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Using rooftop photovoltaic generation to cover individual electric vehicle demand—A detailed case study

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ABSTRACT

The introduction of battery electric vehicles (BEV) and the expansion of rooftop photovoltaic (PV) power generation are both progressing at a fast pace to decarbonize the transport and the energy sector in Switzerland. These parallel developments have an enormous synergy potential as the actual decarbonization impact of BEVs depends heavily on the carbon footprint of the power source and the PV expansion requires local storage as a buffer to reduce negative impacts on the distribution grid. We present an empirical analysis based on a detailed 10-month data set of the charging and mobility behavior of 78 BEV users in Switzerland. It is combined with a fine-grained digital surface model of Switzerland to extract the detailed roof geometry and the corresponding rooftop PV generation capacity of each of the BEV owner's houses.

We test four different smart charging strategies with a varying degree of complexity and find that when charging uncontrolled (the strategy used during the study), BEV owners can only cover 15 % of their BEV's demand using PV generated from the roofs of their own houses. A simple controlled charging approach greatly increases the average coverage to 56 % and up to 90 % or 99 % when using an optimized charging strategy without or with a home battery storage. All charging strategies ensure that the individual mobility behavior of the BEV owners is not affected.

We further show that using rooftop PV power generation for BEV charging has a large potential to further decrease the climate impact of BEVs and propose simple adjustments to consider in charging strategies that help to increase the owners' PV consumption.

1. Introduction

In the light of the threatening progression of climate change 196 countries have negotiated the Paris Agreement and committed to keep the global temperature increase to well below 2 °C compared to pre-industrial levels [1]. To reach this goal, the committing countries formulated national emission targets and measures to achieve a decarbonization of their economies. As examples, China plans to peak in carbon emissions in 2030 and to achieve carbon neutrality by 2060 [2], the European Union (EU) adopted the *European Green Deal* (a set of measures to achieve climate neutrality in 2050[2]) and Switzerland passed the *Climate strategy 2050* that also targets climate neutrality in 2050.

These examples sound promising; however, we are currently losing the global fight against climate change. There is a significant gap between the emission reduction that is achieved if all countries implement their proposed measures and the emission reductions that are required to achieve the goals of the Paris Agreement. This is even true under the consideration of the impact that the COVID-19 global pandemic had on the world's economy [3]. As of 2021, only two larger countries (Morocco and Gambia) are considered to be on track to achieve the stricter 1.5 °C target of the Paris agreement and of the eight countries that fulfill the 2 °C goal India is the only one that is part of the G20.[3]

Abbreviations: BEV, battery electric vehicles; EU, European Union; GHG, greenhouse gas; PV, photovoltaic; SoC, state of charge; DSM, digital surface model

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[2] https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en.
[3] https://climateactiontracker.org/countries/.

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List of abbreviations and units

BEV	Battery electric vehicles
EU	European Union
GHG	Greenhouse gas
PV	Photovoltaic
SoC	State of charge
DSM	Digital surface model

1.1. Joint decarbonization of the transport and electricity sectors

This makes it clear that we must drastically increase our decarbonization efforts.

A major contributor to climate change is the transport sector where the overwhelming majority of energy demand (e.g., 93.7% in Switzerland [4]) is covered by fossil fuels. From today's perspective, the most promising path to a fast decarbonization of the transport sector and especially of individual mobility is given by the introduction of **BEVs!** (**BEVs!**) [5]. However, the decarbonization potential of battery electric vehicles (BEV)s strongly depends on the emissions of the power used for charging [6,7]. This makes the parallel decarbonization of the electricity sector a prerequisite for the decarbonization of the transport sector using BEVs.

The decarbonization of the electricity sector relies mainly on the large-scale integration of wind and solar power into the energy system while their relative importance varies depending on the geographic location [8,9]. Globally, installed photovoltaic (PV) generation grows faster [10] and is expected to be the main driver of the expansion of renewable energy generation [11]. In contrast to wind power generation, small roof-top PV systems installed on the roofs of private homes play a major role in this growth. For example, in Germany, the share of non-utility scale systems (<100 kWp) is close to 50% of the total installed PV generation capacity [12].

1.2. Grid impact of PV and BEV growth, and impact mitigation strategies

A possible obstacle for the fast growth of PV generation and the quick introduction of BEVs is given by the stability of the distribution grid. Both phenomena, large-scale roof-top PV generation and the simultaneous charging of BEVs are possibly threatening the distribution grid stability as they introduce high and intermittent generation capacity and consumption into the grid [13,14].

