hours of the day with a negligible loss of comfort for the occupants [32, 45, 50, 76]. Hence, the optimized HP consumption time series per household corresponds to the empirical observations with parts of it shifted within the day. This results in reduced computational complexity compared to detailed thermal HP models such as implemented in [19, 62] with a loss of accuracy acceptable for the purpose of our studies. The constraints regarding the blocking decisions are defined as follows:

$$E_t^{\text{HP}} \geq \left(1 - \chi_t^{\text{HP,Block}}\right) \cdot E_t^{\text{HP,Empirical}}, \quad \forall t \tag{16}$$

$$E_t^{\text{HP}} \leq \left(1 - \chi_t^{\text{HP,Block}}\right) \cdot P^{\text{HP,Max}} \cdot \Delta t, \quad \forall t \tag{17}$$

$$\chi_t^{\text{HP,Switch}} \geq \chi_{t-1}^{\text{HP,Block}} - \chi_t^{\text{HP,Block}}, \qquad t \in \{2, \dots, T\} \tag{18}$$

$$\sum_{i=t}^{t+23} \chi_i^{\text{HP,Switch}} \leq 3, \qquad t \in \{1, \dots, T-23\} \tag{19}$$

$$\chi_t^{\text{HP,Block}} + \chi_{t+1}^{\text{HP,Block}} \leq 2 \cdot \left(1 - \chi_t^{\text{HP,Switch}}\right), \qquad t \in \{1, \dots, T-1\} \tag{20}$$

$$\chi_t^{\text{HP,Block}} + \chi_{t+1}^{\text{HP,Block}} + \chi_{t+2}^{\text{HP,Block}} \leq 2, \quad t \in \{1, \dots, T-2\} \tag{21}$$

where $\chi_t^{\text{HP,Block}}$ is a binary variable representing the blocking decision in each time step t. When $\chi_t^{\text{HP,Block}}$ equals 1, the HP is blocked and the HP energy consumption E_t^{HP} is zero, as captured in (16) and (17). When $\chi_t^{\text{HP,Block}}$ equals 0, the HP may operate, and the consumption is restricted to lie between the empirically observed consumption $E_t^{\text{HP,Empirical}}$ and the maximum consumption, which results from the maximum power $P^{\text{HP,Max}}$. Constraints (18) and (19) limit the number of blocking events per 24-hour window to three, where the binary variable $\chi_t^{\text{HP,Switch}}$ denotes the end of a blocking event. Finally, based on the real-world implementations [50] and [45], (20) ensures that the HP remains unblocked for at least two hours after a blocking event, and (21) ensures that the duration of a blocking event does not exceed two hours.

Additionally, we enforce that the total HP energy consumption within each six-hour interval remains the same as in the empirical observations:

$$\sum_{t = d \cdot 24 + \kappa}^{d \cdot 24 + \kappa + 5} E_t^{\text{HP}} \geq \sum_{t = d \cdot 24 + \kappa}^{d \cdot 24 + \kappa + 5} E_t^{\text{HP,Empirical}}, \quad \forall d, \forall \kappa \tag{22}$$

where $d \in \{0, \dots, \frac{T}{24} - 1\}$ denotes the day and $\kappa \in \{0, 6, 12, 18\}$ the hour of the day at which the considered six-hour interval starts. Thereby, we ensure that the heating demand is covered in a similar time frame as in the empirical observations so that there is no significant loss in occupants' comfort.

Electric vehicle: For each charging session c in the empirical data, the arrival time, departure time, and the charged energy $E_t^{\text{EV,Empirical}}$ are known. Based on this information, $t_c^{\text{EV,a}}$ is defined as the time step in which the EV arrives, and $t_c^{\text{EV,d}}$ denotes the time step in which the EV departs. EV charging can be shifted within the given time window but must meet the empirical demand:

$$\sum_{t=t_c^{\text{EV,a}}}^{t_c^{\text{EV,d}}} E_t^{\text{EV}} = \sum_{t=t_c^{\text{EV,a}}}^{t_c^{\text{EV,d}}} E_t^{\text{EV,Empirical}}, \quad \forall c \tag{23}$$

Additionally, charging is constrained by the maximum charging power $P_t^{\text{EV,Max}}$:

$$E_t^{\text{EV}} \leq P^{\text{EV,Max}} \cdot \rho_t^{\text{EV}} \cdot \Delta t, \quad \forall t \tag{24}$$

where ρ_t^{EV} denotes the share of time for which the EV is plugged in during time step t. Bidirectional charging, e.g., to feed electricity back to the grid or to cover the demand of other devices, is currently not considered but may be a valuable extension in future work.

5 Regulatory options

Previous studies have identified grid tariffs and feed-in remuneration rates as key policy items that shape consumption patterns and scheduling decisions of flexibility potentials [4, 29, 46].

5.1 Grid tariffs

Volumetric charges (status quo): Volumetric grid charges, where consumers pay a fixed charge per unit of energy consumed, are the most proliferated form of grid tariffs [38, 41]. To include these charges in our model, we compute the electricity tariff p_t^{tariff} in (2) as the sum of a wholesale electricity price $p_t^{\text{wholesale}}$ (which can be either constant or time-varying) and a fixed grid charge p^{grid} per unit of energy consumed:

$$p_t^{\text{tariff}} = p_t^{\text{wholesale}} + p^{\text{grid}} \tag{25}$$

While constant volumetric charges are applied in many countries (e.g., Germany, Great Britain, or Australia), it has been shown that they can lead to an unfair allocation of costs, especially when there is a high share of PV-BESS installations in the system [21, 72]. Furthermore, volumetric charges tend to limit the potential of flexible devices as they do not reflect the current state of the electricity system [8].

Peak demand charges: In this setting, consumers are charged based on their highest consumption within the billing period [79]. Thereby, households are incentivized to flatten their load curve and avoid high peak loads. From a modeling perspective, this can be implemented by setting p^{grid} in (25) to zero and adding the following term to the objective function (1):

$$\max_t \left(E_t^{\text{total}}\right) \cdot p^{\text{grid,demand}} \tag{26}$$

where the highest occurring energy consumption E_t^{total} is multiplied by a given demand charge $p^{\text{grid,demand}}$. Demand charges potentially yield a better alignment of price signals and system costs and could improve fairness [40].

Segmented tariff: Another approach to incentivize households to flatten their load profile is a segmented tariff [51], also referred to as increasing block rate tariff [9]. In the scope of this grid tariff design, consumers pay a different volumetric charge depending on the consumption level in the given time step. The costs C_t in the objective function (1) are computed as:

$$C_t = E_t^{\text{total}} \cdot p_t^{\text{wholesale}} + \sum_{s=1}^{S} E_t^s \cdot p^{\text{grid},s}, \quad \forall t \tag{27}$$

where S is the number of different tariff segments, and E_t^s and $p^{\text{grid},s}$ denote the energy and volumetric charge corresponding to segment s. The energy assigned to each segment cannot exceed the predetermined value $E^{s,\text{Max}}$, i.e.,

$$0 \leq E_t^s \leq E^{s,\text{Max}}, \quad \forall s, \forall t \tag{28}$$

and the sum over all segments must be equal to the household's net consumption:

$$\sum_{s=1}^{S} E_t^s = E_t^{\text{total}}, \quad \forall t \tag{29}$$

Tariff values are increasing with increasing consumption, i.e., $p^{\text{grid},1} \leq p^{\text{grid},2} \leq \cdots \leq p^{\text{grid},s}$, and consumers can reduce their costs by flattening their load profile. A potential benefit compared to peak demand charges is that there is always an incentive to keep consumption below the defined thresholds, while for demand charges, the level to which consumption is reduced may be determined by a few time steps with unavoidable high consumption.

Rotating tariffs: Finally, we introduce a novel "rotating tariff", which aims to reduce the unintended avalanche effects by assigning different time-variable volumetric grid charges to different households. In this system, some households face higher grid charges when wholesale electricity prices are low, potentially discouraging them from shifting their load to those hours. For the implementation of rotating grid tariffs, households are assigned to V different tariff groups, meaning each household n is assigned to a tariff group $v^n \in \{1, \ldots, V\}$. The grid charge $p_t^{\text{grid,rotating},n}$ for household n at time step t is determined by a time-dependent binary parameter ζ_t^v that indicates whether a higher grid charge applies to tariff group v:

$$p_t^{\text{grid,rotating},n} = \begin{cases} V \cdot p^{\text{grid}} & \text{if } \zeta_t^{v^n} = 1 \\ \frac{p^{\text{grid}}}{V} & \text{if } \zeta_t^{v^n} = 0 \end{cases} \tag{30}$$

Thus, when $\zeta_t^{v^n}$ is 1, the grid charge is V times higher than the baseline volumetric charge p^{grid}. For the remaining time steps, the grid charge p^{grid} is divided by V.

