SMART LOAD-MANAGEMENT FOR EV CHARGING INFRASTRUCTURE IN A RESIDENTIAL COMPLEX

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Abstract: Interest in and demand for electric vehicles (EVs) is growing strongly due to the increasing awareness of climate change and the respective long-term decarbonisation goals. One of the biggest challenges remains the provision of large-scale, efficient charging infrastructure (IS) in urban areas with intelligent load-management and appropriate pricing schemes. Our results show an increase of yearly load in the building due to E-Mobility by 39%. Nevertheless, given the appropriate pricing incentives, the existing household load maximum is not exceeded and also steering towards electricity consumption at times of high renewable shares is possible. This represents a promising outlook to avoid additional pressure to the distribution grid and promote the implementation of such IS for the further diffusion of EVs.

Keywords: Electric vehicle, charging infrastructure, load management, E-Mobility, urban area, residential building

Content

1 Motivation

Interest in and demand for electric vehicles (EVs) is growing strongly. Reasons are the increasing awareness of climate change, as well as the obligation of car manufacturers to substantially reduce the CO_2 emissions of their fleet by 2030. One of the biggest challenges associated with this development is the provision of appropriate charging infrastructure (IS). Major questions include, not only where charging can take place (e.g. private and public charging, charging at work, etc.) and at which charging speed and capacity, but also how the potential temporal distribution of this load develops. Whereas for single-family buildings and small company applications, many projects have already been conducted, research on how to provide optimal IS in large-scale residential buildings and the implementation of an optimal load-management (LM) for this application has been scarce.

The main objective of this paper is to analyse various LM strategies for EV charging in large-scale residential buildings, determined to meet the growing demand for E-Mobility and considering to which extent these strategies may offer relief to the distribution grid. In our analysis, we aim at keeping in mind the global perspective and consider it as essential for social welfare to avoid a further increase of existing load peaks through E-Mobility, regardless of the capacity available in one building or the regional distribution grid. Therefore, this paper puts a focus on detecting pricing and LM strategies that shift EV charging load away from the household (HH) load peaks and also analysing the amount of renewable electricity available while charging. This research is carried out within the cooperative R&D project URCHARGE powered by the Austrian Climate and Energy Fund within the programme “Zero Emission Mobility” with a focus on IS. The paper starts with an analysis of the technical and scientific state of the art in Chapter 2, focussing on the distribution of EV charging load in the first part and on potential pricing schemes and their impact on charging behaviour in the second part. Chapter 3 describes the methodology with the parameters and assumptions based on the project environment and the considered LM approach and pricing schemes. In Chapter 4, the results are presented for each of the LM approaches and finally, Chapter 5 provides comprehensive conclusions of our work.

2 State of the art

The technical state of the art of LM within our project currently provides a solution to distribute charging power across a maximum of 15 charging stations. This LM system, however, does not operate dynamically or intelligently based on an input from distribution grid constraints but simply carries out an equal distribution of total available capacity as soon as the EVs are plugged in. Concerning the interface between the charging station and the EV, there is no knowledge of the cars battery state of charge (SoC). This is planned to change through the implementation of the ISO standard 15118 in the near future, which shall equip the battery or EV with the capability to share information on the battery SoC [1]. Furthermore, there are few applications that allow the user to provide any demand data or potential charging time-periods to the LM system. Since large-scale applications of LM are still not commonly applicable and EV charging currently largely remains connected to a single home with a private charging station or charging at public stations, there are hardly any standardized tariff schemes defined to incentivize efficient LM from user side. In the public area, charging cost in the case study area Austria is usually set as a time-based tariff dependent on the maximum charging power used, to reduce the time a car is parked at a public parking space. The tariff increases with charging speed from 3.7kW to 22kW.

Our research on international literature on charging IS and LM software for EVs specifically in urban areas reveals evidence, that scientific investigation in particular for large-scale residential buildings, has still been scarce. Up to the best of our knowledge, no analysis with a focus on cost-minimal charging with a focus on IS and smart LM has been conducted in this respect. Efficient LM is also referred to as smart charging in literature, representing an adaption of the EV charging cycle to both the restrictions of the distribution grid and the needs of EV users [2]. IRENA [2] claims, that smart EV charging enables the following peak shaving, network congestion management and results in reduced grid IS investments by reducing pressure on the grid from E-mobility. Our paper, hence, aims at analysing the impact of efficient LM and appropriate pricing schemes on the load development in a large-scale residential building, with the goal of avoiding an increase in existing HH load peaks.

2.1 Load increase through private EV charging

As already mentioned, private charging IS still lacks appropriate research and resembles a promising opportunity to impose LM on a large amount of charging processes, since charging mostly takes place at home. With appropriate IS available, the share of controlled home charging may even be increased. As a basis for our research, we analyse literature on typical EV charging load profiles and the effect of controlled charging. Current literature suggest certain pricing schemes to shift charging load away from the HH load peaks. Limmer & Rodemann [3] focus on public charging IS and point out that peak demand charging represent a substantial part of the operating costs of public EV charging stations. They argue that today, the majority of public charging stations for EVs are uncontrolled, meaning that the EV is charged at full capacity as soon as it is plugged in, which usually coincides with overall load peaks. Furthermore, they claim that intelligent control of the charging processes supported by the use of a dynamic pricing scheme can help to reduce the peak load and the corresponding fees. In order to be able to ensure the largest possible range of distribution of the charging load, the period of time in which the car is available for charging must be as long as possible. Consequently, the price needs to decrease with time or the deadline the customer allows for charging. Bitar & Low [4] proposed such a pricing scheme and called it deadline differentiated pricing.