One idea to mitigate the negative grid impact of rooftop PV generation and BEV charging at the same time is to charge the BEVs directly using power generated from rooftop PV systems installed on the BEV owners' home [15]. In this case the power is used directly where it is generated without entering and stressing the distribution grid. This idea is especially important for BEV charging as the majority of the BEV charging processes are undertaken at home [16].

Another advantage of the use of residential rooftop PV for BEV charging lies in the potential for faster decarbonization of the transportation sector. The reason for this is that the self-consumption of rooftop PV has considerably lower greenhouse gas (GHG) emissions than most other electricity sources [17,18] and especially than the electricity generation mix of most countries.

1.3. Research gaps and contributions

In an optimistic, hypothetical future, a large share of the individual energy demand could be covered by PV cells that are installed directly on each person's house, as this could reduce the complexity and required capacity of the electric distribution grid and would increase the decarbonization potential of BEVs. Several studies consider the self-consumption potentials of individually generated renewable energy [14], however there is a lack of studies that analyze the combination of high-resolution BEV charging data with detailed PV generation models [19]. It is therefore still unknown how well the individual electricity demand for mobility can be covered when considering the intersection of when the BEV is at home and available for charging and the availability of PV generation at these times.

To fill this gap this study analyzes what share of the energy demand of a BEV can be covered by rooftop PV generation installed on the house of the BEV owner. This study has the following main contributions:

- We use a high-resolution data set of 78 BEVs that includes GPS position information, information about the battery's state of charge (SoC) and about the charging activity to calculate the energy demand of each of the BEVs over time.
- We estimate the potential rooftop PV generation based on a high-resolution digital surface model in combination with building footprints to extract the surface, tilt, and aspect of the roof of the actual house of every BEV owner. This allows us to create a PV generation profile with a half-hour resolution for each house.
- We match the potential PV energy generation with the recorded BEV usage of each of the 78 households and then analyze to what extent it is possible to fuel their BEVs with self-generated power.

Our study confirms findings of more theoretical work, e.g., by [20] that there is only a limited potential for increased self-consumption for BEVs if they charge uncontrolled. However, we can extend these results and demonstrate that this potential is greatly enhanced if an appropriate charging algorithm is used.

1.4. Paper outline

In the next section, we review previous research related to our case study. Section 3 explains the data used in detail and highlights strengths and weaknesses of the dataset. In Section 4 we explain how the data sources are integrated, in particular the different movement and mobility tracking data, as well as the data from the building and PV production models. Finally, Section 5 presents the results. In the last sections we discuss our findings, potential generalizations and conclude the paper by providing an outlook on future research.

2. Background

2.1. Decarbonization paths for the transportation sector

The energy consumption of the transport sector is still mostly covered by fossil fuels. Globally, we use about 32% of our energy for mobility and transport. Out of these 32% only about 3.3% are covered by renewable energy sources [21]. On a European level road transportation accounted for 26% of the EU GHG emissions in 2018 and was the only energy sector which has increased its GHG emissions since 1990 [22]. The situation in Switzerland is similar where the transport sector is with 32.4% of the GHG emissions the largest emitter [23].

With regard to these numbers, it is clear that a quick decarbonization of the transport sector has to become a high priority in view of reaching the goals formulated in the Paris Agreement. Among the strategies to decarbonize the transport sector we find soft incentives targeting mobility behavior [24–26], policy interventions that use a top-down governing approach [27], and technological innovations such as synthetic fuels [28,29] or battery improvements that foster quicker transitions to electric vehicles [30]. While many of these proposals consider a wide range of different decarbonization measures, our study focuses only on BEVs as electrification is likely to be the main factor for the decarbonization of transport. Ruhnau et al. summarize their review of 22 scenarios from 12 independent studies about possible decarbonization paths as: "the more the emissions are to be reduced, the more road transport is expected to be electrified" [31, p. 997]. At

this point it is important to mention that the environmental impact of BEVs will depend on the conditions under which the battery was produced [32,33] and on the emissions created to generate the energy necessary for charging the BEV [34].

