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Another Source of Inequity? How Grid Reinforcement Costs Differ by the Income of EV User Groups

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Another source of inequity? How grid reinforcement costs differ by the income of EV user groups

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Abstract

The power demand for electric vehicles in future mobility scenarios may lead to peaks and overloads threatening grid stability. The necessary infrastructure investments vary by the number and model type of vehicles driven and the residents charging preferences. These attributes significantly depend on socio-economic factors such as income. Our power flow simulations predict massive cost asymmetries up to 33-fold in higher-income compared to lower-income neighborhoods. This effect could amount to a cost asymmetry of up to €14 billion on an EU level. Hence, grid operators will have to prioritize higher-income neighborhoods in their planning. As many grid operators redistribute their costs through an across-the-board electricity price increase for all households, the high infrastructure costs could lead to unwanted inequitable costing allocation. Policymakers should consider countermeasures like dynamic electricity pricing schemes, peak power pricing, or income-based electric vehicle subsidies to ensure energy equity in future mobility scenarios.

Keywords: electric vehicles; electric grid; grid planning; socio-economic factors; energy equity

With tightening carbon emission regulations in the transportation sector, more and more consumers are switching to electric vehicles (EVs). However, charging a high number of EVs poses challenges to the distribution grids: Most consumers favor charging their EVs at similar times during the day, especially in the early evening hours. This parallel charging of multiple EVs could lead to significant load peaks causing overloads within the grids [1–3]. These overloads increase with EV adoption and depend on the EV model choice as well as the applied charging patterns. All these factors may be correlated with socio-economic attributes like household income [4–8]. Therefore, grid operators may have to over-proportionally enhance the grid infrastructure in areas with many high-income households. Our paper investigates how the necessary grid reinforcement costs differ between lower and higher-income neighborhoods. From these calculations, we quantify the over-proportional grid reinforcement cost impact of higher-income EV users as well as the potential for energy inequities and derive policy recommendations accordingly.

Our work contributes to the larger field of energy inequity, which is increasingly relevant: [9] find that the clean energy transition might further disadvantage lower-income households. [10] reveals that lower-income neighborhoods experience stronger grid limitations, reducing their access to residential photovoltaics and potentially hindering EV adoption. Hence, efforts to accurately measure energy inequity and strive for energy justice and equity through policy measures are increasing [11, 12].

[1, 2, 13, 14] are among the first to investigate the impact of EVs on the distribution grids. [1] uncover that plug-in hybrid electric vehicle penetrations levels between 10% and 30% lead to significant voltage imbalances and power losses. Building on these findings, numerous authors find similar results with grids being unable to handle EV charging loads in different countries and grid scenarios [2, 3, 14, 15]. [13] and [16] contribute to the discussion by providing general overviews and outlooks of the challenges coming when integrating electric vehicles into the grid. The recent technological shift towards sole battery-powered electric vehicles (BEVs) and higher charging powers could further increase the pressure on the grid, requiring new solutions and improvements within the infrastructure [17–19].

When analyzing EVs' impact on the distribution grids, most studies model all households within the simulated distribution grid with homogeneous EV adoption and usage behavior. However, socio-economic factors such as income, age, gender, occupation, level of education, ethnicity, home ownership, or political orientation play a role in EV adoption [4–6, 20–25]. The homogeneous modeling of grid impact could hence be prone to significant errors. [4] analyzed sales data from 20 countries like China, Norway, Germany, and the US. Although every country included provides tax benefits or government subsidies decreasing the purchase costs, the authors find that of all possible socio-economic factors, income still is the primary driver of EV adoption. [20] find that above-average household income increases the likelihood of owning an EV by as much as 200%. [21] and [22] support these claims, finding that medium to high-income groups tend to show higher EV adoption. [5] find the same phenomenon in the UK. Analyzing survey data from more than 5000 respondents in the Nordics, [6] uncover that higher income is associated with an increased likelihood of owning an EV and more expensive car models. [26], [27] and [23] find similar results. These more expensive and frequently larger car models tend to have higher electricity consumption, increasing charging loads [28].

Besides EV adoption and car model choice, driving patterns greatly affect EV charging patterns and potential load peaks. The driving patterns depend on socio-economic factors, including age, gender, and level of education or occupation. Depending on these factors, the number of trips per day as well as the departure and arrival times impacting charging times vary significantly [7, 29–31]. Since socio-economic factors may lead to higher worst-case power flows, papers like [8] or [32] criticize current charging modeling approaches and call to include these factors in load assessments: [31] simulate EV charging demand accounting for socio-economic factors such as household income or occupation and analyze the related load curves in a German setting. The recent 2035 forecast for the US, as developed by [32], also criticizes current charging modeling approaches. Using a data-driven model distinguishing driver income, housing, and miles traveled, they find that EV charging loads increase peak net electricity demand by up to 25% and deduct related implications as for example the charging point dissemination. [5] simulate EV charging loads of UK households with differing economic statuses. They find that higher-income households cause larger load peaks, potentially leading to over-proportionally high grid reinforcement costs. Their paper hence raises the issue of a fair grid cost allocation. While only a few studies include socio-economic factors in their load assessment, none of these studies provide estimations on the related distribution grid reinforcement needs or related grid reinforcement costs.