Yi et al. [5] provide valuable work for our research and focus on residential charging coordination for a large-scale diffusion of EVs. They find that Plugged-in EV (PEV) charging tends to occur together with distribution grid peak loads, which is generally undesirable because utilities may need to take actions to serve this increased load reliably. Five different scenarios with varying PEV penetration are simulated to show the difference between uncontrolled and controlled charging, see Figure 1. Each scenario includes 100,000 households and considers PEV penetrations between 10% and 90%. Simulation results based on real-world driving data show that home charging is able to meet the energy demand of the majority of Plug-in EVs in an average condition [6]. Wang et al. [6] conclude from their research, that with common battery capacities and if vehicle to grid technology is not considered, workplace charging would contribute to neither meeting EV owners' charging requirements nor improving their economic benefits under their assumptions. Furthermore, they claim that with more than 7h of off-peak price, the charging load peak can be minimized based on minimum charging cost.

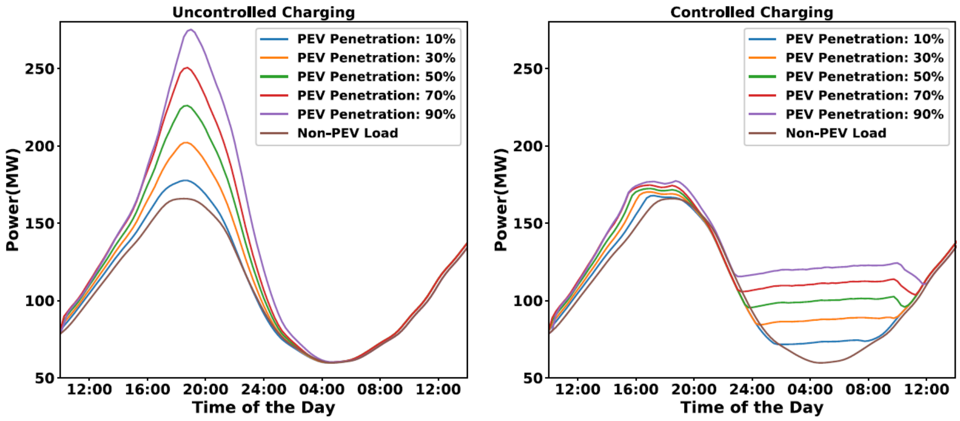

Figure 1 Residential power load for uncontrolled and controlled charging under differing PEV penetration [5]

Hu et al. [7] claim that without any management of EV charging load, peak loads may substantially increase in future electricity grids and point out that charging pricing mechanisms are essential to limit negative effects on the grid. Avoiding uncoordinated charging helps to fill valleys in the existing load pattern as shown in Figure 1. Hu et al. suggest a time-of-use (ToU) pricing mechanism, which incentivises the users to charge at low price or valley times. Their results show, however, that even with ToU pricing, new charging load peaks may arise, which is why the authors even suggest dynamic load-based pricing which adjusts the price according to the amount of EVs charged at a time. The price function for charging should, therefore, include charging and non-deferrable - in our case HH - load. Since their work represents a modelling approach it is, however, not very clear how this would work in reality. Dynamic pricing while the users' EV is already plugged in seems to result in high price uncertainty. Hence, the strategy might have to be based on some prediction of common times with high charging demand or at least an opportunity for the user to set the charging strategy upfront. Nevertheless, our analysis will analyse the combination of a ToU with a capacity price based EV load and total load (see Chapter 3.4), given the chance for such user settings in the future.

According to our analysis, uncontrolled charging leads to a steep increase in the evening load peak. With LM, it is possible to almost eliminate this peak increase and instead fill the HH load valley in the second night half with charging demand. This may reduce pressure imposed on the grid substantially and help to avoid investment in distribution grid expansion that may have been needed soon with the uncontrolled charging situation. An improved availability of large-scale private charging solutions in the urban area, equipped with intelligent LM, would decrease the need for uncontrolled, public fast charging IS at least for daily purposes. In our point of view, deadline differentiated pricing suggested by Limmer & Rodemann [3], however, is a concept designated for private applications, since for public charging stations this would mean parking lots blocked for a considerable amount of time.

2.2 Pricing schemes around the world

The Northern-European countries represent leaders in the diffusion of E-mobility and provide valuable insights on EV charging and pricing. Norway's pricing model for public fast charging includes a price per minute of charging regardless of how much energy is consumed and offers home charging at a cheaper rate [8]. The authors find that to be able to avoid queues at the parking spaces, a combination of a time and energy based tariff is essential. Additionally, they clearly support a focus on low cost charging IS at home or at work realised as a larger-scale project to enable the application of efficient LM, instead of individual solutions that require greater investments per station. Surveys of Norwegian Battery-EV and Plug-in Hybrid EV owners show, that charging is mostly done at home or at work, relying on slow chargers, matching the usually shorter trip length of EVs, mostly used for commuting (92%) and common day trips (57%) [9]. In Sweden, up to 80% of EV users live in individual homes, compared to around 50% of the general population. In Sweden, customers usually pay per kilowatt-hour (kWh) or per minute with different pricing schemes for public fast- and slow charging, as well as private charging, see Figure 2.

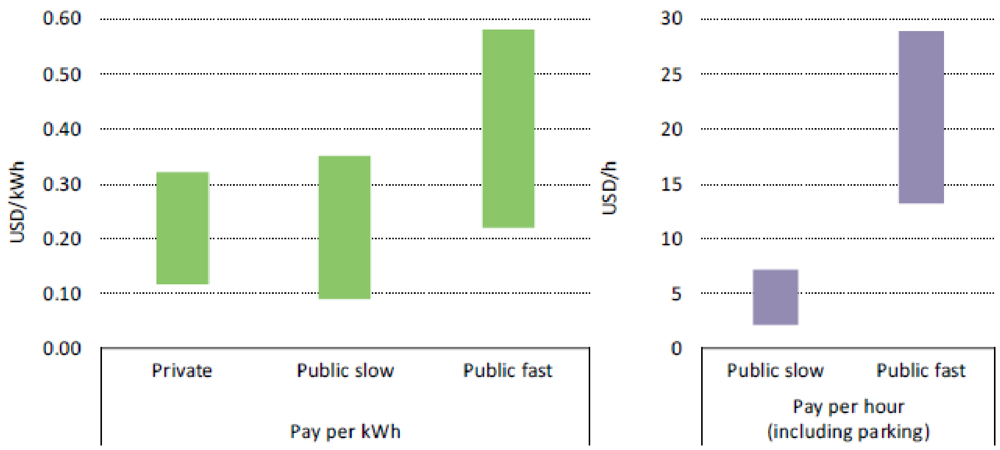

Figure 2 Price ranges for common charging practices in the Nordic Region [9]

Across the Nordic Region, the pricing schemes described in Figure 3 can be detected [9]. There is a range of pricing schemes from variable pricing per kWh, to a combination of a price per charging session and per minute, down to a one-time fixed fee or no fee at all. The latter, however, probably represents a temporary offer to further promote E-Mobility.