It is estimated that by 2030 approximately 20% of all vehicles in Switzerland will be electric [35], a value that changes to around 6% (or 125 million vehicles) globally [36]. This is driven by the desire of many people to travel and behave more sustainably, but also because the costs for BEV batteries are falling rapidly and are expected to decrease further [37].

2.2. Grid impact of battery electric vehicles

Apart from the mostly positive impact on CO_2 emissions, BEV charging has a potential impact on the stability of the distribution grid [13,15,38,39]. Clement-Nyns et al. [13] propose and evaluate coordinated charging strategies for BEVs to keep the impact of residential distribution grids within bounds. They find that BEV penetration levels of 10%–30% already significantly impact power losses and grid voltages, which can be counteracted to some degree by coordinated charging strategies. On the other hand, the smart chargers of BEVs could even be used to help stabilize the grid, especially considering that vehicles are typically unused 23 out of 24 h per day [40].

2.3. Photovoltaic potentials and self-consumption of solar power

A potential solution to both problems, the slow decarbonization and potential grid impact of a BEV large-scale roll-out, is utilizing the distributed nature of many renewable energy sources and charging the BEVs using locally generated power. As Luthander et al. [14] note, problems arising from a high penetration of distributed intermittent power generation such as the threat to exceed voltage limits can be mitigated with increased self-consumption of the distributed generation and Hoarau and Perez argue that BEVs in combination with PV systems can lead to higher self-consumption [15].

Of particular interest for distributed generation are PV installations on rooftops. Researchers explored the automatic extraction of rooftops from satellite or remote sensing imagery, e.g., Wiginton et al. [41] analyze the PV potential in Ontario, Canada, and find that approx. 30% of the region's energy demand could be met using on-house PV installations. Similarly, [42] classify satellite imagery by hand to estimate the potential of PV energy in Andalusia, Spain, and find that around 80% of the residential housing sector energy demand could be covered. Several studies computed the rooftop PV potential in Switzerland. In [43], the rooftop PV potential was modeled based on a detailed digital elevation model and building footprints. They estimated the PV energy potential in the range from 48.6 TWh to 58.8 TWh if the rooftops of all buildings within Switzerland would be covered by PV panels and assuming a conversion efficiency from solar irradiation to generated electricity of 10.33%. Compared to the total Swiss electricity consumption of 58.3 TWh in 2015, this is a considerable amount. Note that especially in regions like Ontario or Switzerland, the solar irradiation is largely dependent on the seasons of the year.[4] As costs of PV panels have dwindled over the last decade, more and more PV installations are available. It is aimed that PV energy will contribute at least 11.4 TWh by 2030 and at least 34 TWh by 2050 to the total energy demand of Switzerland [44,45].

With dropping prices for PV panels, it becomes increasingly interesting to add batteries to individual homes in order to further decrease the stress on the grid and bridge cloudy days. These batteries have the potential to reduce peak loads, especially in combination with smart meters and adaptive control systems [46]. Regarding the direct influence on electric mobility, Buffat et al. [47] analyzed the effects of home-installed batteries on the provision of energy for BEVs used for commuting. The study shows that vehicles are concentrated during working hours in areas with a high workplace density while a significant share of the PV production is in suburban areas. Using home installed batteries would enable using the produced PV energy locally without the grid. However, as this study used no real trajectories of BEVs the assumed charging scenarios could not reflect the spatio-temporal characteristics of PV energy production and BEVs.

2.4. Effects of self-consumption on the decarbonization of the mobility sector

Mohammadi and Taylor [48] show that human mobility and the power consumption in buildings are strongly related. Using the battery from electric vehicles to increase the self-consumption of a household is seen as difficult because of the low coincidence between PV generation and the charging of electric vehicles [20]. It was also shown previously that changing mobility behaviors in combination with the provision of PV energy provides important steps to reach lower greenhouse gas emissions and thus fulfills the goals of various energy strategies [47,49]. However, the question stays how much residential roof-top solar power may contribute to the decarbonization of the mobility sector by charging electric vehicles. Also, the multi-modality of transportation and flexible working concepts like home-office are forecasted to increase in the future (the latter even received an unexpected boost due to the global COVID-19 pandemic), which could unlock new potentials for the usage of BEV charging to increase residential self-consumption.