Fairness in the allocation of these grid reinforcement costs is a matter of perspective. [33] distinguishes the allocation of costs between three principles: The allocation of costs along the need, along the contribution to a problem, or to a simple equal share. In the context of reducing CO2 emissions, [34] find that most individuals prefer the principle of contribution (equity), where people who contribute more emissions should have to achieve higher emission reductions. The issue of fairness in bearing the here-mentioned grid infrastructure costs is slightly more complicated, as higher-income households with more electric vehicles might cause over-proportionally high infrastructure costs but also reduce CO2 emissions. However, in the coming years, EVs are expected to become cheaper with economies of scale. In the long run, we may assume an equally high share of vehicle electrification in lower- and higher-income households. At that point, we may still face differing costs in required grid reinforcements due to driving behavior and vehicle ownership. Applying the principle of fairness according to contribution would require higher-income households to carry the caused asymmetry in grid reinforcement costs to the full extent.

However, residential grid reinforcement costs in many countries are compensated for as part of the electricity price via a fixed component as well as a fee per kWh (see [35, 36] and, for example, [37, 38] in Germany). Without adjustment for maximum loads, increased grid reinforcement costs would lead to an overall electricity price increase for all consumers. This price increase could be considered inequitable to the principle of fairness according to the contribution, as higher-income neighborhoods over-proportionally cause these grid reinforcement costs. Previous literature does not quantify the related grid cost asymmetry and could not uncover potential unfairness.

Connecting to this issue, we focus our analysis on household income as a critical socio-economic factor and raise a discussion on energy equity. Our paper aims to quantify the over-proportional grid reinforcement cost impact of higher-income EV users. We, therefore, use real trip data from [39] in a grid power flow analysis to compare the grid reinforcement costs of above-average with below-average income neighborhoods. The contribution should be highly relevant for policymakers, who increasingly incorporate energy equity as a critical factor in electricity pricing and energy policy overall [40–43]. Furthermore, our paper helps grid operators and illustrates the need to include socio-economic factors such as income in their grid planning models, which some providers are starting to incorporate [44].

The paper is organized as follows: Section 1 presents and discusses the results and related implications, while Section 2 concludes. The general methodology and input parameters are outlined in Section 3.

1 Results and Discussion

1.1 Impact on grid overloads

Based on simulated load profiles, we investigate the overloads occurring for below-average (lower) and above-average (higher) income rural, suburban, and urban neighborhoods. This overload analysis is relevant for grid planning, as it displays which neighborhoods require prioritization. Figure 1 illustrates the number of 5-minute intervals in which an overload occurs. For example, on average, the rural grid experiences 5 overloads during a week in the lower-income neighborhood, while 70 overloads occur in the higher-income neighborhood.

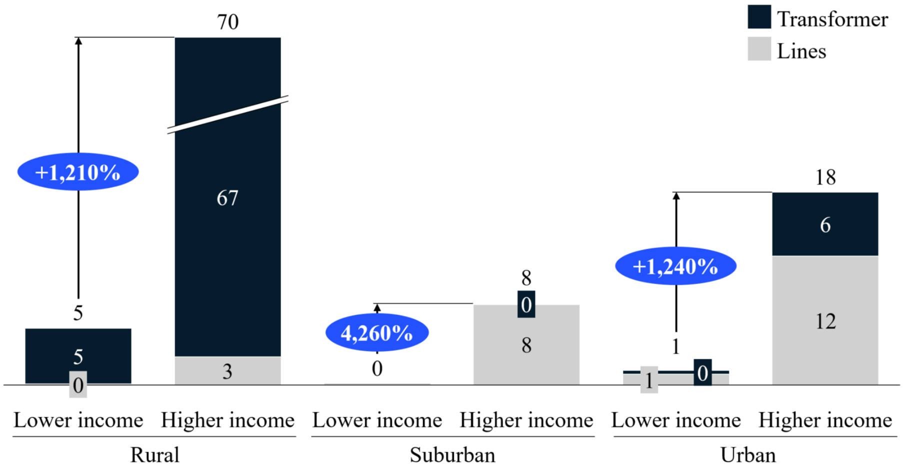


Fig. 1: Average simulated number of weekly overloads in December.

In all area types, higher-income neighborhoods would experience significantly more grid overloads, putting these neighborhoods higher on the grid operators' agenda for grid reinforcements. As the number of overloads and hence the probability for a blackout differ significantly between lower and higher-income neighborhoods, the importance of including socio-economic factors such as income in grid planning models becomes apparent. The rural grid is the weakest and exhibits the most overloads. However, a transformer replacement in this grid would solve the vast majority of overloads occurring, while mostly grid lines are the bottleneck in the other grid types.