Variable pricing

Pay per kWh	CLEVER (Nordic region), Clean Charge (Denmark), E.ON (Sweden), Helen (Finland), Vattenfall (Sweden).
Pay per hour (including parking)	City of Oslo (Norway), Fortum (Nordic region), Grønn Kontakt (Norway), Helen (Finland), Vattenfall (Sweden).
Pay per charging session and per minute	BKK (Norway), Lyse (Norway).
Pay per charging session	CLEVER (Nordic region).
Monthly fee	E.ON (Denmark).
One-time fixed fee	Tesla (Nordic region).
No fee	City of Oslo (Norway), ICA (Sweden), Lidl (Sweden), ON Power (Iceland).

Fixed Pricing

Figure 3 Potential pricing models [9]

For the US, Kim [10] finds that San Diego Gas & Electric (SDGE) offers time-of-use (ToU) pricing plans to its residential customers. In a standard ToU plan, each day is broken into on-peak and off-peak time zones with a lower price during the off-peak hours. The ToU plans are also tiered plans so if a customer exceeds the baseline allowance by a certain threshold, the rates increase. This resembles a combination of time and quantity based pricing. The authors point out that one of the key factors that support a response to such tariffs is the users' ability to work with smartphone applications ("apps"), taking advantage of the off-peak rates by setting the charging time.

3 Methodology

3.1 Parameters and assumptions

To determine the EV charging demand and pattern, we assume a scenario in 2030, with a 30% share of EVs in individual transport [11]. Our simulation includes 150 parking spaces, whereas 50 of them require charging IS. The building in total consists of 200 households with typical HH electricity consumption, which we extrapolate from a variation of 72 HH load profiles. In this first analysis, we do not add any flexibility to HH load but aim at analysing how overall building load develops with different LM and pricing strategies for charging EVs. Typical Austrian charging profiles are determined from a study analysing usual driving purposes and distances during weekdays and on weekends [12]. Based on the probability distribution of common start and return times and the trip length per purpose during a day, driving patterns are determined. We run this random distribution of diving patterns once and use the same profiles for all the approaches. A maximum capacity of 11kW for private stations in the building and 22kW for public charging stations is defined.

In a first connection dimensioning assumption by our project partners, total charging capacity for the 50 EVs is determined as 50kW, available for all EVs within the local charging network. This represents an average capacity of 1kW per EV and is expected to be sufficient for the case study on hand, considering simultaneity and LM. The private charging stations are controlled by one master station that coordinates the distribution of the available 50kW across all its so-called slave stations at the parking spaces (see Figure 4).

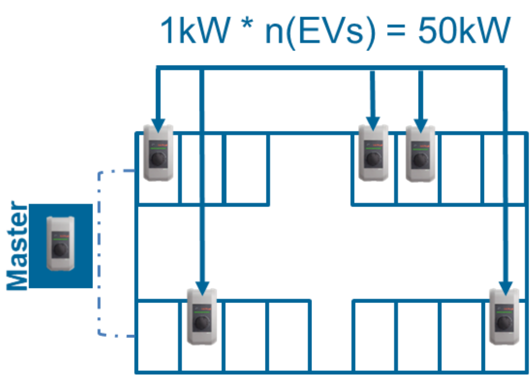

Figure 4 Master-Slave Network for Load Management

The aim of the project Urcharge is an extension of LM functionalities for this master-slave network. The LM shall eventually be controlled dynamically from two sides. On the one hand, the control station shall receive input from current distribution grid restrictions as an input to charging capacity control. On the other hand, customer behaviour shall receive appropriate incentives through pricing schemes. The focus of this analysis clearly addresses LM triggered through pricing from demand side and tests the impact of several approaches on grid load and renewable electricity use. Nevertheless, this can also offer valuable knowledge for future intelligent LM and appropriate steering of the master-slave network through a more central, top-down approach.

When it comes to distribution grid constraints, however, we do not include any external limitations to the LM in this paper to avoid the complexity of adding assumptions about detailed load flows in the grid. Our model is restricted by the capacity per charging station and the described assumption for the total charging capacity. Overall, 15% of charging may take place at public stations, while 85% of charging shall take place at home. The battery capacity of the vehicles is determined as 40kWh for 80% of the cars and 60kWh for the remaining 20%. Their consumption is shown in Figure 5 and modelled as an interpolation between 15kWh/100km in summer and 17kWh/100km in winter, due to additional power consumption for heating and the batteries temperature sensitivity [13].

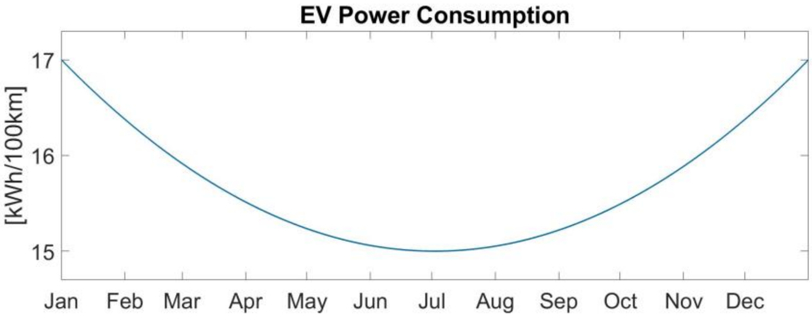

Figure 5 Development of EV Power Consumption throughout the year

Charging is possible from the time of return at the home station and limited to the required battery SoC. LM is carried out across all EVs currently charging and flexibility for the system obviously increases with the time-period an EV is plugged in. In our analysis, we determine different tariffs for private charging in the case study such as a flat rate per kWh, time-dependent tariff, power-dependent tariff or charging based on the electricity spot price 2018. The model is set up as a linear optimization model with the aim of minimizing the costs of EV charging.