3. Data

3.1. Mobility data

We analyze the energy consumption from BEV usage, based on Swiss BEV users who participated in the SBB Green Class E-Car pilot study[5] from Feb 1st to Dec 23rd, 2017. Participants of the study were equipped with a comprehensive Mobility as a Service (MaaS) package, containing (among others) a general public transport pass valid everywhere in Switzerland and a BEV for their personal use. Participation in this pilot study required paying a participation fee of 12'200 CHF, which led to a sample of participants with above-average income who travel more than the average Swiss person [50]. All study participants had access to a garage to install a home-charging station for the BEV, 83% of the participants lived in single-family homes and all participants had access to more than 1 car at a household level (including the E-Car), however, participants had to pledge that at least 80% of all drives of the BEV are done by themselves. The original Green Class E-Car pilot study had 144 participants of which we excluded participants who dropped out of the study early, who never used their BEV, users who could not be matched to houses (see Section 4.3), users who were matched to vacation homes or work locations (distinguished based on mobility patterns) and users with too large houses that resulted in PV system sizes with peak generation capacities over 30 kWp. For the remaining 78 users we also exclude the data between the 24st of December and the 31st of December because of low data coverage during these days. Furthermore, about 5 days of data are missing for most users in late September and early October [50]. These days are therefore also excluded from the study. Fig. 1 shows the percentage of cars that are at the home location for every hour of the day over the full study period. The Figure allows to draw conclusions on the usage behavior of the study participants as it shows distinct usage patterns during the night and during the day as well as during the week and on week-ends.

[4] To help people plan individual PV installations, a number of online calculators and estimators are available such as www.sonnendach.ch from the Swiss Federal Office of Energy or www.solarpotenzial.ch from a local grid and power plant operator.

[5] More information about SBB Green Class can be found under www.sbb.ch/en/travelcards-and-tickets/railpasses/greenclass/pilotprojects.html.

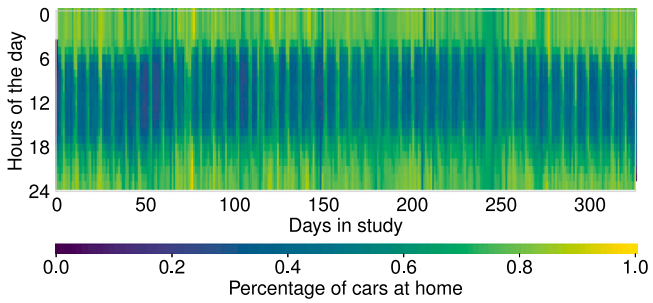

Fig. 1. Share of BEVs at home or not at home.

The BEV of the participants records data event-driven and creates a new entry when the engine is started, the engine is stopped, the car starts charging or the car stops charging. For the start and the end of every entry, the following relevant information is stored: Timestamp, mileage, SoC and geographic position. The entries are labeled as either *charging*, *driving*, *pausing* or *gap*. In total the data set of the 78 used BEVs contains 189'446 entries with 77'065 drives and 19'867 charging processes and covers a total distance of 791'273 km. This corresponds to an average of about 10'145 km per car accumulated over 10 months.

3.2. Data used for solar irradiation estimation

The *Federal Register of Buildings and Dwellings*[6] contains for each building in Switzerland associated properties such as a unique identification number, the coordinates of the building, the complete address, or the building type (e.g. if it a single or multi-family house).

In combination with the home addresses, we can match each participant to a building. However, the register does not contain the exact building footprint or rooftop shape (i.e., its slope and orientation), which is required for an accurate estimation of the PV potential.

We retrieve building shapes from the swissBUILDINGS3D 2.0 dataset of the Federal Office of Topography.[7] This dataset contains the most current building data available for Switzerland and includes 3D vector data for each building. Furthermore, to model the shading effects of canopy and topography we use a digital surface model (DSM) with a resolution of 0.5 m derived from LIDAR data [51]. To extract the PV potential in 2017 (when the mobility data was recorded), we additionally utilized solar irradiation data as provided by the Satellite Application Facility on Climate Monitoring (CM SAF) Surface Solar Radiation Data Set – Heliosat (SARAH) [52]. This dataset contains direct as well as diffuse solar irradiation data derived from weather satellites and covers Switzerland with a spatial resolution of 0.05°, corresponding to rectangular grid cells of roughly 3.8 km × 5.6 km, and provides one data point for each cell every 30 min. Additionally, to estimate the efficiency of PV cells we use hourly ambient temperature data from MeteoSwiss weather stations extracted from IDAweb.[8]

Combining the building footprint, DSM and solar irradiation data (cf. [43]) lets us compute accurate energy production values for each building in intervals of 30 min.