1.2 Asymmetry in grid reinforcement costs and underlying effects

In this section, we derive the related grid reinforcement costs to mitigate the overloads previously outlined and stabilize the grid. The average reinforcement costs to be expected are illustrated in Figure 2. While the analysis does not prove a causal relationship between household income and grid reinforcement costs caused, it provides illustrating scenarios for future grid reinforcement costs to be expected for a representative higher-income compared to a lower-income neighborhood.

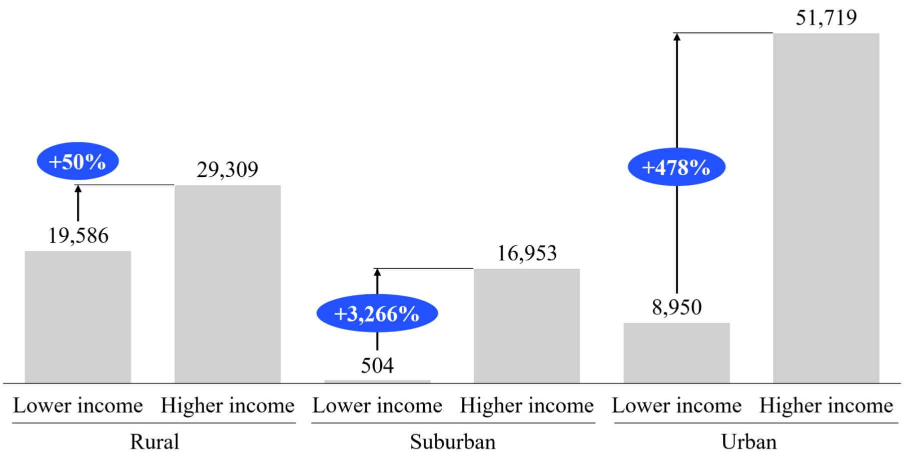


Fig. 2: Average simulated grid reinforcement costs (in €) in December.

We see 50% additional grid reinforcement costs for higher-income neighborhoods in the rural, 3,266% in the suburban, and 478% in the urban grid compared to lower-income neighborhoods. The additional reinforcement costs are the lowest for the rural grid as this grid is the least resilient overall. An upgrade of its bottleneck, the transformer, becomes inevitable even for lower EV charging loads. These significant asymmetries in grid reinforcement cost further illustrate the necessity for grid operators to include socio-economic factors such as income in their grid planning models to represent future grid costs adequately. These significant asymmetries also prevail when testing for the inclusion of residential electricity generation and storage. When extrapolating our findings to the around 119 million residential buildings in the EU and accounting for their distribution to rural, suburban, and urban areas, the potential grid cost asymmetry between higher- and lower-income neighborhoods could reach around €14 billion [45–48].

In order to derive appropriate mitigating policy measures, we further analyze the impact of the underlying drivers for the additional grid reinforcement cost of higher-income neighborhoods. We quantify the standalone impact of differences in EV adoption, model choice, and driving patterns by neighborhood type. For that purpose, we keep all other parameters equal (ceteris paribus) and adjust one driver as follows.

- EV adoption: We derive the effect of EV adoption by assigning both income groups the same EV adoption rate of 31.1%.
- Model choice: We quantify the impact of model choice by assigning the car segment distribution of lower-income households to higher-income households.
- Driving patterns: We analyze the impact of driving patterns by assigning the driving patterns of lower-income groups to higher-income groups.

It is important to note that these three drivers are not additive. However, this analysis provides an understanding of the most effective levers for diminishing grid cost asymmetry and related inequities. In Figure 3, we first analyze the effect of EV adoption.

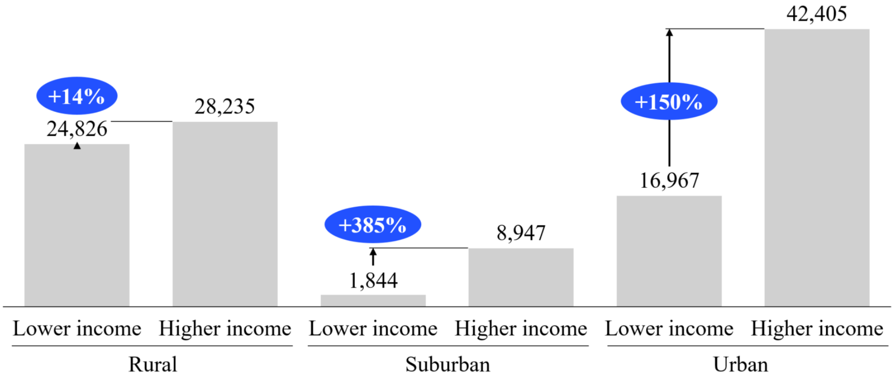


Fig. 3: Average simulated grid reinforcement costs (in €) assuming equal EV adoption levels in December.