The point of time of high grid charges varies depending on which tariff group the respective household is mapped to. We analyze a simple rotating grid charge with two tariff groups ($V = 2$) that have alternating high grid charges. The advantage of this approach lies in its relatively simple setup. However, the optimal implementation of such a tariff design, its impact on fairness, and its cost-reflectivity have to be discussed in future studies.

5.2 Feed-in remuneration

In addition to the different grid charges, we investigate two different regulatory options for the remuneration of PV production fed into the grid. Feed-in remuneration design is seen as a major driver of investments in renewable energy infrastructure and the way the flexibility potentials of households are used [18, 58].

Constant feed-in tariffs (status-quo): Many countries (e.g., Germany, Japan, UK) have introduced feed-in tariffs that compensate every unit of PV production fed into the grid with a constant rate $p^{\text{feed-in}}$ [4, 22, 29]. While constant feed-in tariffs have been identified as an effective policy tool to increase PV penetration, they also proved to be expensive and not cost-effective [64]. Furthermore, it has been shown that constant feed-in tariffs lead to a feed-in profile that is not necessarily aligned with the power system's needs [48].

Dynamic feed-in tariffs: A potential alternative and widely discussed measure to align PV feed-in with market signals is the implementation of a dynamic feed-in remuneration. In this case, the compensation of excess feed-in is based on the wholesale market price [4, 48]. An exemplary implementation of dynamic feed-in tariffs can be found in the state of Victoria, Australia, where retailers can offer their customers a time-varying remuneration for electricity exported to the grid [17]. We model this approach in our study by setting the feed-in compensation to the respective market price $p_t^{\text{feed-in}} = p_t^{\text{wholesale}}$ for each t, based on [4].

The scenarios derived from the potential policy compositions consisting of the described grid charges and feed-in remuneration are summarized in Table 1 in the Appendix. We investigate the interplay of these scenarios and varying dynamic pricing adoption rates.

6 Data

This section describes the empirical data sources used in our study. By leveraging empirical data instead of purely simulated profiles, we aim to create a realistic representation of residential loads in distribution grids [4, 53]. We put together a dataset of 500 single-family households in Hamelin, Germany, for the year 2019. The dataset includes time series for the inflexible load, HP consumption, EV charging, and PV generation of every household in hourly resolution. Furthermore, the dataset includes a specific BESS capacity and power for every household. The various data sources are introduced in the following.

Heat pump and inflexible household load: Our study is based on household and HP load profiles from [73]. The dataset consists of 38 single-family households in Hamelin, Germany, and includes hourly energy consumption data from mid-2018 to the end of 2020. The buildings from the dataset have water-water HPs with 7.4-11.3 kW thermal power and a 6kW backup heating rod. We follow the approach from [74] to increase the HP load profile variance, leveraging a k-means clustering and random sampling method. The method clusters temperature measurements of the empirical dataset from [73] and maps the observed HP load profiles on these days to the clusters. Then, based on the temperature measurements observed in Hamelin in 2019, daily HP and household load profiles are randomly drawn from the clusters. For a more detailed description of the method, we refer to [74].

Electric vehicles: The EV charging time series are based on the empirical dataset in [78]. The data was collected from a housing cooperative in Norway between December 2018 and January 2020 and includes the plug-in time, plug-out time, and the charged energy for a total of 6878 charging sessions of 97 EV users. We only consider the charging sessions of users with a private charging point, as this reflects the setting of single-family homes as investigated in our study, and there are significant differences between the charging habits of EV users with a private charging point and EV users with shared charging points [77]. As not all users in the dataset are registered from the start of the specified time period, we only consider users for which the first charging session is no later than March 2019. With all of these exclusions, 13 EV charging time series with 2359 charging sessions remain. For each of the 500 households, one of these 13 EV charging time series is randomly assigned, and the time series is randomly shifted by $k \in [-4, 4]$ weeks to increase variance between households while keeping the usage patterns on different day types intact.

Figure 4 in the Appendix depicts the households' resulting weekly aggregated energy consumption. It shows that the inflexible household load and EV load are rather constant throughout the year, while there are HP-induced peak loads during the winter months.

BESS sizing: For the sizing of household battery storage systems, we draw from an empirical sample of systems installed in Germany, adhering to the size distribution. Within the representative sample, the systems either have a capacity of 2.5kWh (6.7%), 5kWh (37.2%), 7.5kWh (31.5%), or 10kWh (24.6%). The average power-to-energy ratio, which sets the BESS power rating in relation to energy capacity, is 0.41. We assign larger batteries to households with a larger yearly household and HP energy consumption.

PV generation: We create an hourly PV generation profile for a 1kW installation in Hamelin in 2019, based on the open-source tool renewables.ninja [63]. We use the default settings of renewables.ninja, assuming a 35° tilt of the panels, a south orientation (180° azimuth), and a 10% system loss. Furthermore, we assume that households with larger PV installations tend to have larger battery storage systems. Therefore, we assume that the individual household's PV peak power takes the same value as the previously assigned BESS capacity, i.e., for a household with a 10kWh BESS, the PV peak power is assumed to be 10kW. The PV profile of each household results from scaling the PV profile obtained from [63] with the household's PV peak power. We note that in reality, installed PV panels would likely exhibit more diverse tilt and orientation angles, leading to slightly different generation profiles.

Wholesale market prices: Our study compares two different retail pricing schemes for household electricity consumption: a flat and a dynamic tariff. Both are based on the hourly day-ahead price in Germany for 2019 [15], but shifted to the positive range. We set the flat tariff to the mean of the observed, shifted series. For the dynamic tariff and feed-in remuneration, we directly use the shifted series. We note that this is a rather simplistic implementation of dynamic prices. However, we argue that our approach reflects the structure of more sophisticated dynamic tariffs and is easy to comprehend. Furthermore, our open-source model enables a simple adaption of tariffs and market prices in future studies.

Grid charges and feed-in tariffs: The constant volumetric grid charges are set to 0.0722 EUR per kWh, based on actual values of the local distribution grid operator in Hamelin [6, 13]. The demand charge is set at 67.94 EUR per kW per year, derived from the demand charge of the grid reserve capacity for the same year [6]. Weekly or monthly peak demand charges could also be considered in further studies. For the segmented tariff, we consider three segments. The price values are defined as 0.0361, 0.0722, and 0.1444 EUR per kWh, which corresponds to the constant volumetric charge scaled by a factor of 0.5, 1, and 2, respectively. Similar to [9], the corresponding consumption limits are set to $E^{1,\text{Max}} = E^{2,\text{Max}} = 2$ kWh, while there is no upper limit on E_t^3. We set the fixed PV feed-in remuneration to 0.1187 EUR, as was the case in Germany for PV installations below 10kWp installed in January 2019 [14].

Grid topologies: We use representative German distribution grid topologies based on geo-referenced load and generation data

[2]. The data comprises medium voltage (MV) grids with underlying low voltage (LV) grids for the whole of Germany. These German grids were then clustered with a k-medoids approach into ten representative grids based on their installed capacities of PV, wind, HPs, and electromobility [33]. In total, we select ten representative grids based on the clustering process. These grids vary in their urban settings (urban, suburban, or rural). Figure 8 in the Appendix depicts an overview of the ten analyzed grid topologies. We note that the grids vary in installed PV and wind generation, as well as residential demand. The grid topologies include highly spatially resolved data on lines, transformers, and connected load, generation, and storage units. One exemplary grid is displayed in Figure 7 of the Appendix.

7 Results and discussion

In this section, we present the results of the household-level optimization for the different regulatory settings. In the second step, we randomly assign the 500 household profiles to the investigated grid topologies. Finally, we evaluate the associated reinforcement costs per scenario and discuss the implications of our results.

7.1 Household-level optimization

When a household switches to a dynamic retail tariff, the individual flexibility decisions and resulting load profiles change: the EV is charged during the night with low prices, HP operation during high-price hours is avoided, and battery charging decisions are altered.

Figure 2 displays the resulting net load profiles for all scenarios, aggregated over all 500 households. We differentiate between 100% of households with constant retail tariffs and 100% of households with dynamic retail tariffs and show the results on different specific days. These days correspond to the days with the highest aggregated inflexible household load (3rd March), EV load (18th November), HP load (1st December), and PV feed-in (13th May), respectively. While we run the household-level optimization for the whole year, we focus on investigating the reinforcement costs on these particular days to reduce the computational complexity of the simulation. Figure 9 and Table 2 in the Appendix depict the loads on these days without any load shifting or BESS usage.