[6] More information can be found under https://www.bfs.admin.ch/bfs/en/home/registers/federal-register-buildings-dwellings.html.

[7] More information can be found under https://shop.swisstopo.admin.ch/en/products/landscape/build3D2.

[8] More information can be found under https://www.meteoschweiz.admin.ch/home/service-und-publikationen/beratung-und-service/datenportal-fuer-lehre-und-forschung.html.

4. Methods

4.1. Mobility data preparation

We preprocess the BEV tracking data in two steps. At first, we fill in missing tracking locations, then we aggregate all entries where the BEV is successively at the home location or not at the home location of the user.

Out of all available BEV entries 34% have a missing start and/or end location. However, we can define rules to fill in trivial missing locations that leverage the available location information and the reading of the mileage counter. Given a BEV, we define the following rules about its starting location l^i_{start} and its stopping location l^i_{stop} for a tracking entry i:

$$
\begin{aligned}
l^i_{start} &= l^i_{stop} \quad \forall\, \Delta m_i = 0 \\
l^i_{stop} &= l^i_{start} \quad \forall\, \Delta m_i = 0 \\
l^i_{start} &= l^{i-1}_{stop} \\
l^i_{stop} &= l^{i+1}_{start}
\end{aligned}
$$

with Δm_i being the difference of the mileage counter between the start and the end of the same segment. The first two rules state that the car is still at the same location when the mileage counter has not changed, the third rule states that a car starts at its last stopping location, and the last rule states that a car stops at its next starting location. If any of the right-side locations are known, we can use them to fill in the left counterpart. These rules are sufficient to fill 61% of the gaps which leaves 13% of the total tracking entries without complete location information.

In the next preprocessing step, all BEV entries of a user are aggregated into segments where the BEV was continuously either at the home location or not at the home location. For this we label the tracked locations as *at home* if the car is less than 500 m away from the users' home location as it is defined in Section 4.3. The threshold of 500 m is chosen relatively high because the BEVs are often parked in the garage which leads to a higher than usual GPS localization error. We then aggregate all information of all entries when a BEV was continuously *at home* or *not at home* into one new entry that we call segment. We especially keep the first starting time of an entry and the last ending time of an entry as the start and end time of the segment, the total energy consumption within the segment and the difference in the SoC of the first and last entry of the segment.

A one-week example of a single BEV user can be seen in Fig. 2. Here the dark green patches correspond to segments where the BEV was at the home location and the light green patches correspond to the segments where the BEV was not close to the home location. The black line shows the SoC of the BEV over this period and the blue line the theoretical PV generation available at the house of the BEV owner (see Section 4.3 for information about PV generation).

4.2. Energy demand of the BEV

The BEV provides data about the SoC at the beginning of a drive and at the end of a drive, as well as the consumed energy. However, we do not know exactly how much energy is required to fully charge the BEV based on a specific SoC. We take advantage of the large amount of data we have access to and determine how much energy is required to fully reload the BEV as the solution to an ordinary least squares problem:

$$\hat{\alpha} = arg\min_{\alpha} \|y - X\alpha\| \tag{1}$$

For the fit we exclude outliers where either the SoC or the consumed power are ≤0 and we enforce the intercept to be 0 to account for the physics of charging, meaning that there is no change in the SoC if no power was consumed. We chose a polynomial with a square root term in order to account for the small bend close to zero. Therefore, in our

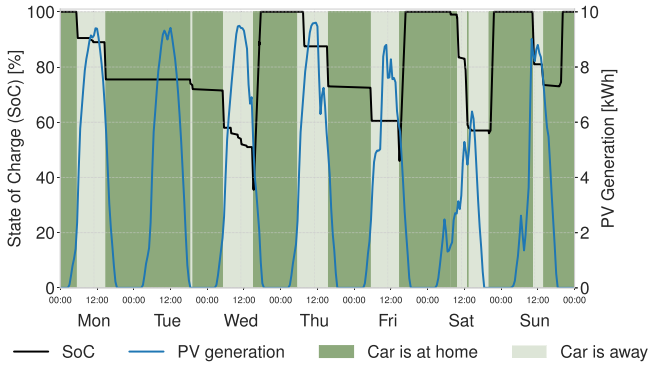

Fig. 2. Exemplary week of a single user showing the usage of the BEV as well as the energy production by rooftop PV. In this recorded charging pattern (i.e., the baseline scenario, as explained below), it would be beneficial to not immediately recharge the car to the maximum, but instead wait for periods of increased PV energy generation.