If EV adoption were equally distributed over all neighborhoods, the grid reinforcement cost asymmetries would shrink significantly. This effect, however, is partly caused by a related grid cost increase for lower-income neighborhoods. Nonetheless, our results show that even if equal EV adoption levels across income levels could be achieved, significant additional grid reinforcement costs for higher-income neighborhoods prevail, especially for the suburban and urban grids.

Figure 4 illustrates the impact of model choice and driving patterns of higher-income households. We discuss only the urban grid, as the effects for the other two grid types are similar.

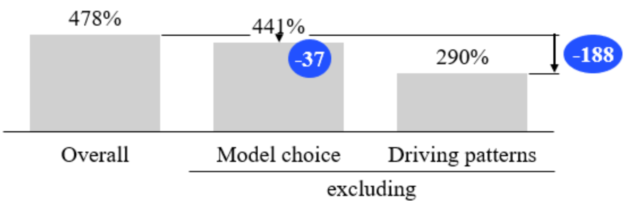
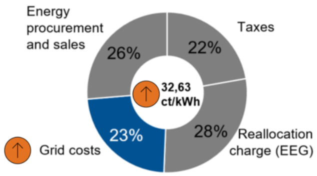


Fig. 4: Breakdown of grid reinforcement costs asymmetries by the underlying drivers of model choice and driving patterns, urban grid.

Driving patterns strongly impact grid cost asymmetry, while the effect of model choice is relatively small. This can also be observed for the rural and suburban grids, with additional costs shrinking in the suburban and slightly also in the rural grid. For more details on this matter, please refer to Section 3.7. These findings indicate that policymakers may foster EV adoption with all model sizes but focus more on reducing peak-hour charging to mitigate some behavioral effects of higher-income households.

1.3 Electricity pricing implications, related inequity and possible mitigating policy measures

Residential grid reinforcement costs are currently paid for via the consumer electricity price, which is determined per kWh [37, 38]. These prices do not vary with the load or maximum power demand but are reimbursed with a flat-rate cost allocation [37]. As can be seen in Figure 5, the proportion of the electricity price allocated to grid costs for an average household in 2021 was around 23% [38].



$$Electricity\ cost = Base\ rate + Price\ per\ kWh \times kWh\ consumed$$

Fig. 5: Electricity price split and cost calculation, Germany 2021 [38].

If grid costs increase, the electricity price for all consumers is inflated, and electricity costs increase for all households. Due to their higher total electricity consumption and related higher electricity costs, higher-income neighborhoods carry more of the grid reinforcement costs in total. However, as they only consume 16%-18% (based on the area type) more electricity than lower-income households, this contribution fails to offset the massive additional grid reinforcement costs caused. Furthermore, grid operators often split grid costs into a base rate in addition to a volumetric (per kWh) component. This base rate is not scaled with regards to consumption and hence further limits the grid cost contribution of higher-income households [37]. With household electricity prices at a record high (32.63ct/kWh in 2021 and quickly increasing during the European Energy Crisis in 2022 [46, 49, 50]), a further across-the-board electricity price increase to cover the additional grid reinforcement cost of higher-income neighborhoods could be considered inequitable with respect to the principle of fairness according to contribution. As this grid reinforcement cost asymmetry can be traced back to higher-income neighborhoods, equitable cost allocation would require higher-income households fully bear this cost asymmetry, not affecting the electricity prices of other consumers.

However, it is important to note that the rationale for this potential inequitable cost allocation is not the difference in income between the two neighborhood types but the difference in usage of the electric distribution grid as a common resource. According to the principle of fairness according to contribution (equity) [33], households in a higher-income neighborhood should rather pay grid fees which reflect the contribution to the grid reinforcement costs induced by them. We focus on mitigating policy actions directly related to households' grid cost impact, not socio-economic attributes such as income.

Policymakers should consider alternative electricity pricing models that adjust for maximum electricity loads induced. They could also encourage a dynamic electricity pricing strategy increasing peak time electricity prices for households, for example, implemented by a large grid operator in Denmark. In their pricing policy, grid tariffs more than double between 5 and 8 p.m. during the winter months [51]. [40] recommend similar electricity price adjustments to promote energy equity. Any dynamic electricity pricing, load-based or adjusted for peak times, does, however, require the installation of a smart meter. The smart meter installations are, unfortunately, lagging behind. In Germany, for example, only 19% of households own any smart energy management device in 2022. Since energy companies fall behind their smart meter installation ambitions [46, 52], alternative measures are worth considering.

EV adoption greatly impacts the magnitude of the inequitable grid cost allocation. As it is not desirable to reduce overall EV adoption and limit the electrification of mobility, policymakers could reduce the inequity in cost allocation by increasing subsidies for EV adoption in lower-income households, where EV subsidies have shown the strongest impact on EV adoption [53]. A fuel efficiency-dependent reduction in government EV subsidies based on car models could also compensate lower-income households and mitigate some of the inequities. However, the effect of model choice on grid costs is limited, as seen in Figure 4. Households that can not afford an electric vehicle will not profit from any of such actions but will still face higher grid costs.