Figure 2 shows that, especially on the days with the highest inflexible load, EV demand, and HP consumption, the switch from constant tariffs (top row of plots) to dynamic tariffs (middle row) significantly alters the aggregated consumption profile. In the dynamic tariff scenario, households react to the price signals from the wholesale market, for instance, by shifting EV charging to low-price morning hours. The scenarios with the volumetric grid charges consistently lead to the highest peak loads, while the alternative grid charges reduce them. This preliminary result is in line with previous studies that mention avalanche effects as a result of a high degree of dynamic tariff adoption [20, 49]. We note that even on the peak inflexible load day, the aggregated consumption profile is shifted according to the price signals since a considerable HP demand is present (as depicted in Figure 9 in the Appendix)[3].

[3]On the HP type of day, the scenario with peak demand charges and dynamic feed-in remuneration led to a noticeable load valley at 12:00. The reason for this lies in the peak wholesale price, which then leads to an HP blocking decision over all households, enabling well-remunerated feed-in of excess PV production.

The load profiles on the peak feed-in day are largely unaffected by the level of dynamic tariff adoption but vary significantly across regulatory scenarios. Notably, scenarios with dynamic feed-in tariffs cause the peak feed-in to shift to earlier hours, coinciding with periods of higher spot market prices. This effect is particularly pronounced under dynamic feed-in tariffs with peak grid charges.

While our study focuses on a potential future scenario with 100% PV, BESS, EV, and HP adoption, we conduct a peak load sensitivity analysis for varying adoption rates in the Appendix (Figures 5 and 6). We note that also for lower adoption rates (e.g., only 25% of households are equipped with PV, BESS, EV, and HP installations), the conclusions remain the same: when the households switch to dynamic tariffs under the current regulatory scenario with volumetric grid charges, peak loads substantially increase. On the other hand, an exemplary alternative regulatory scenario with segmented grid charges leads to reduced dynamic tariff-induced peak load increases. We note that, in general, peak loads increase with higher PV, BESS, EV, and HP adoption independent from the regulatory scenario, which is in line with the results of previous research [52, 55, 70].

7.2 Impact on grid reinforcement costs

After the initial evaluation of aggregated load profiles, we now randomly assign the individual household profiles to the distribution grid nodes. Thereby, we simulate the impact of an increasing share of households subscribing to dynamic tariffs on grid reinforcement costs and evaluate alternative regulatory settings. Figure 3 shows the reinforcement costs that result from the computations for the investigated types of days and a combination of all days[4].

7.2.1 Status-quo regulation (volumetric charges and constant feed-in tariffs). The results of our grid reinforcement cost analysis confirm the ones from previous studies [53, 80]: under the currently widely proliferated constant volumetric grid charges, high additional grid reinforcement costs can be expected when a large share of households switch to dynamic tariffs. These reinforcement needs are triggered by transformer and line overloading and voltage issues. Some of the investigated topologies already require reinforcement measures starting at a 25% dynamic tariff adoption rate onwards. At the same time, at 100% adoption, all grids except one have to be substantially reinforced to endure simultaneous household reactions on common price signals. An additional analysis in the Appendix (Figure 11) shows that the previously calculated peak loads correlate with the resulting grid reinforcement costs.

Our analysis of different types of days enables a more granular analysis of the causes of the high reinforcement costs under constant volumetric grid charges, fixed feed-in tariffs, and high dynamic tariff penetration. On the day with the highest aggregated household load, even in a 100% dynamic tariff scenario, only minor reinforcement costs occur, while most grids do not even have to be reinforced. We note that the EV and HP consumption and PV feed-in on this particular day are lower compared to the other days. On the other hand, on the day with the highest aggregated EV or HP consumption, the higher the share of households with dynamic

[4]In the Appendix, the detailed reinforcement costs per type day and regulatory setting are depicted in Tables 5 to 9, as well as an overview of occurring grid issues (i.e., voltage violations and overloading events) in Figure 10. In addition, for the *Volumetric FIT* scenario, also a detailed breakdown of reinforcement costs per grid and penetration rate is provided in Table 4.

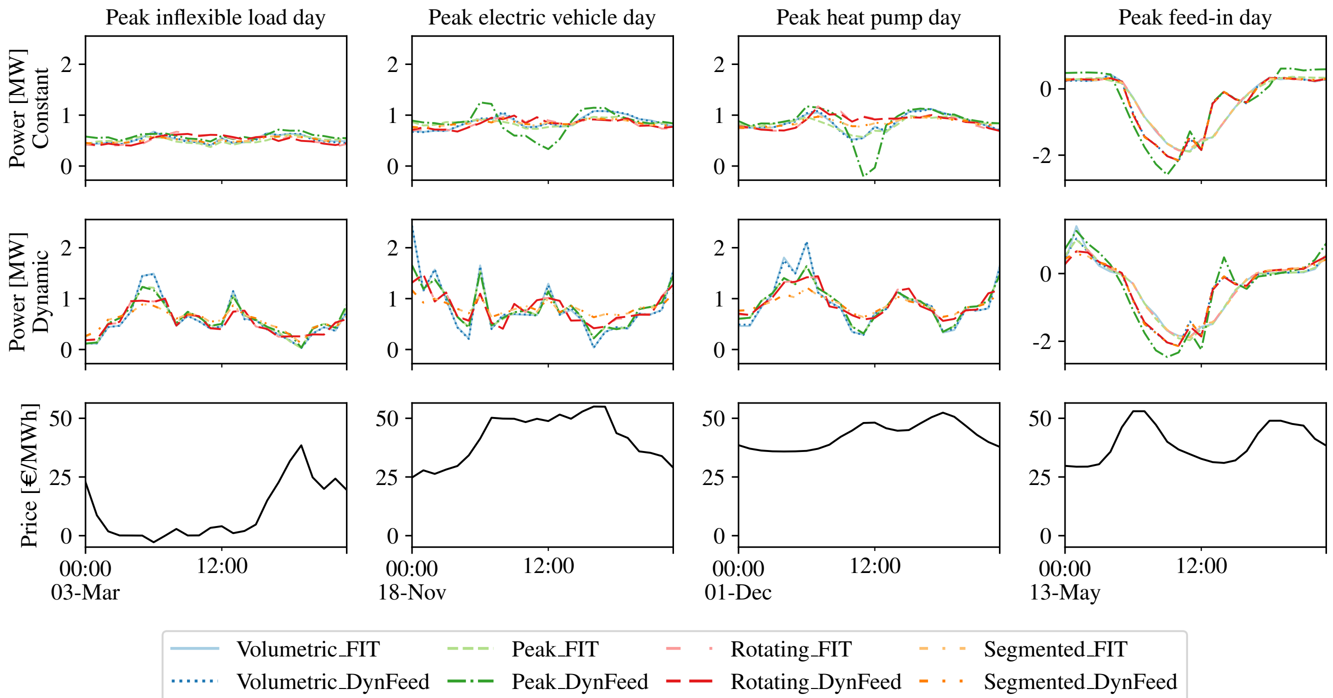

Figure 2: Aggregated household load for the simulated 500 households on the analyzed days with constant (top row of plots) and dynamic (middle row) retail prices under the different policy options. Dynamic retail prices and feed-in remuneration are based on the day-ahead spot market price (bottom row).