1 Objective Function $$Min\ f\left(P_{Ch_p}, c_{ch_p}, P_{Ch_h}, c_{ch_h}\right) = \sum\sum_{n,t,i} P_{Ch_p} * c_{ch_p} + P_{Ch_h} * c_{ch_h}$$

P_{Ch_p}	…	Charging power at public station	n	…	number of EVs
c_{ch_p}	…	Cost of charging at public station	t	…	time steps
P_{Ch_h}	…	Charging power at home station	i	…	number of driving purposes
c_{ch_h}	…	Cost of charging at home station			

3.2 Household load characteristics

Figure 6 shows the pattern of the existing HH load and its common noon and evening peaks. To evaluate the HH peak and base load range, we make use of the percentile method, e.g. evaluating the HH load value that is exceeded by only 10% of all values, the 90th percentile (P90), which amounts to 98.8kW. Whereas everything above represents peak load, any value below represents a load valley.

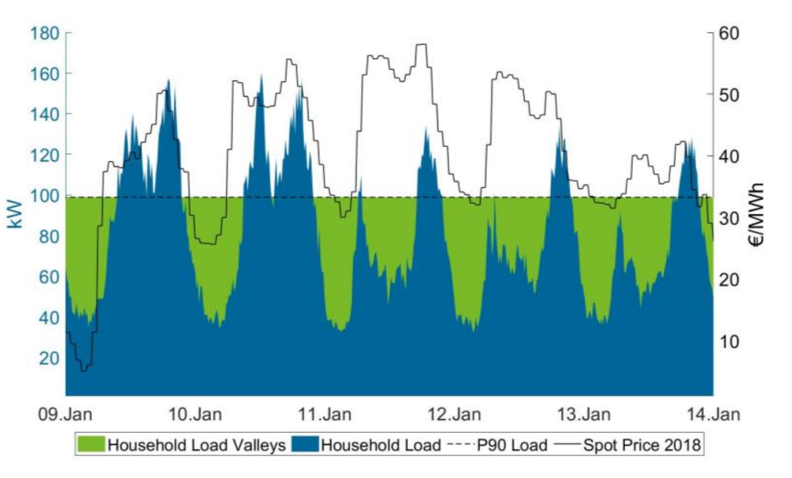

Figure 6 Household Load Peaks and Valleys

Furthermore, the spot price of 2018 is displayed, to show the given correlation with the HH pattern, with a correlation coefficient of 0.29, and its potential as a tariff scheme. The different tariff schemes described in Chapter 3.4 have the purpose to avoid an increase in the existing HH load maximum and fill the load valleys instead. With the spot price as a tariff scheme, we aim at considering the CO_2 aspect of EV charging analyzed through the correlation coefficient of fossil fuel power generation and total load. This correlation should ideally be negative to achieve high load at low fossil fuel electricity generation. The LM approach is outlined in the upcoming chapter followed by a description of the applied tariff schemes.

3.3 Load-management approach

The considered LM approach includes an optimization of EV charging load with full information of the EVs power consumption for the upcoming year, based on the calculation of charging profiles described in Chapter 3.1. The optimization of charging demand is carried out according to the exact requirements of the users, representing an ideal situation for most efficient LM according to the defined limitations and the chosen pricing scheme. Based on upcoming driving distances and respective power consumption, the EVs can be charged from the time of their return to the home station until their next trip, up to the maximum capacity of the battery. In addition, the model has the possibility to charge EVs at public charging stations at a slightly higher price. Obviously, the approach largely differs from reality in which, currently, no information on the upcoming consumption of the EV is available. Still, such a scenario offers valuable insight on the benefit of exact customer information. Even a foresight of several days could be favourable to consider e.g. the weather forecast and predict potential longer weekend trips in nice weather or renewable power availability. For a seasonal shift of charging demands the battery capacity of 40kWh, however, appears to be too small.

3.4 Pricing approach

The goal of pricing schemes is to avoid any increase in the maximum HH load through EV charging demand, and shift charging into HH load valleys. Table 1 provides an overview of the pricing schemes that are applied and the structure that is followed throughout our results. For public charging, we always set a flat rate price that is slightly higher than the home charging tariff. At first, we apply a basic flat rate tariff without any incentives and control function for the charging load distribution. We then compare the impact of other pricing approaches on charging load as, e.g. the historic spot price of 2018. In our analysis, we assume that the additional demand from E-Mobility has no effect on the spot price. We regard this as no harm to our approach, since we aim at showing the impact of pricing on the shift of charging load in general, with no means of delivering an exact pricing scheme or business model for a specific time in the future. A tariff based on the EXAA spot price manages charging load according to the countrywide electricity price determined by the share of renewable electricity and the overall load (Figure 6). This, obviously, does not mean that the approach favours the local grid situation.

The ToU tariff is derived by applying a higher price at times of high HH load and a lower price during load valleys. In Figure 6, the P90 mark indicates at which times the higher ToU price is imposed. As a result, charging power is mostly consumed when HH load is beneath this threshold, if the EVs are available at the home station during these times. Finally, all three tariff schemes may be combined with a capacity price, specifically imposed on high charging load or high total load in the building, to further decrease pressure on the load situation. This tariff links situations of high charging load to a higher price. If it is even based on the total load situation, a higher price occurs when charging plus HH load is high. Table 2 provides a summary of the tariff approaches and the defined parameters. In our results, we analyse the impact of the pricing schemes on total load and the capability of these two capacity pricing options to further control the load situation.