Our findings on potentially inequitable EV-related grid cost allocation contribute to the larger field of energy inequity, which has gained importance globally in recent months [41–43, 54–56]. With energy and electricity prices rapidly increasing due to the Ukraine war, lower-income households in Europe are over-proportionally affected, experiencing a larger cost of living increase and disposable income decrease compared to higher-income households [42, 54, 55]. In Germany, energy poverty is quickly becoming an issue affecting also middle-class households [56]. Targeted, income-adjusted government relief measures could be required to support lower-income households and allow equitable cost allocation [42, 56]. Unfortunately, current energy crisis relief measures are frequently falling short of this goal (see e.g. 12, 41, 43, 57).

2 Conclusion

Our work analyzes the difference in grid reinforcement costs induced by EV charging in lower- compared to higher-income neighborhoods. In the analyzed potential scenario, the number of grid overloads occurring for higher-income neighborhoods exceeds those for lower-income neighborhoods by over 12-fold on average across area types. Hence, the stronger need for grid reinforcements puts higher-income neighborhoods at the top of grid operators' agendas. While grid reinforcement costs from higher-income neighborhoods in rural grids are only 50% higher, we see a more significant effect in suburban and urban grids, with costs diverging by up to around 3,300% and 480%, respectively. For the EU, these cost asymmetries could potentially amount to €14 billion. The current policy setting would cover the related grid reinforcement costs via an across-the-board electricity price. This could be considered inequitable regarding the principle of fairness according to contribution, as these grid reinforcement costs can be over-proportionally traced back to higher-income neighborhoods. Policymakers should hence consider adopting a load-based pricing policy to prevent assigning these costs to all electricity consumers. As grid cost asymmetries between neighborhoods are mostly caused by differences in EV adoption and driving patterns, policymakers may try to establish maximum-load-based electricity pricing or compensate for inequities with income-dependent EV subsidies. However, households that can not afford an electric vehicle will not profit from such compensations and may still face higher grid cost allocations.

3 Methods

We simulate electricity usage for two neighborhood types: below-average (lower) and above-average (higher) income. For these two neighborhood types, we assign respective EVs considering adoption and model choices and fit the corresponding mobility behavior. We use representative distribution grids in urban, suburban, and rural settings to account for the differing structure and load capacity [58]. After allocating the electric vehicles amongst the grid nodes, the simulations check each setting for overloads. While we showcase the approach with inputs for distribution grids in Bavaria in the South of Germany, the approach may be applied to any grid or geographical region. The simulation builds upon [59] and is structured as displayed in Figure 6.

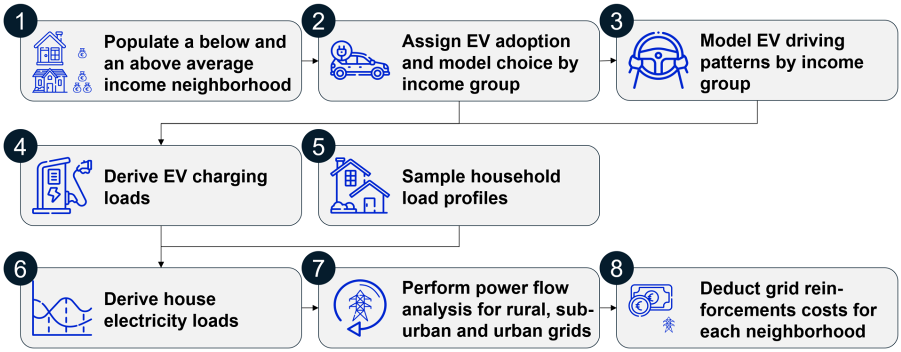


Fig. 6: Simulation approach to quantify the costs of reinforcing distribution grids, own illustration using [60].

For both neighborhood types,

1. we populate the grid with the related income group (above- or below-average-income households).
2. we assign the related EV adoption level and model choice depending on the income group.
3. we model the driving patterns for each EV depending on the income group.
4. we derive the EV charging loads resulting from the EV driving patterns.
5. we sample household electricity load profiles on a household level.
6. we consolidate the EV charging loads and household electricity load profiles.
7. we perform a power flow analysis, and if overloads occur, we reinforce the respective overloading grid element.
8. we calculate grid reinforcement costs to resolve these overloads.

We derive the grid reinforcement cost asymmetry between the two neighborhood types within the simulation. The power flow analysis is performed using the Newton-Raphson method of the matpower package in MATLAB, which is frequently used in load analysis [61]. To consider the most challenging season for electricity usage, we perform the simulation using five-minute intervals over a week in December.

3.1 EV portfolio and driving patterns by income class

First, we create a set of below- and above-average-income households for a German neighborhood. Using current German household net income data, we find that the average net income lies around 3,600€ per month [62, 63]. We leverage the household data from the German Mobility Panel to separate this data set by household income [39]. The data set states monthly income with steps of 500€ granularity. We separate into below- (lower) and above-average (higher) income households at 3,500€ net household income per month.