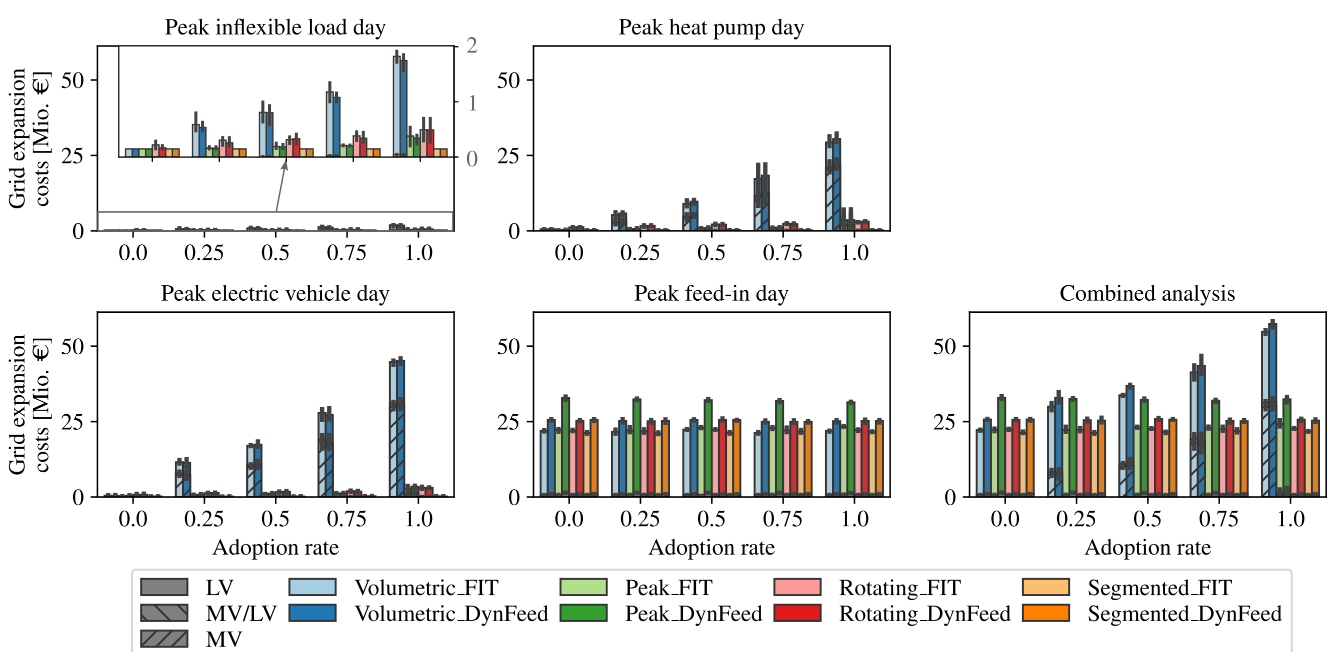

Figure 3: Grid reinforcement costs across all investigated grid topologies and policy options, given varying dynamic tariff adoption rates. The black lines indicate the 95% confidence interval between the five simulated runs.

tariffs, the higher the reinforcement costs and the number of grid topologies that must be reinforced. These results suggest that automated load-shifting from EVs, and to a lesser extent HPs, are the primary drivers of avalanche effects under dynamic tariffs. Most of these reinforcement needs occur in the medium-voltage grid.

On the day of the feed-in peak, there are consistent reinforcement needs independent of the dynamic tariff adoption rate. This is caused by simultaneous feed-in, which also cannot be alleviated by demand shifting from HPs or EVs. As a result, overvoltage issues in the investigated distribution grids arise (which Figure 10 illustrates in further detail in the Appendix).

7.2.2 Susceptibility of grid topologies. When analyzing grid reinforcement costs under the scenario with volumetric grid charges and constant feed-in tariffs (the current regulation in Germany), we find that the impact of rising dynamic tariff adoption rates varies significantly between grids (see Table 4 in the Appendix). For instance, the "rural-wind-1" or "suburban-balanced" grids show no increase in reinforcement costs due to dynamic tariffs. In contrast, the "rural-pv" grid experiences a substantial increase, with costs rising from €1.3 million at 0% adoption to €10.4 million at 100% adoption—an overall increase of €9.1 million. Both grids that do not require reinforcement are relatively small, featuring short medium-voltage (MV) lines and a low number of transformers (see grid characteristics in Table 3 in the Appendix). In contrast, the "rural-pv" grid has a relatively high number of transformers and the second-highest line length on the MV level. In addition, the grid has the lowest mean nominal transformer capacity.

A similar trend is observed when examining the correlation between reinforcement costs and grid characteristics across all topologies (see Fig. 12 in the Appendix). The length of medium-voltage (MV) lines show the highest positive correlation, while the mean nominal power of transformers exhibits a negative correlation. It is important to note that these findings represent statistical associations rather than causal relationships. Additionally, the analysis is based on a limited sample of grids, which may affect the generalizability of the results.

7.2.3 Impact of alternative regulatory options. In addition to the prevalent regulatory framework featuring volumetric grid charges and constant feed-in tariffs, we have analyzed the impact of alternative tariff schemes on grid reinforcement costs. As previously discussed and shown in Figure 2, alternative grid charges, such as peak charges, rotating tariffs, and segmented tariffs, effectively reduced peak loads on the inflexible load, EV and HP peak days. Similarly, Figure 3 demonstrates that these alternative grid charge designs can mitigate the adverse effects of a high share of households adopting dynamic tariffs on grid reinforcement costs. For example, in the combined analysis, aggregated reinforcement costs across all grids in the Volumetric FIT scenario rise significantly, from €22.2 million[5] to €54.8 million—an increase of €32.6 million. In contrast, under the Segmented FIT regulation, the costs increase only marginally, from €21.4 million to €21.8 million, representing a modest rise of €0.4 million (see Table 5 in the Appendix). The alternative grid charge designs create a monetary incentive to flatten the demand curve and distribute it over the day, reducing the number of undervoltage and overloading issues significantly, thereby reducing the associated grid reinforcement costs.

Although alternative grid charge designs mitigate the adverse effects of increasing dynamic tariff adoption rates on grid reinforcement costs, a similar impact cannot be observed for the introduction of dynamic feed-in remuneration rates, despite their prominence in policy discussions [4, 48]. On the contrary, the introduction of dynamic feed-in remuneration rates is associated with slightly higher reinforcement costs across all levels of dynamic tariff adoption. The underlying reason is illustrated in Figure 2: under dynamic feed-in remuneration, households collectively shift their feed-in to hours with higher prices, ultimately leading to increased grid reinforcement costs. However, this effect on reinforcement costs is relatively minor compared to the steep cost increases observed under volumetric grid charges. This is primarily because, for the households studied, excess PV production on sunny days significantly surpasses their flexibility potential, given the limitations of small battery capacities and low heating demand during the summer months. Apart from the volumetric case, the reinforcement requirements for the feed-in day exceed the measures on the other types of days in most cases. Or, in other words: when we consider alternative grid charge designs, the grid reinforcement measures required to accommodate 100% of households having PV installations are mostly sufficient to also deal with dynamic tariff-induced grid stress.

7.3 Discussion

Our work underlines an important result from past studies [20, 49, 80]: developments that are beneficial on a transmission system level, e.g., the widespread adoption of dynamic electricity tariffs, can lead to issues on the distribution grid level. Simultaneous reactions to the considered wholesale market prices trigger these issues. Our findings indicate that replacing volumetric grid charges with alternative designs that mitigate the simultaneous operation of flexible devices, such as HPs and EVs, prevents spot market-induced price signals from generating new peak loads and associated issues at the distribution grid level.

The investigated alternative grid charge designs include peak demand charges, segmented tariffs, and rotating tariffs. All three options demonstrate reduced grid reinforcement costs with increased dynamic tariff adoption rates, compared to the volumetric grid charge design. However, their practical applicability requires critical examination. Peak demand charges, while effective in the idealized conditions of our simulation, may face challenges in real-world implementation due to the need for accurate predictions of future household demand. Reliable scheduling of flexibility potentials to reduce peak loads is essential for these charges to have a tangible impact. Without robust home energy management systems capable of reliably shifting flexibility to reduce peak loads, the effectiveness of this policy would remain uncertain in practice. Segmented tariffs achieved the lowest grid reinforcement costs at 100% dynamic tariff adoption (see Table 5). Unlike peak demand charges, segmented tariffs do not target individual peak demands but incentivize a general flattening of the household load curve. However,

[5]We note that also initial grid reinforcement costs can vary across the different scenarios investigated, as regulatory options influence how household flexibility potentials are utilized, even in the absence of households subscribing to dynamic tariffs.

the design of segmented tariffs by grid operators must carefully balance grid reinforcement cost reductions with network fee revenues. Striking this balance to achieve a Pareto improvement for grid operators presents a valuable area for further research. Rotating grid charges also succeeded in avoiding sharp increases in reinforcement costs at higher dynamic tariff adoption rates. Similar to segmented tariffs, rotating tariffs are not aimed specifically at peak load reduction but employ time-variable charges that rotate among households. While these tariffs could discourage some households from shifting load to low-price periods, they may conflict with the "non-discriminatory tariff" requirement imposed on distribution system operators (DSOs) in many countries [80]. However, in certain jurisdictions, such as Finland, DSOs have greater flexibility in tariff design, potentially enabling the inclusion of rotating tariffs [82]. The detailed design of rotating tariffs—such as the number of tariff groups and the differentiation between high and low tariff levels—remains an open question for future research. Furthermore, to enable dynamic tariff adoption and the suggested alternative grid charges, a high penetration rate of smart meters would be necessary, which is not yet the case in many European countries [85].