Table 1 Structure of pricing approaches

A1 Flat rate tariff	**B1** Spot price 2018	**C1** ToU tariff
A2 Flat rate tariff + price on EV load **(CP_{EV})**	**B2** Spot price 2018 + price on EV load **(CP_{EV})**	**C2** ToU tariff + price on EV load **(CP_{EV})**
A3 Flat rate tariff + price on total load **(CP_{Total})**	**B3** Spot price 2018 + price on total load **(CP_{Total})**	**C3** ToU tariff + price on total load **(CP_{Total})**

Table 2 Defined pricing schemes

<table>
<tr><th></th><th>A. Flat Rate</th><th>B. Spot Price</th><th>C. ToU</th></tr>
<tr><td></td><td>Flat rate price determined as €/kWh.

Expected incentive
No incentives to users for the control of charging demand.

Charging demand may lead to an increase in existing HH load peaks.</td><td>Historic EXAA spot price for 2018. Largely determined by renewable power share and current national load. No interaction with demand in our model.

The objective is the analysis of charging load shift based on the overall pattern of the spot price and its correlation with renewable power generation and suitability to avoid HH load peaks. We therefore do not add any grid cost etc.

Expected incentive
A high spot price usually represents low renewable power share and/or high demand. As a result, the spot price is expected to function as valuable incentive for a load shift away from peaks and low renewable power shares.</td><td>High peak and low off-peak price based on current HH load. The threshold is defined at 98.8kW representing the P90 of the HH load (see Chapter 3.1). Charging power above the threshold receives the peak price.

Expected incentive
The aim of a ToU price is to fill the HH load valleys and avoid increasing existing HH load peaks.

This guarantees a low impact of e-mobility on the load peaks of the building and is considered to have minimum impact on the distribution grid.</td></tr>
<tr><td>+ Capacity Pricing</td><td colspan="3">The Capacity Price is applied to charging at peak load times in addition to one of the defined tariff schemes A-C.
1. CP_{EV}: Price on peak EV charging capacity: Peak defined at above 2/3 of max. charging capacity 50kW = 33.33kW to avoid charging at maximum available capacity.
2. CP_{Total}: Price on peak total load: Tariff is imposed above maximum HH load to avoid total load exceeding HH load peak.</td></tr>
</table>

4 Model results

The results show the development of total load through EV charging compared to existing HH load, applying the pricing schemes and structure described in Chapter 3.4. For the analysis, we define the parameters in Table 3 as essential for the LM approach evaluation. In our view, these indicators can be used as a measure of the effectiveness of the various price mechanisms. We are interested in the absolute peak load, which should be avoided as far as possible and in the valleys during which the EVs are to be charged. The volumes serve to represent the energy consumed in the previously defined base or peak load band. In order to evaluate the ecological impact of EV charging and the CO_2 emissions of the electricity consumed, the correlation factor with fossil generation is used.

Table 3 Important result parameters

Category	***Parameter***	***Description***
Peaks & Valleys	Maximum [MW]	Maximum load discovered in the year
	Minimum [MW]	Minimum load discovered in the year
Volume	Peak volume [MWh]	Load volume in the peak range above P90. Overall development of peak load
	Base volume [MWh]	Load volume in the base range below P90. Overall development of base load
CO_2 effect	R_{CO2}	Correlation Coefficient of load with national fossil fuel power generation from coal and gas (2018 data)

4.1 Results overview

This chapter provides a results overview in graphs and a table to introduce the upcoming detailed analysis for overall load for each tariff scheme. We first analyse the exact characteristics of the existing HH load in the building as a baseline scenario, to which the situation with EV charging demand is compared. According to our assumptions and methodology, irrespective of the LM approach and the tariff scheme, the yearly charging demand of the 50 EVs accounts for about 213MWh and increases yearly electricity consumption of the building by about 39%. Figure 7 in the results overview shows the HH load boxplot, with a median of 59.9kW and a maximum at 173kW. Daily peak load usually occurs between 4pm and 8pm. Figure 7 shows the boxplot for the HH load only and Table 4 summarizes the HH load characteristics in absolute numbers.

Secondly, an overview of the developments including EV charging is presented. Figure 8 represents a general overview of the charging load with a mark at the 50kW available charging capacity and HH load with a mark at P90 per pricing scheme applied, for an exemplary time-period. Figure 9 shows how total load is distributed and includes a label for the maximum HH load at 173kW as a reference. The subplots can be compared for each of the pricing schemes and the analysis in the following chapters will refer to them.

Table 5 offers a summary in numbers of the proportional changes due to EV charging load compared to HH load for each of the tariff schemes defined in our methodology and is visualized in Figure 10. The results represent the parameters defined and explained at the beginning of this chapter.

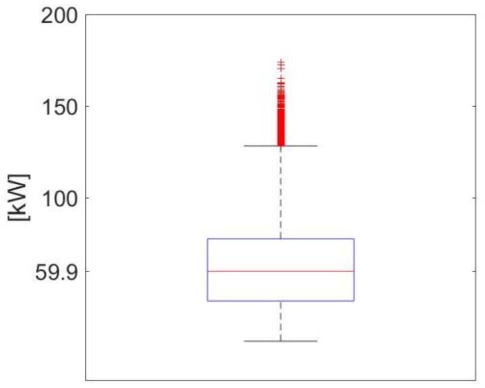

Figure 7 Boxplot HH load

Parameter	***Results***
HH Load / Year	550 MWh
Maximum HH Load	173 kW
Median HH Load	59.9 kW
Minimum HH Load	20 kW
P90 HH Load	98.8 kW
Base Volume <P90	537 MWh
Peak Volume >P90	13 MWh
R_{CO2}*	40%

Table 4 Characteristics of existing HH load
**Correlation HH load & fossil power*