We again use household data from the German Mobility Panel to assign EVs to households by determining the number of private cars owned per household based on the area type [39]. When analyzing the average number of cars per household by income group, we can see significant differences, with lower-income households owning, on average, 0.94 and higher-income households 1.77 cars. When including EVs in our model, we choose to use BEVs only as this reflects the markets' direction to reduce all conventional vehicle powertrain technologies [18, 19]. We separate the EV into different segments: Mini (Volkswagen e-UP), Small (Renault Zoe Z.E. 40 R110), Compact (Volkswagen ID.3 Pro), Medium-sized (Tesla Model 3 Long Range Dual Motor), SUV (Audi e-tron 55 quattro) and Luxury (Porsche Taycan Turbo S). The different vehicle classes allow considering the varying power consumption and the corresponding charging needs. We derive the usable battery capacity from [64], which compiles technical specifications for EVs currently on the market. The electricity consumption data is based on real-live driving tests by [65, 66]. Table 1 lists the car segments' specifications. Since our simulation investigates the demanding December conditions, we utilize climate data by [67, 68] to fine-tune the electricity consumption considering the ambient temperature. This adjustment is needed as ambient temperature significantly affects the energy efficiency of an EV. Specifically, temperatures between 0°C and 15°C decrease vehicle ranges by up to 28% in comparison with driving at moderate temperatures from 15°C to 25°C [67, 69].

Table 1: Car segment battery capacity and consumption [64–66].

Segment	Mini	Small	Compact	Medium-sized	SUV	Luxury
Usable battery (kWh)	32	41	58	76	87	84
Electricity consumption (kW/100km)	17.7	20.3	19.3	20.9	25.8	33.0

To find the appropriate segment sizes for the German car market, we aggregate the newly registered cars per segment of 2021 as provided by the German federal transport agency (Kraftfahrtbundesamt) [70]. To separate between lower and higher-income households, we leverage the car segmentation included in the German Mobility Panel to reflect model choice differences between income classes [39]. We choose to re-scale the newly registered car segment distribution from [70] instead of simply using the 2019 German Mobility Panel's car segment distribution to reflect future car model choice instead of the existing German car park. The resulting impact of income on the car model choice can be seen in Table 2.

Table 2: Car segment distribution by income class.

Household group	**Mini**	**Small**	**Compact**	**Medium-sized**	**SUV**	**Luxury**
Lower-income	8%	19%	21%	12%	31%	8%
Higher-income	6%	13%	19%	17%	25%	19%
All	7%	16%	20%	15%	28%	14%

To simulate car driving patterns by income class, we use real-live driving data from the German Mobility Panel collected between September 2019 and the beginning of March 2020 [39]. This data set includes weekly trip data for 70,796 trips covering various modes of transportation, provided with travel times, trip purposes, and timings. After selecting only trips performed by car and outlier removal by excluding drivers performing holiday trips or very long journeys (above 200km, longer than 132 min), we arrive at a data set of 22,803 trips representing common driving patterns. We assume that the first trip of each day always starts at home and the last trip of each day ends at home. We generate synthetic trips for both income groups using this trip data set through a time-inhomogeneous first-order Markov chain. Markov chain models are a commonly used method for uncertainty modeling, particularly in the context of EV charging loads, due to their ability to achieve high accuracy at moderate computational costs [71]. In this work, the Markov chain is employed to create trip samples between "Home", "Work" and "Other" locations, resulting in synthetic EV driving and charging profiles. Differentiating between weekdays, weekends, and times of day, we fit a time-inhomogeneous Markov chain for our mobility simulation. We choose the Markov chain to be time-inhomogeneous, as the probability of transitioning between locations is time-dependent. The simulation is conducted at five-minute intervals since self-reported recordings exhibit a rounding bias with approximately 75% of timing data points ending in a right-hand digit of either 0 or 5.

The EV driving and charging simulation is based on [31] adapted by separating households only according to income to reduce complexity. To start our simulation, we first sample the number of trips performed by each car of the lower (higher) income household on that day. In the second step, we use the first-order Markov property to define trip destinations, distances, speeds, and associated parking times depending on the start location of the current trip and its time of day (as time-inhomogeneous). Our model fits the empirical data well, with average daily driving time differing by 1.1% and an average daily trip frequency differing by 1.2% from the empirical data, respectively.