Our study also examined an alternative policy design for feed-in tariffs, specifically dynamic, market-oriented remuneration. However, due to the significant excess feed-in from the investigated households and the misalignment between wholesale market price valleys (where feed-in is discouraged) and local peak PV production, no positive effects on grid reinforcement costs were observed. On the contrary, dynamic feed-in tariffs resulted in higher grid reinforcement costs across all scenarios.

The chosen time-series-based approach likely underestimates the necessary reinforcement costs compared to the currently used worst-case estimations. However, it is necessary to analyze detailed time series data to accurately capture changes in simultaneity and peak loads between the different policy options. Furthermore, when more households are equipped with smart meters, the grid operators can likely access data and measurements across the grids. Grid planning might move from the worst-case approach towards using real-world data on grid utilization in this case, which aligns more with our chosen approach.

We also note that our study is focused on a perfect foresight scenario, where household loads are determined by an optimization problem. Translated into a real-world setting, a household energy management system would have to make real-time decisions under uncertainty. However, we argue that also in a real-world scenario, the results should go in the same direction since previous studies have shown that through economic model predictive controllers, 63-98% of the perfect foresight savings can be reached [44]. Different providers may use different load and price forecasts, particularly in a system with a high share of volatile renewable generation. This can lead to more diverse decisions and load profiles and potentially lower load peaks. In addition, we note that the results are purely simulation-based and may neglect individual behavior and preferences. However, a German empirical study on the interaction of households with their PV/BESS energy management system showed that the observed behavior in the field resembles the outcomes of simulation-based studies [75]. To better understand the impact of household behavior and preferences on the resulting decisions of dynamic tariff-operated home energy management systems, future studies should also empirically investigate this.

Our study is constrained to a limited number of empirical load profiles and only considers one year of day-ahead market prices. Furthermore, we acknowledge that due to limited data availability, our analysis relied on datasets from two different geographies (Germany and Norway), which may introduce minor modeling inaccuracies. For instance, the colder climate in Norway could influence factors such as personal mobility patterns and EV battery efficiency. However, our open-source framework facilitates the analysis of alternative datasets and more price years in future research.

Furthermore, our study focuses on energy systems with a regulatory framework that promotes the self-consumption of households' PV generation. In this regulatory setting, PV production fed to the grid is remunerated with a fixed feed-in tariff. Through the consumption of energy stored in the battery, volumetric grid charges can be avoided [29]. In contrast, several states like the United States [35], Spain or Ecuador [56] have net metering or net billing policies in place, where feed-in is compensated by credits, which reduce the electricity bills. While we have not investigated the interplay of an increasing dynamic tariff adoption, policy options, and net metering policies for the sake of conciseness, we see it as a worthwhile avenue for further research.

8 Conclusion

Our study investigates the impact of an increasing share of households with dynamic tariffs on grid reinforcement costs on the low- and medium-voltage levels. We provide a four-step open-source simulation framework that includes data preprocessing of empirically observed individual household loads, household-level optimization of shiftable loads like HPs and EVs, as well as the operation of battery storage, a PyPSA-based power flow analysis and a subsequent eDisGO-based calculation of grid reinforcement costs. We compare the status-quo policy design with volumetric grid charges and fixed feed-in tariffs with alternative policy designs. We find that the currently widely proliferated volumetric grid charges lead to simultaneous reactions of households to wholesale market price signals, leading to avalanche effects, which in turn lead to substantial reinforcement costs. We show that alternative grid charges, such as segmented or rotating ones, potentially alleviate the negative effects of high penetration of dynamic tariffs. We publish our code, data, and model as an open-source framework. Thereby, we enable researchers, policymakers, and practitioners to evaluate the impact of novel policies and technologies - in combination with an increasing share of dynamic tariffs - on the distribution grid.

Future valuable research avenues include investigating varying household settings (e.g., varying shares of PV, EV, and HP adoption), fairness issues (e.g., energy equity of grid charge options), novel technological options (e.g., vehicle-to-grid), and alternative regulatory options. In addition, future studies could elaborate on particular modeling aspects of the study at hand, for instance, by implementing sophisticated thermal building models or by incorporating operation under uncertainty on a household level (e.g., through a model predictive control approach).

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Table 1: Investigated policy options and resulting scenarios.

Scenario	Feed-in Tariff $p_t^{\text{feed-in}}$	Grid Charges	Retail Tariff $p_t^{\text{wholesale}}$	Operation
Constant Volumetric_FIT without flexibility	constant	volumetric	constant	constant
Constant Volumetric_FIT	constant	volumetric	constant	dynamic
Dynamic Volumetric_FIT	constant	volumetric	dynamic	dynamic
Constant Volumetric_DynFeed	dynamic	volumetric	constant	dynamic
Dynamic Volumetric_DynFeed	dynamic	volumetric	dynamic	dynamic
Constant Peak_FIT	constant	peak	constant	dynamic
Dynamic Peak_FIT	constant	peak	dynamic	dynamic
Constant Peak_DynFeed	dynamic	peak	constant	dynamic
Dynamic Peak_DynFeed	dynamic	peak	dynamic	dynamic
Constant Rotating_FIT	constant	rotating	constant	dynamic
Dynamic Rotating_FIT	constant	rotating	dynamic	dynamic
Constant Rotating_DynFeed	dynamic	rotating	constant	dynamic
Dynamic Rotating_DynFeed	dynamic	rotating	dynamic	dynamic
Constant Segmented_FIT	constant	segmented	constant	dynamic
Dynamic Segmented_FIT	constant	segmented	dynamic	dynamic
Constant Segmented_DynFeed	dynamic	segmented	constant	dynamic
Dynamic Segmented_DynFeed	dynamic	segmented	dynamic	dynamic

Table 2: Aggregated peak loads [kW] per scenario on the day with the peak empirical HP load (2019-12-01), PV feed-in (2019-05-13), EV demand (2019-11-18) and the highest yearly peak load per scenario.

	Heat pump peak [kW]	Feed-in peak [kW]	EV peak [kW]	Yearly peak [kW]
name				
Constant Volumetric_FIT without flexiblity	1189.9	1969.3	1183.9	2272.3
Constant Volumetric_FIT	1179.7	1865.7	1095.6	2270.2
Dynamic Volumetric_FIT	2258.9	1891.8	2352.3	2788.4
Constant Volumetric_DynFeed	1202.1	2189.0	1122.4	2496.5
Dynamic Volumetric_DynFeed	2257.1	2159.0	2351.2	2787.8
Constant Peak_FIT	996.4	1892.5	989.0	2267.1
Dynamic Peak_FIT	1693.6	1944.1	1670.4	2560.1
Constant Peak_DynFeed	1204.5	2597.8	1277.7	2652.3
Dynamic Peak_DynFeed	1699.6	2512.5	1668.6	2650.3
Constant Rotating_FIT	1227.6	1876.1	1096.4	2246.8
Dynamic Rotating_FIT	1437.6	1890.0	1449.2	2290.5
Constant Rotating_DynFeed	1229.4	2192.9	1093.1	2496.6
Dynamic Rotating_DynFeed	1442.2	2134.6	1448.5	2492.4
Constant Segmented_FIT	959.8	1827.3	937.5	2296.3
Dynamic Segmented_FIT	1264.0	1863.2	1184.8	2263.1
Constant Segmented_DynFeed	990.5	2178.3	924.0	2496.8
Dynamic Segmented_DynFeed	1248.4	2192.1	1185.0	2495.6

A Appendix

Regulatory scenarios

In Table 1, a detailed overview of the investigated regulatory scenarios is depicted. The ramp-up from 0% to 100% households with dynamic tariffs constitutes replacing *Constant* with *Dynamic* profiles at the nodes of the distribution grid, in the scope of the respective regulatory scenario.

Peak loads of aggregated household profiles

In Table 2, the aggregated peak loads of all 500 households within the given regulatory scenarios are depicted.

Peak loads with varying PV/BESS/HP/EV adoption rates

Figure 5 shows a sensitivity analysis for varying PV/BESS/HP/EV adoption rates under the status-quo *Volumetric_FIT* regulatory scenario. In Figure 4, the weekly aggregated energy consumption of all 500 modelled households is depicted.

Figure 6 depicts the impact of varying adoption rates under the alternative *Segmented_FIT* regulatory scenario, showing remarkably lower peak loads and lower peak load increases through the introduction of dynamic tariffs.