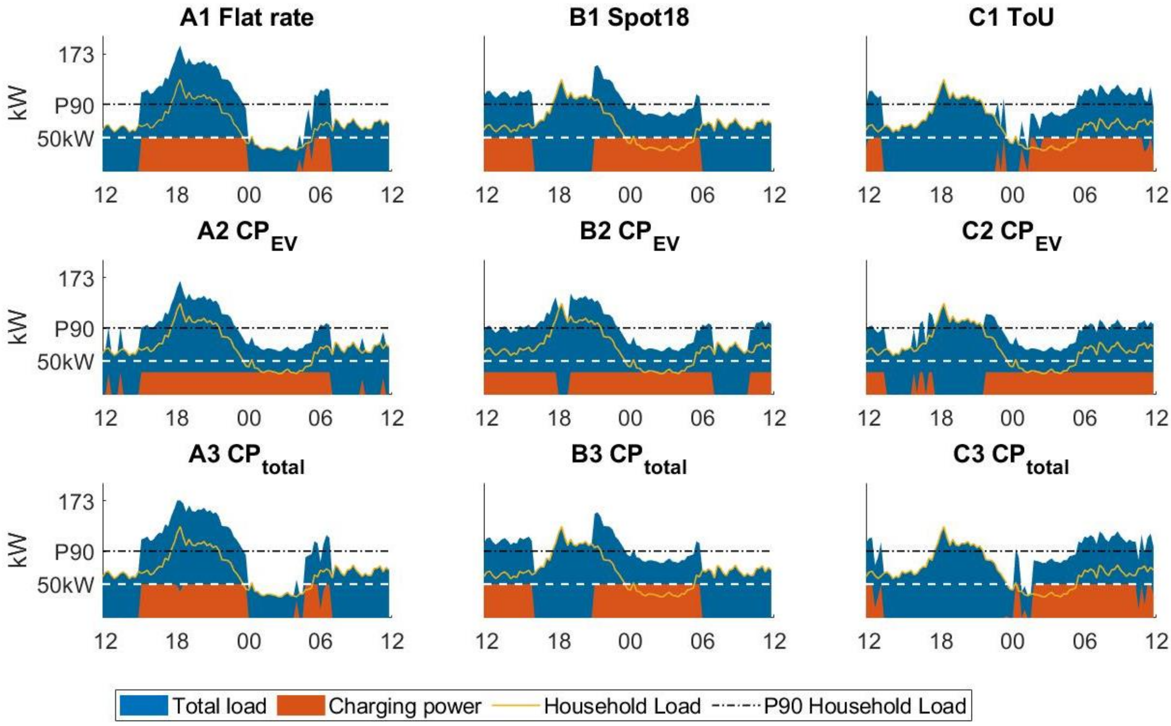

Figure 8 EV charging load and household load for each pricing scheme

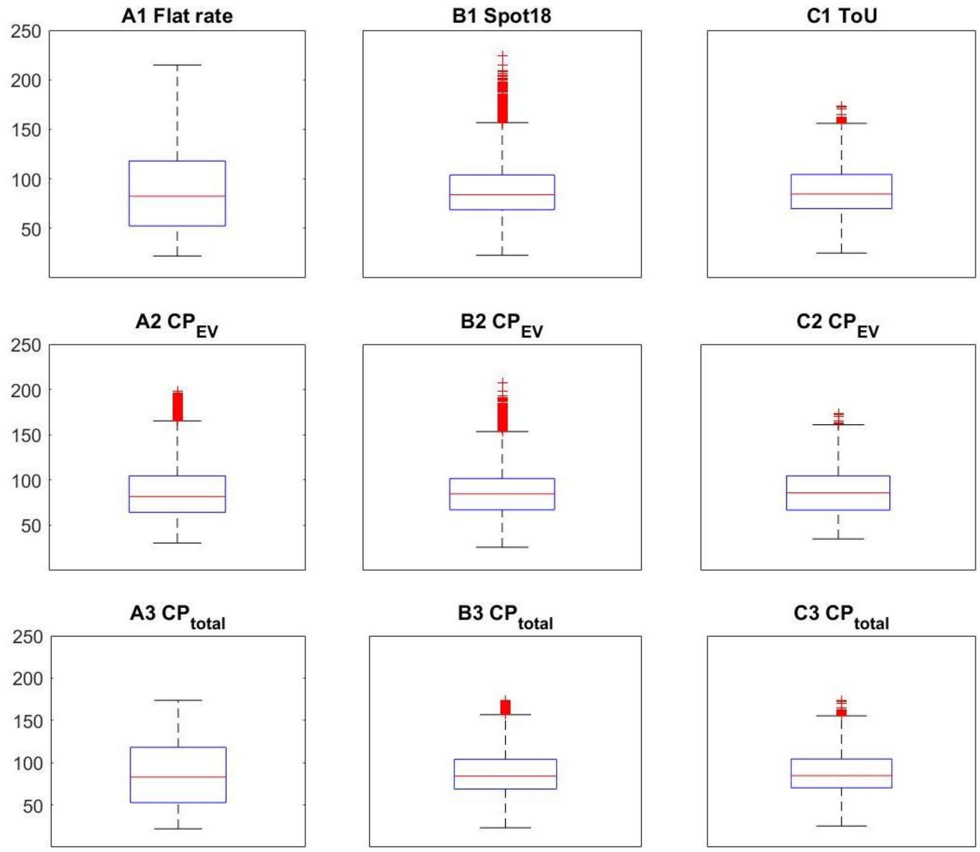

Figure 9 Boxplot for total load per pricing scheme

Table 5 Changes compared to HH Load due to 30% EVs

	A1 Flat rate	**B1** Spot18	**C1** ToU
Maximum	24%	29%	0%
Minimum	10%	14%	25%
Peak volume	700%	288%	241%
Base volume	22%	32%	33%
R_{CO2}	23%	13%	32%
	A2 +CP_{EV}	**B2** +CP_{EV}	**C2** +CP_{EV}
Maximum	15%	20%	0%
Minimum	51%	28%	73%
Peak volume	364%	255%	215%
Base volume	30%	33%	34%
R_{CO2}	27%	28%	36%
	A3 +CP_{Total}	**B3** +CP_{Total}	**C3** +CP_{Total}
Maximum	0%	0%	0%
Minimum	8%	14%	25%
Peak volume	690%	287%	238%
Base volume	22%	32%	34%
R_{CO2}	23%	13%	32%