3.2 EV and household loads

The charging logic applied does not vary by income group. However, the differing mobility behavior of lower and higher-income households impacts charging patterns. After each EV trip, the EV updates its state of charge (SOC) to reflect the distance driven. Once the EV arrives home and parks for more than 10 minutes, the probability of starting the charging process is determined based on the state of charge as an inverse s-shaped relationship found in a six-month German field study of 79 EV drivers [72]. The charging probability model from [72] defines the probability of starting the charging process as

$$p_{charge} = \min\left(\left(1 - \frac{1}{1 + e^{-0.15(SOC - 60\%)}}\right) c_l, 1\right)$$

with the parameters calibrated using an analysis of the charging behavior of EV fleets in Germany performed by [73]. The factor c_l can be chosen location-dependent. We focus on charging at home, representing most charging instances [74]. We adjust c_l for whether a private charger is available or the charger is public and assumed to be located in front of the house. The charging process ends once the next trip is started or the EV battery is fully charged. Applying charging patterns to stop at a charge level of 80% to improve battery health would lead to similar results.

We generate the household loads via empirical sampling in two steps: First, we generate 1,000 representative German household electricity load profiles for December using the Load Profile Generator of [75] frequently used and validated by previous literature like [76–78]). It creates representative synthetic household electricity load profiles based on a full behavior simulation of the related households [75]. We categorize these load profiles by household size. In the second step, we construct the electricity load a typical neighborhood in rural, suburban, and urban areas for our exemplary setting of Bavaria, Germany. Therefore, we sample household load profiles according to the distribution of household sizes per area type according to [79]. We also use area-specific distributions of households per building, as those vary by area type according to [80]. The respective household size and household per building distributions can be found in Section 3.6.

The loads $L_{h,t}$ occurring for each house h in the neighborhood at a five minute interval time point $t \in \{1, 2, ..., 2016\}$ in a week are hence defined as follows

$$L_{h,t} = \sum_{hh=1}^{k} \left(e_{hh,t} + \sum_{n=1}^{n_k} c_{n,t}\right)$$

where k is the number of households in the house h, $e_{hh,t}$ the household electricity load profile associated with the respective household hh at time t and $c_{n,t}$ the charging load of an EV n of the n_k EVs of owned by household k at time t.

3.3 LV distribution grids and synthetic neighborhoods

As in [59], we use the SimBench low-voltage (LV) distribution grids [58, 81], which are designed to represent benchmark distribution grids for Germany. We opt for the SimBench grids as they allow us to analyze differing area types and the related differences in distribution grids. We perform our analysis on the SimBench LV 02 as the rural, the SimBench LV 05 as the semi-urban, and SimBench LV 06 as the urban LV grid. These encompass 95, 109, and 108 houses, respectively. To perform our analysis, we create synthetic lower (higher) income neighborhoods by allocating households sampled from the lower (higher) income data set to the SimBench grid nodes. We run a power flow analysis, and if overloads occur, we reinforce the respective overloading line or transformer.

Overloads occur, if for any grid element $g \in \{1, ..., G\}$ within a grid consisting of G elements the related capacity Cap_g is exceeded at any time point $t \in \{1, 2, ..., 2016\}$, meaning

$$\sum_{h \in H_g} L_{h,t} \leq Cap_g$$

is violated at any time t where H_g is the set of all houses supplied through the grid element g.

Investment costs for line reinforcements in Germany are estimated as 85–125€/m according to [82]. We assign investment costs of 26,970€ to a 250kVA transformer upgrade used in the rural grid and 61,730€ to a 630kVA transformer upgrade for the suburban and urban grid in line with [83].

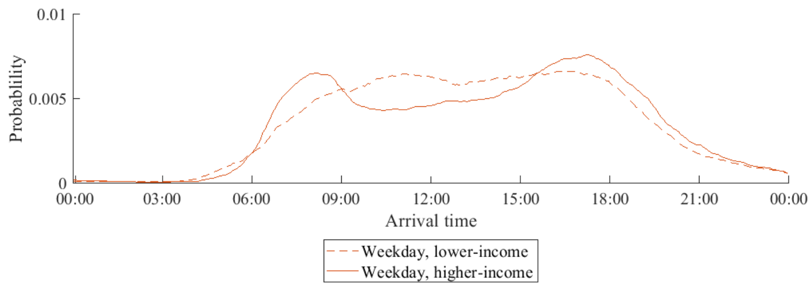
3.4 EV adoption scenario analyzed

In order to simulate realistic future EV penetration levels, we use the current German government target of 15 million EVs on German roads by 2030 as the basis for our scenarios [18]. Relative to the 2021 German car park of 48.24 million cars, this would equate to an EV adoption rate of 31.1% [84]. Analysis of current EV sales reveals that a household's probability of owning an EV is up to three times as high for higher-income than for lower-income households [20]. Using the 15 million EV target as a base (equating to an overall EV adoption rate of 31.1%) and accounting for higher-income households owning more cars, EV adoption rates would lie at 22.4% for lower-income and 35.7% for higher-income households. As we could expect this effect to become smaller as more EVs enter the market and prices decrease, we will include an analysis of equal EV adoption rates for both income groups in Section 1.2.