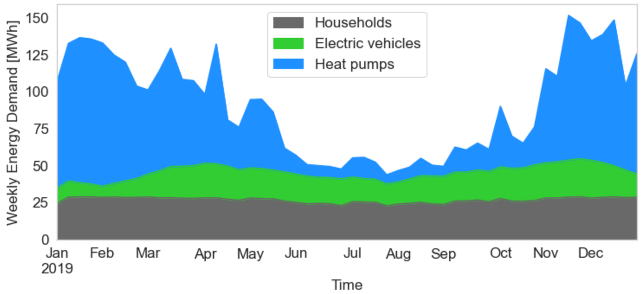

Figure 4: Weekly aggregated energy consumption of all households.

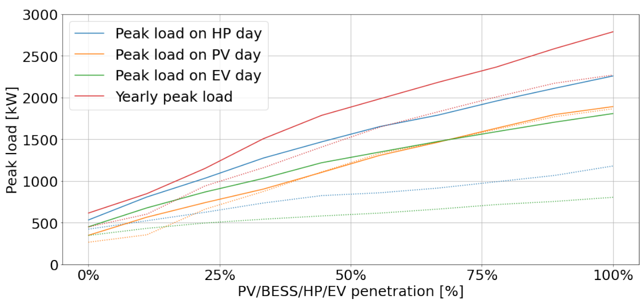

Figure 5: Peak loads on specific days in the scope of varying PV/BESS/HP/EV adoption rates under the *Volumetric_FIT* regulatory scenario. 100% dynamic tariff adoption with solid lines, 0% dynamic tariff adoption with dotted lines.

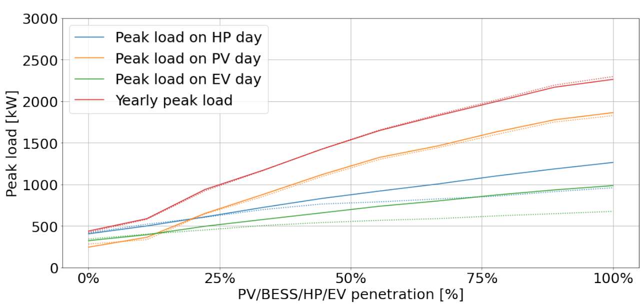

Figure 6: Peak loads on specific days in the scope of varying PV/BESS/HP/EV adoption rates under the *Segmented_FIT* regulatory scenario. 100% dynamic tariff adoption with solid lines, 0% dynamic tariff adoption with dotted lines.

Grid topologies

Table 3 describes the properties of the investigated grid topologies in terms of nominal transformer capacity (in MW), installed renewables capacity (in MW), line length (in km) and transformer numbers. Figure 7 depicts an exemplary grid topology consisting of transformers, lines, and connected generators and loads. In Figure 8, an overview of the simulated grids and the types of installed loads and generation capacities is depicted.

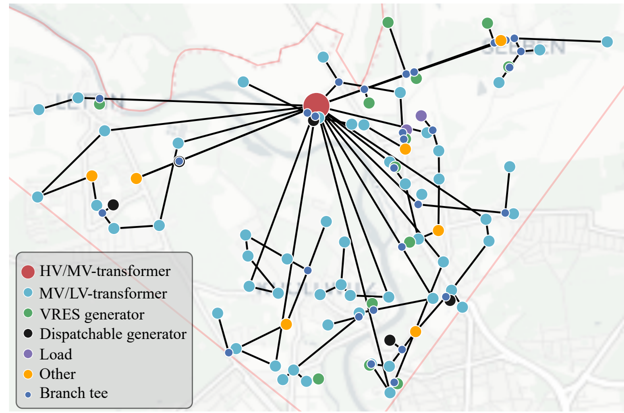

Figure 7: Topology of exemplary grid.

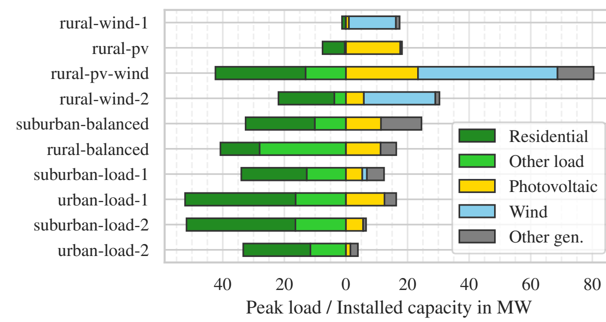

Figure 8: Overview of simulated grids with total peak load and installed feed-in capacities.

Empirical consumption on type days

Figure 9 shows the aggregated empirical loads on the investigated days, exhibiting particularly high peak loads on the HP and EV day.

Grid reinforcement results

In Table 4, the grid reinforcement costs per penetration rate are split up into the analyzed grids and then aggregated for one exemplary regulatory scenario (*Volumetric FIT*). In the following experimental results per type day (Table 5, 6, 7, 8 and 9), only the aggregated costs are considered per regulatory scenario. In Figure 10, an overview of the grid issues that led to the necessary reinforcement measures is provided.

In Figure 11, we show that the peak loads observed in Table 2 are correlated with the resulting grid reinforcement costs. The Pearson correlation factor between the yearly peak loads and resulting grid reinforcement costs lies at 0.68, indicating a strong relationship between the two variables. This demonstrates that the peak loads observed in Figure 2 can serve as a reliable initial indicator for determining whether grid reinforcement measures may be necessary. However, the coefficient of determination (R^2) of 0.47 reveals that annual peak loads alone cannot fully explain the variability in grid reinforcement costs. Consequently, this underscores the importance

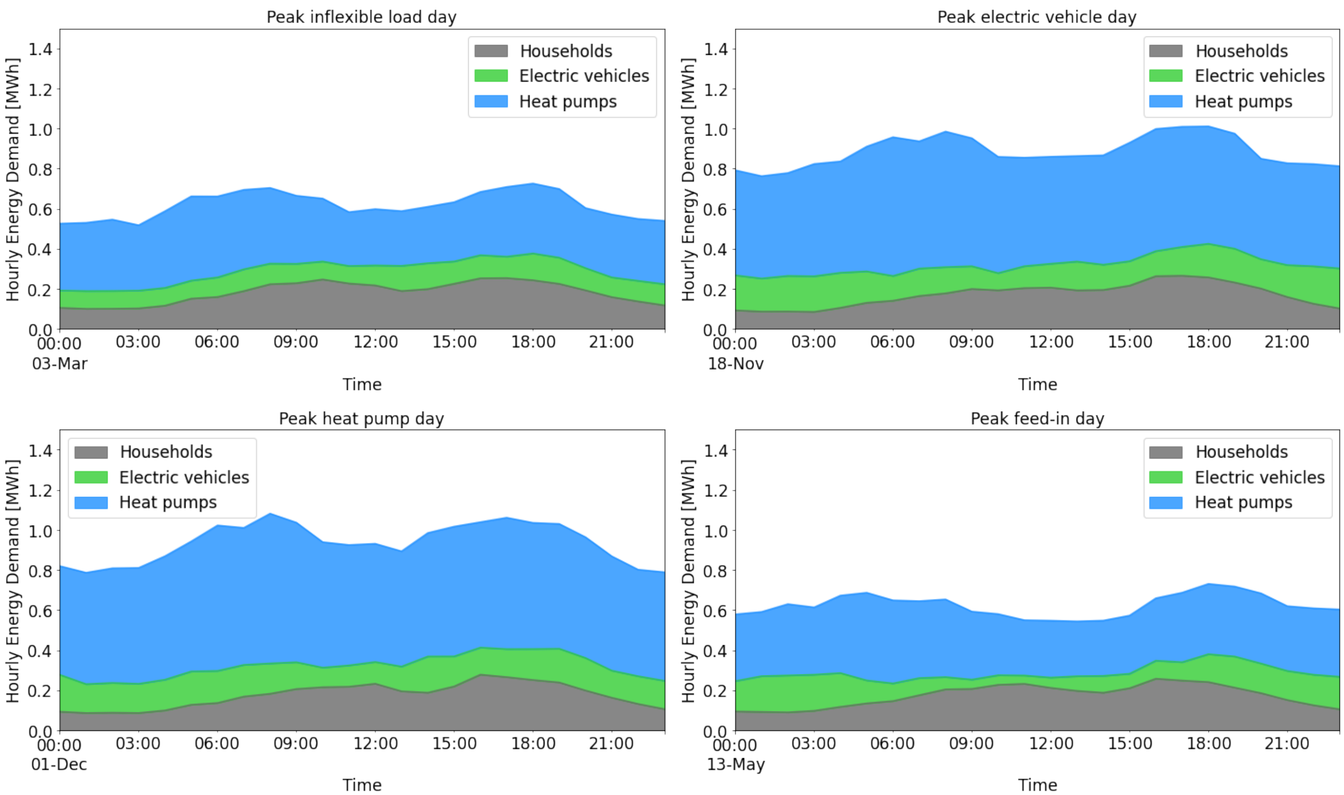

Figure 9: Hourly empirical aggregated energy consumption on type days.