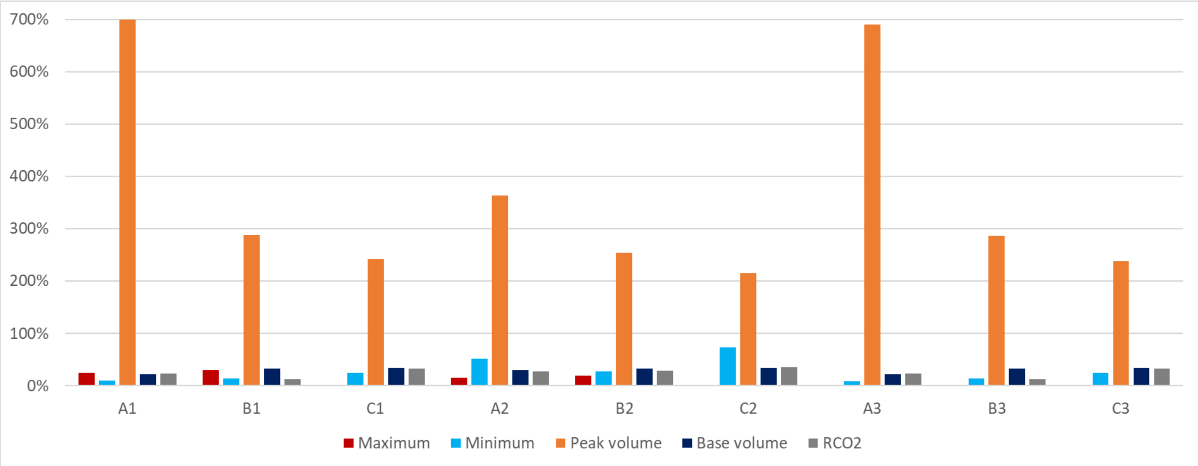

Figure 10 Visualization of changes compared to household load according to Table 5

4.2 A. Flat rate tariff

The result for charging load distribution based on the flat rate tariff shown in Figure 8 is characterized by a clear lack of control and appropriate incentives to the user for load shifting (A1). The time of return to the home station obviously largely correlates with the HH load peaks, leading to a load increase through EV charging demand, even with a simultaneity factor of 28%. In Table 5, the significant rise of the load maximum is described with 24% and the peak volume is increased remarkably by 700%, resulting from uncontrolled charging. Regarding the 50kW mark of total available charging capacity, Figure 8 for A1 indicates that this estimation is not fully utilized, but that EV charging power is compressed into few hours during the day, due to a missing incentive for greater distribution at lower charging power. The model does not yet make use of any public charging possibilities, making clear that sufficient availability of private charging IS reduces the need for fast charging options at least for common, daily business. Regarding the boxplot graphs in Figure 9, the simple flat rate tariff (A1) leads to a rather broad range of charging load values, which confirms the lack of control through this constant tariff.

Consequently, a price on EV charging capacity (CP_{EV}) in scenario A2 seems applicable and still offers appropriate convenience not leading to any additional public charging requirements. The capacity price indirectly leads to a capacity limitation, since users avoid these times and demand can also be met with only 33kW instead of 50kW (see Figure 8), distributed across a longer time period, though. This leads to a lower impact on total load if charging coincides with HH load peaks and achieves a shift into valley times, due to greater distribution. Figure 10 points out that the load maximum only increases by 15%, whereas the load minimum is increased substantially by 51%, signifying that load valleys are filled successfully. Also the boxplot in Figure 9 is characterized by a very dense median area with a few outliers. Finally, a capacity price imposed on total load above the HH maximum (CP_{Total}) in scenario A3 successfully avoids any increase in the load maximum. In this case, the boxplot in Figure 9 shows a rather compact median area. Still the peak volume increases by 690%, which is substantial (see Figure 10). The correlation with fossil fuel power generation (R_{CO2}) is at about 25% for all flat rate tariff approaches. This leads us to the conclusion that a flat rate tariff requires additional control by limiting the EV charging capacity, as in scenario A2, to avoid a high impact on total load.

4.3 B. Historic spot price

As already indicated in Figure 1, charging according to a spot price shows at a positive correlation with the common HH pattern. This already implies that the spot price may be a reasonable control measure as an incentive to users to shift EV charging away from the HH load peaks into the valleys. Figure 11 below, additionally, supports the correlation of the spot price with national renewable electricity feed-in with a coefficient ranging between -0.11 and -0.2 depending on the season. Price dips occur at noon times and specifically at periods of high wind power generation. This would resemble a favourable approach concerning the CO_2 performance of E-Mobility. The results for the spot price approach B in Table 5 exactly confirm this capability. Whereas the spot price on its own does still lead to a significant increase in the maximum load of 29% and the peak volume of 288%, R_{CO2} is weakened substantially down to 13%. The boxplot B1 in Figure 9, however, shows that the spot price as such is not sufficient as a load control measure and still causes many outliers exceeding HH load. Adding a price on EV charging capacity (B2) still causes a moderate increase in the maximum load of 19%, but a rather small increase in overall peak volume of only 255%.

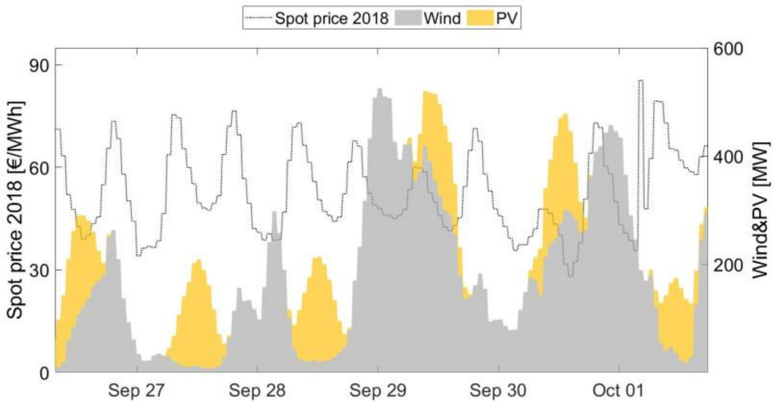

Figure 11 Spot price vs. renewable power generation

Nevertheless, with EV users avoiding higher charging capacity, charging times are distributed more at lower charging power. As a result, charging load is shifted into times of higher fossil fuel power generation, increasing the ecological impact. Hence, the price on charging capacity reduces the flexibility to always follow the incentives given by the spot price. Nevertheless, approach B2 provides a rather good compromise between a comparatively low CO_2 impact with a correlation of 28% and, at the same time a smaller impact on the peak volume with a desired shift into the base volume. Finally, the spot price together with a capacity price based on total load (B3) looks quite promising, leading to total load below the maximum HH load and again achieving the lowest R_{CO2} of 13%. Figure 10, however, makes clear that this leads to a quite substantial increase in the overall peak volume of 287%.