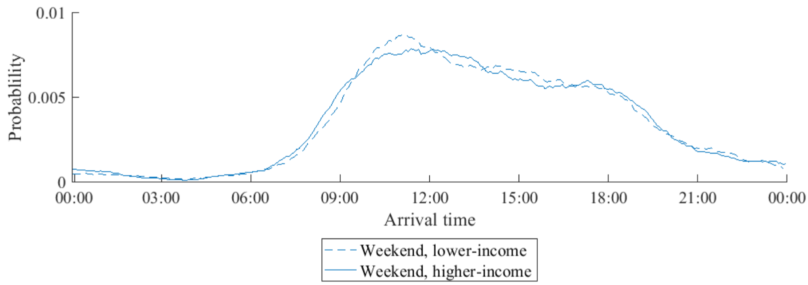
3.5 Driving patterns and load profile implications

First, we investigate the differences in driving patterns, EV charging behavior, and resulting load curves. In line with existing literature, we find that higher and lower-income households differ in their driving patterns. The German

Mobility Panel trip data reveals that higher-income households perform more daily trips, with an average of 2.2 daily trips instead of 2.0 daily trips for lower-income households [39]. They also exhibit longer trip durations of, on average, 42 minutes instead of 38 minutes. Furthermore, higher-income households show more concentrated weekday home arrival times, leading to stronger load peaks, as visible in Figure 7.



(a) Weekdays.



(b) Weekends.

Fig. 7: Probability of car arrival at home for an average weekday and weekend.

These effects are most likely also linked to differences in occupation and level of education between the two income groups, which have been shown to affect mobility behavior [29–31]. While 46% of drivers in higher-income households are working full-time, this only applies to 25% of drivers in lower-income households within the data of [39]. The proportion of drivers with a university degree, which is often linked to a "nine-to-five" work schedule, is 43% for higher-income and only 26% for lower-income households. This may be the reason why we observe more concentrated weekday arrival times and increased car usage for high-income households. Due to the longer driving times, the hence higher electricity consumption, and the more pronounced weekday arrival time peaks, we expect the high-income households to induce stronger load peeks, especially on weekdays. This effect is also enhanced by the difference in EV adoption as well as model choice. Figure 8 shows the exemplary case of the induced load curves a week in December in the rural grid.

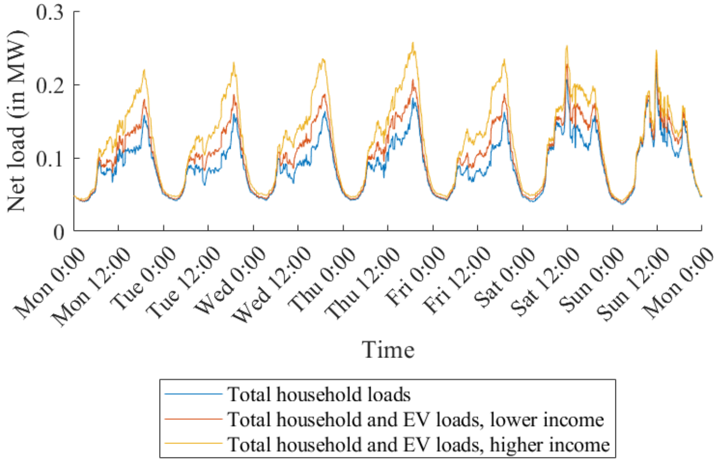


Fig. 8: Net load profiles of households and EVs in the rural grid.

As expected, the load peak difference between higher- and lower-income households is especially pronounced on weekdays. Due to the stronger load peaks, we expect the higher-income neighborhood grids to be more at risk for overloads caused by EV charging.

3.6 Additional input data: Household size and households per building

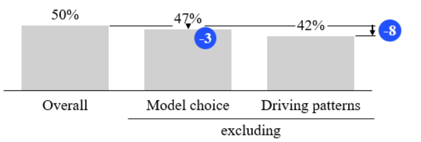
Table 3: Average distribution of household size per area type in Bavaria, Germany [79].

Persons per household	Rural	Suburban	Urban
1	35%	40%	54%
2	35%	33%	27%
3	14%	12%	10%
4	12%	11%	7%
5 or more	4%	4%	2%

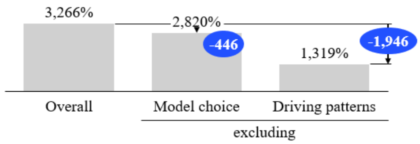
Table 4: Average distribution of households per building in Bavaria, Germany [80].

Households per building	Rural	Suburban	Urban
1	70%	55%	53%
2	17%	13%	10%
3-6	9%	16%	14%
7-12	3%	12%	15%
13 or more	1%	4%	8%

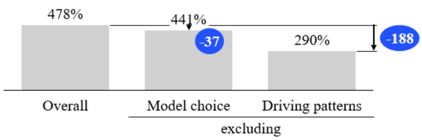
3.7 Additional results: Breakdown of grid reinforcement costs asymmetries



(a) Rural.



(b) Suburban.



(c) Urban.

Fig. 9: Breakdown of grid reinforcement costs asymmetries by the underlying drivers of model choice and driving patterns for all area types.

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