Table 3: Grid characteristics

Grid name	transformers_snom_mean	installed_wind_capacity	length_lines_median	nr_lines	nr_buses	length_lines_lv	installed_pv_capacity	nr_transformers	length_lines_total	length_lines_max	length_lines_mean	length_lines_mv
urban-load-2	0.60	0.00	0.02	5776	5830	173.20	1.46	83	247.53	6.86	0.04	74.33
suburban-load-2	0.59	0.01	0.02	11224	11312	319.60	5.59	143	438.87	8.03	0.04	119.27
rural-balanced	0.52	0.00	0.02	5142	5188	149.51	11.25	79	281.10	15.65	0.05	131.58
urban-load-1	0.53	0.00	0.02	10222	10331	312.06	12.51	165	408.32	6.71	0.04	96.27
rural-wind-1	0.28	15.25	0.03	516	530	17.94	0.96	16	49.00	9.11	0.09	31.06
rural-pv-wind	0.24	45.30	0.03	13439	13730	540.74	23.39	319	1035.10	15.79	0.08	494.36
suburban-load-1	0.41	1.50	0.02	8396	8485	251.35	5.30	131	408.13	18.86	0.05	156.78
rural-pv	0.14	0.00	0.03	3668	3855	160.57	17.64	207	611.96	14.23	0.17	451.39
rural-wind-2	0.22	23.20	0.03	8728	8910	381.40	5.82	201	723.43	18.21	0.08	342.03
suburban-balanced	0.58	0.00	0.02	5197	5259	178.25	11.37	103	269.54	6.25	0.05	91.30

Table 4: Volumetric FIT detailed reinforcement costs [M€] per grid in the combined analysis

Dynamic Tariff Penetration [%]	urban-load-2	suburban-load-2	rural-balanced	urban-load-1	rural-wind-1	rural-pv-wind	suburban-load-1	rural-pv	rural-wind-2	suburban-balanced	Aggregated
0	0.6	2.2	1.1	1.9	0.2	8.3	0.9	1.3	4.5	1.2	22.2
25	0.6	3.6	3.3	1.9	0.2	9.5	1.0	2.3	6.4	1.2	30.0
50	0.6	5.0	5.0	2.0	0.2	9.5	1.3	2.3	6.5	1.3	33.7
75	1.2	6.1	5.0	2.3	0.2	9.9	2.0	5.6	8.0	1.2	41.3
100	1.5	8.2	4.9	2.5	0.2	10.4	3.6	10.4	11.9	1.2	54.8

of conducting a more granular, scenario-specific analysis of grid reinforcement costs, as detailed in Section 7.2.

In Figure 12, the correlation between the increase of grid reinforcement costs (from 0% to 100% dynamic tariff adoption under the $VolumetricFIT$ scenario) and characteristics of the 10 investigated grid topologies is investigated. Among the grid characteristics, the length of medium-voltage (MV) lines exhibits the strongest positive correlation with reinforcement costs, whereas the mean nominal power of transformers demonstrates a negative correlation.

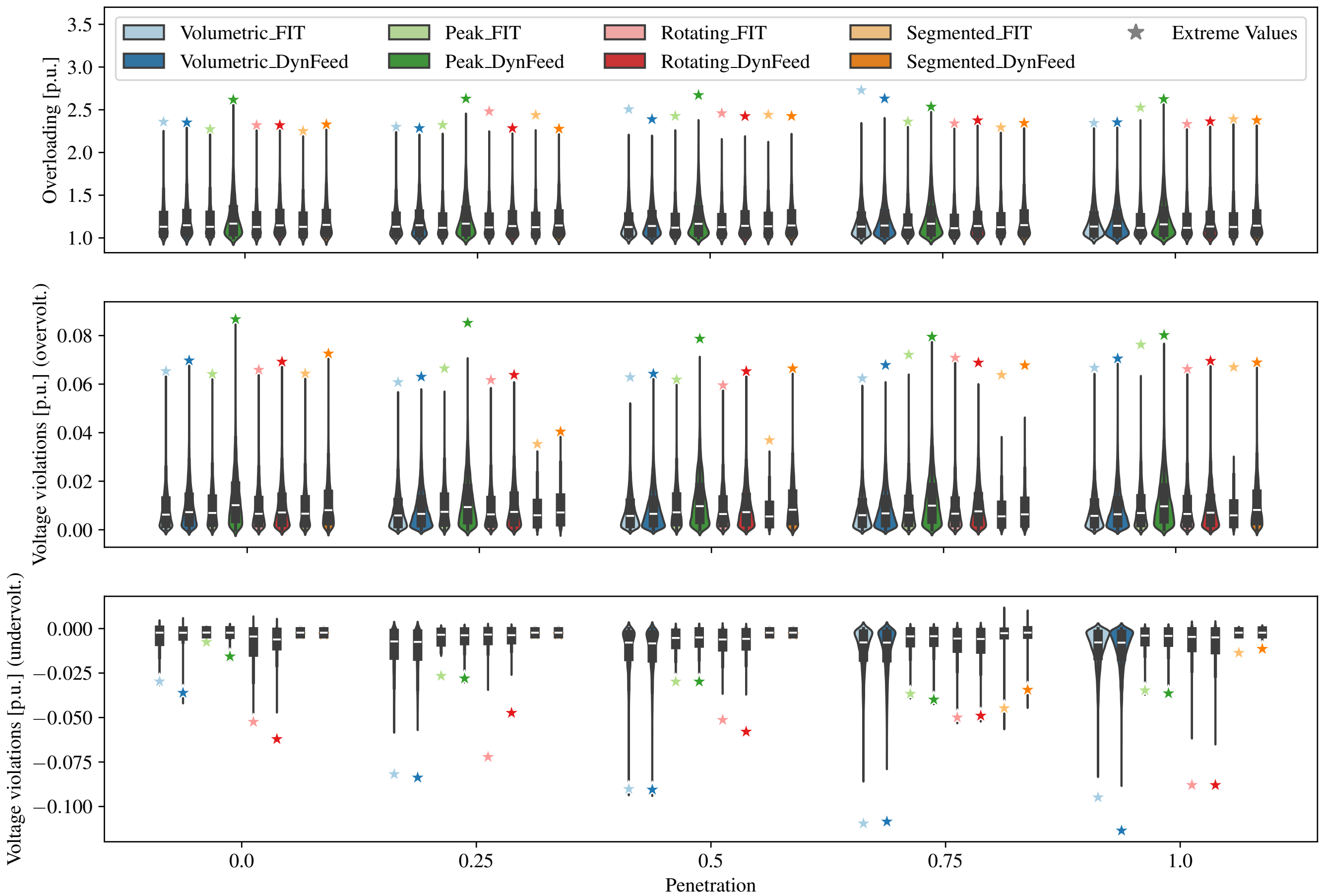

Figure 10: Grid issues occurring for the different policy scenarios and penetrations for one representative run.

Table 5: Combined analysis reinforcement costs [M€] per regulatory setting

Dynamic Tariff Penetration [%]	Volumetric_FIT	Volumetric_DynFeed	Segmented_FIT	Segmented_DynFeed	Rotating_FIT	Rotating_DynFeed	Peak_FIT	Peak_DynFeed
0	22.2	25.7	21.4	25.7	22.4	25.6	22.4	32.9
25	30.0	32.9	21.2	25.4	22.2	25.5	22.2	32.5
50	33.7	36.8	21.5	25.7	22.6	25.8	23.1	32.2
75	41.3	43.4	21.9	25.1	22.5	25.2	23.0	32.0
100	54.8	57.5	21.8	25.3	22.7	25.7	24.2	32.4

Table 6: Electric vehicle type-day reinforcement costs [M€] per regulatory setting

Dynamic Tariff Penetration [%]	Volumetric_FIT	Volumetric_DynFeed	Segmented_FIT	Segmented_DynFeed	Rotating_FIT	Rotating_DynFeed	Peak_FIT	Peak_DynFeed
0	0.5	0.5	0.2	0.2	0.8	0.8	0.2	0.4
25	11.5	11.3	0.2	0.2	1.3	1.3	0.6	0.8
50	17.0	17.4	0.2	0.2	1.6	1.7	1.0	1.2
75	27.8	27.3	0.2	0.2	1.9	1.8	1.1	1.2
100	44.7	45.1	0.2	0.2	3.0	3.0	2.8	3.4