4.4 C. Time-of-use tariff

In our analysis, the ToU price achieves the best result when it comes to avoiding an increase in the load maximum, with a specifically good result in shifting load into the minimum of the HH load valley. Throughout the approaches, the boxplots in Figure 9 for the ToU price approach B present the most compact load results, indicating its capability of efficient charging power control. Table 5 shows that the maximum HH load is not exceeded by the additional EV charging demand in any of the ToU approaches and also the minimum total load always increases. Additionally, the base volume is increased substantially, indicating a favourable distribution of charging load. We detect that a combination with a price on EV charging capacity (C2) even improves the result in all of these matters. Analysing Figure 10, with a peak load volume increase of only 215% and the shift into base load this approach represents the best result in almost all aspects, apart from the correlation with fossil fuel power generation. The CO_2 impact appears highest in this case with R_{CO2} at 36%. High charging load is now avoided by the users resulting in a broader distribution into day times, also including higher HH load periods during noon. A capacity price based on total HH load (C3), however, shows a rather good result in all the aspects, specifically as combination of avoiding the load maximum and minimizing an increase in the peak volume amounts to 238% (see Table 5).

The analysis of results in this chapter clearly indicates the complexity of determining an appropriate tariff scheme, depending on the exact objective of the LM system. If tariff approaches are combined, several interdependencies may lead to unexpected results and hence, require appropriate research upfront. Still, this first analysis provides insight on the advantages and disadvantages of certain pricing approaches, of which we derive a conclusion in the upcoming chapter.

5 Conclusions

Our results show a yearly load increase through E-Mobility in the residential building of 39%. In average, we calculate a fourfold increase in the peak volume and a base volume increase of about 33% due to charging demand, differing slightly between the different tariff-schemes applied (see Table 5). This, of course, depends on the threshold defined in this study. Due to peak load shifting through LM into “valleys”, a manipulation of currently existing and very predictable load patterns occurs, flattening the variation in HH load throughout the day. This analysis indicates that, if private charging IS is conveniently available, public charging is not necessarily required for common daily trips. Of course, it needs to be pointed out that these results rely upon our chosen methodology and parameters. Quite independently of the tariff scheme applied, the LM system operates throughout most of the time the EVs are plugged in, demanding as much time as possible for the most efficient operation of charging distribution. In our analysis, a mere flat rate pricing scheme for EV charging results in a remarkable increase in the building’s peak load. We, therefore, conclude that more specific control measures are required. The ToU tariff succeeds in staying below the HH load maximum and can provide incentives to avoid an increase in the peak volume. Together with a price on high charging capacity, this represents the best result of all approaches. The ToU tariff is a valuable approach for private charging, when EVs are plugged in for a long time at their private parking space. In this situation, the LM software can optimize the charging process according to current HH load which is very predictable, if allowed by the customer. Still, the ecological effect of the current share of renewable power generation is not considered in a ToU tariff. For this purpose, the spot price would provide a valuable incentive to charge while the renewable power share is high in the system. Obviously, specifically the ToU and spot price approach would be supported by the opportunity for the user to state a certain deadline at which the charging process needs to be completed, following the deadline-differentiated pricing described in Chapter 2.1. This would allow the LM software to distribute the charging load using the maximum amount of hours granted. Furthermore, we claim that a certain amount of foresight of a few days enables a more successful LM process, due to a better consideration of forecasts on spot prices, potential driving distances or power consumption per 100km.

Analysing the impact of increasing EV charging demand on the requirement of power generation through fossil fuels e.g. gas and coal we can conclude that a tariff such as the spot price may represent a capable measure to minimize the correlation between high charging total load and a high share of fossil fuel electricity in the system. However, considering an implementation of a PV rooftop system to supply charging power, we find that total load and PV generation hardly show any or often even a negative correlation, meaning that storage will be required as flexibility. In any case, we do see a potential impact on the electricity mix consumed, if peak hours increase causing higher import or thermal power requirements. This would lead to a negative impact on the CO_2 balance, as long as Europe's electricity market is not 100% renewable, and requires attention.

Our future research within the Urcharge project will include rolling optimization between one and three days under less foresight on EV power consumption and pricing to analyse a scenario closer to reality. Additionally, we aim at an extension of the model to a common urban region in Austria including several large-scale residential buildings, also with a rooftop-PV system, and a public building (e.g. shopping centre) with EV charging opportunities and differing load patterns. Furthermore, our future research shall put a focus on the load and CO_2 aspects of E-Mobility within this larger environment, also deriving more general conclusions not only for this case study, but applicable on a national scale. To analyse the effect of an increasing share of renewable power generation, we will model the potential power generation in 2030 and derive a spot price estimation, which again may represent an input to the defined LM approaches.

Abbreviations

CO_2	Carbon dioxide
CP_{EV}	Capacity Price on EV charging load
CP_{Total}	Capacity price on total building load
EV	Electric Vehicle
HH	Household
IS	Infrastructure
LM	Load management
PEV	Plug-in Electric Vehicle
P90	90th percentile
R_{CO2}	CO_2 correlation coefficient between load and fossil power
SoC	State of charge
ToU	Time of use

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Figures&Tables