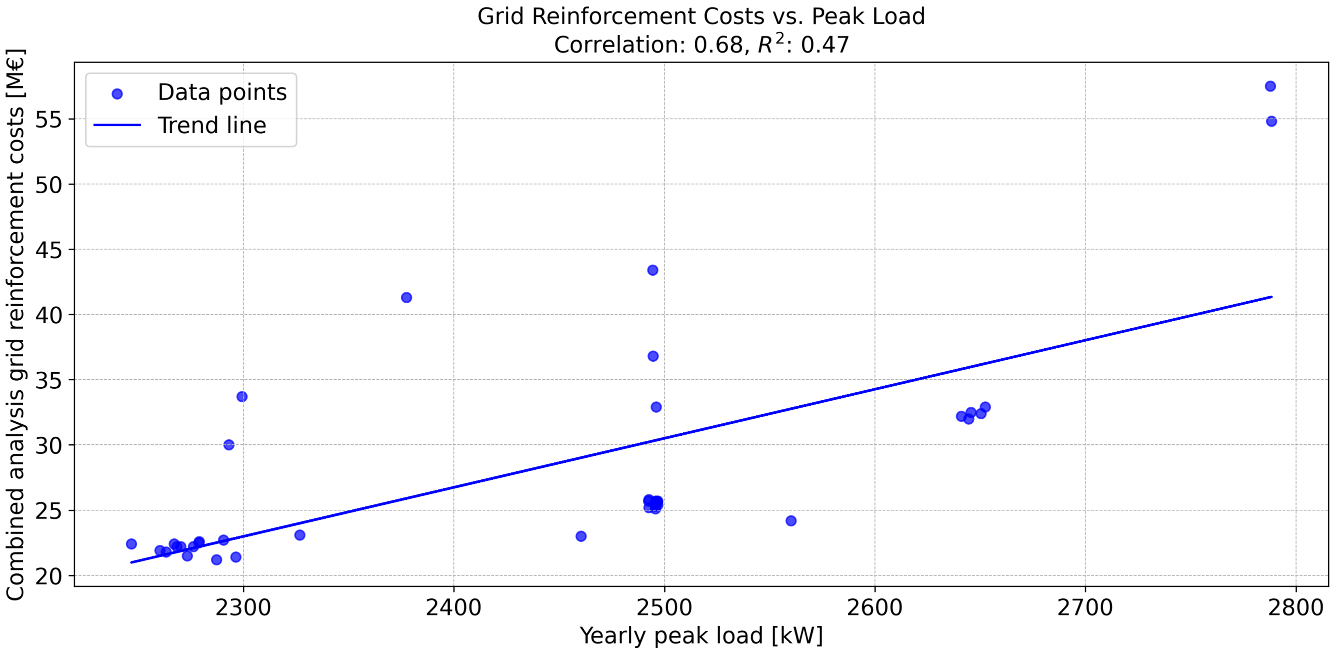

Figure 11: Relationship between yearly peak loads of the 500 investigated households (see Table 2) and the "combined analysis" grid reinforcement costs (see Table 5), for all policy scenarios, grid topologies and adoption rates.

Table 7: Feed-in type-day reinforcement costs [M€] per regulatory setting

Dynamic Tariff Penetration [%]	Volumetric_FIT	Volumetric_DynFeed	Segmented_FIT	Segmented_DynFeed	Rotating_FIT	Rotating_DynFeed	Peak_FIT	Peak_DynFeed
0	21.9	25.5	21.2	25.6	22.1	25.3	22.2	32.8
25	21.7	25.2	21.1	25.2	21.8	25.1	22.1	32.4
50	22.4	25.5	21.4	25.5	22.3	25.5	23.0	32.1
75	21.3	25.0	21.7	25.0	22.1	24.9	22.9	31.8
100	21.9	25.1	21.6	25.2	22.2	25.2	23.4	31.4

Table 8: Heat pump type-day reinforcement costs [M€] per regulatory setting

Dynamic Tariff Penetration [%]	Volumetric_FIT	Volumetric_DynFeed	Segmented_FIT	Segmented_DynFeed	Rotating_FIT	Rotating_DynFeed	Peak_FIT	Peak_DynFeed
0	0.5	0.5	0.2	0.2	1.1	1.2	0.2	0.3
25	5.2	5.7	0.2	0.2	1.6	1.7	0.5	0.7
50	9.0	9.7	0.2	0.2	2.1	2.1	0.8	0.9
75	17.2	18.3	0.2	0.2	2.4	2.2	1.0	1.1
100	29.3	30.5	0.3	0.2	2.9	3.1	3.5	3.6

Table 9: Inflexible load type-day reinforcement costs [M€] per regulatory setting

Dynamic Tariff Penetration [%]	Volumetric_FIT	Volumetric_DynFeed	Segmented_FIT	Segmented_DynFeed	Rotating_FIT	Rotating_DynFeed	Peak_FIT	Peak_DynFeed
0	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1
25	0.6	0.5	0.1	0.1	0.3	0.3	0.2	0.2
50	0.8	0.8	0.1	0.1	0.3	0.3	0.2	0.2
75	1.2	1.1	0.1	0.1	0.4	0.3	0.2	0.2
100	1.8	1.7	0.1	0.1	0.5	0.5	0.4	0.3

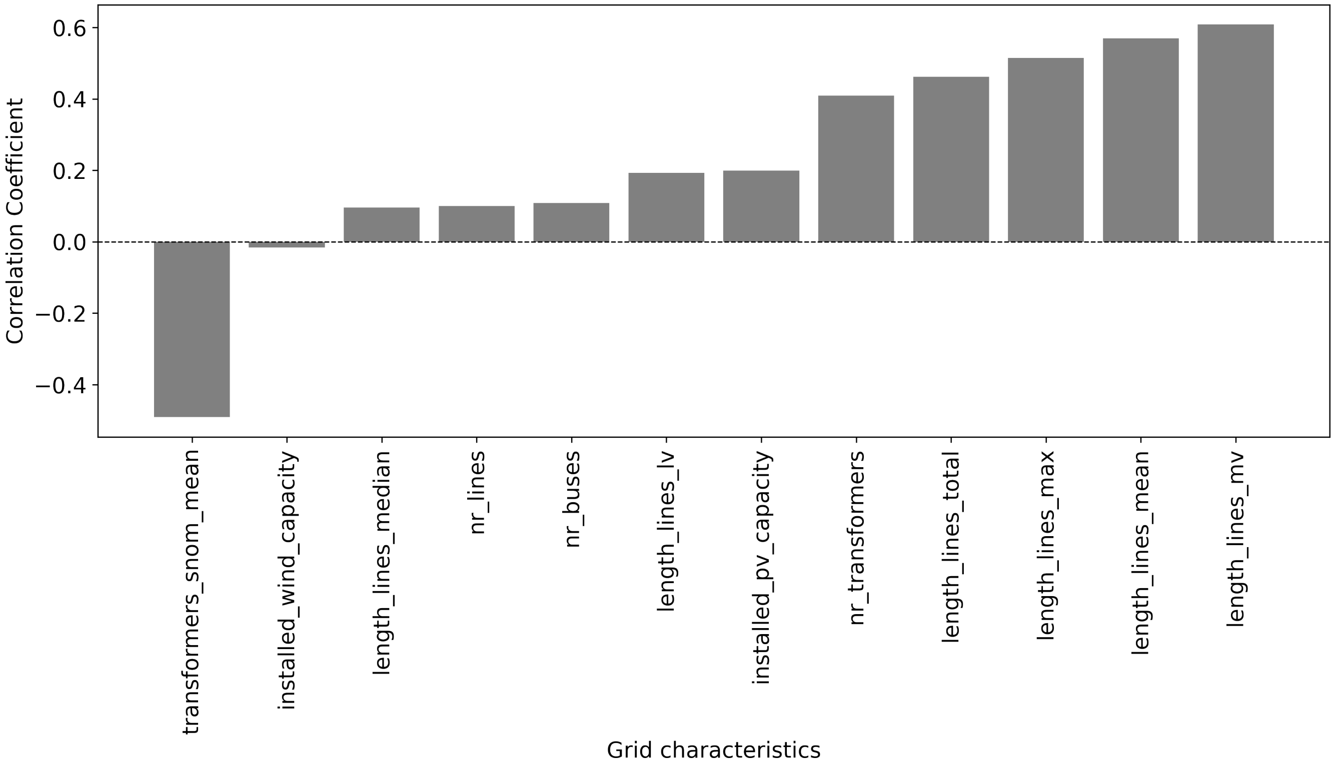

Figure 12: Correlation between increase in reinforcement costs (Table 4) and grid characteristics (Table 3) in the Volumetric FIT scenario.