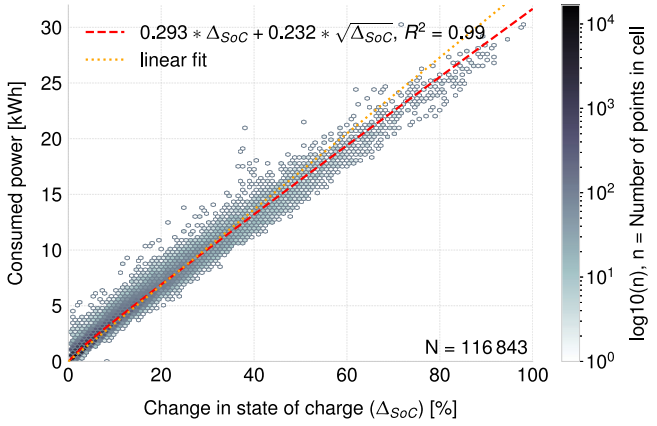

Fig. 3. Scatterplot of the difference of the SoC before and after a drive and the consumed energy.

case y in Eq. (1) is the consumed power during one drive and X is the data matrix that was combined using the vector of the change in the SoC and the vector of the square-root of the change in the SoC. Fig. 3 shows a hex bin plot of the data together with the polynomial fit and a linear fit as a reference. The result of the least squares regression is:

$$\text{Consumed power} = 0.293\,\text{kWh} \cdot \Delta_{SoC} + 0.232\,\text{kWh} \cdot \sqrt{\Delta_{SoC}} \quad (2)$$

This method assumes that the battery capacity of the BEVs of all users is constant over the study period. All our study participants use the same (newly bought) type of BEV; however, we are neglecting ageing and temperature effects.

Over the whole study period the 78 BEVs consume and charge a total of 134.03 MWh of which 80% is charged at home. Fig. 4 (left) shows the average daily demand of all study participants and its 95% confidence interval. This Figure shows that there is a slight seasonality in the consumption data such that participants consume more per week in cold months. Fig. 4 (right) shows the daily energy demand for mobility over the course of the study and aggregated per weekday. It reveals the aggregated demand does not depend on particular weekdays which have median values between 6.28 kWh and 6.56 kWh with the exception of Sundays where the demand is considerably lower with a median value of 4.63 kWh.

4.3. PV generation

To estimate the PV energy production potential of rooftops, we use building footprints, a custom-created DSM, and satellite-based spatio-temporal solar irradiation data (at a spatial resolution of roughly

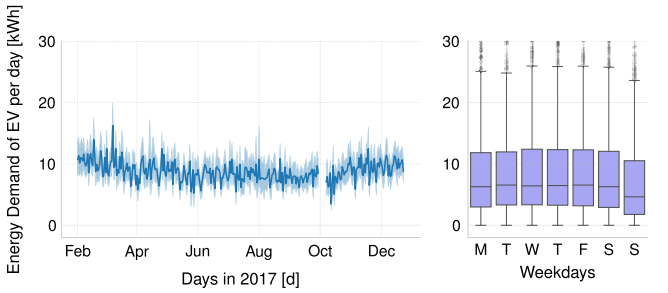

Fig. 4. Daily energy demand of the electric vehicles of study participants. On the left, the average demand and its 95% confidence intervals are shown over the course of the study. The data shows a week of excluded data in the beginning of October. On the right, box plots of individual weekdays are shown. Outliers in the box plot go up until about 100 kWh which corresponds to the consumption of three full charges in a single day.

5 km and a temporal resolution of 30 min). We calculate the solar irradiation for each cell of the DSM within a building footprint for every 30 min during the case study period taking the shadowing effects of neighboring buildings and topography into account. Thereby we assumed that the complete roof can be used for PV generation. As the available technology impacts the overall electricity generation, we model the PV generation two folds. For all detailed analyses, we model the PV cell and inverter efficiencies for each 30 min based on the current conditions. The PV cell efficiency is estimated based on the PV cell properties (see Appendix), the amount of solar irradiation hitting the cell, as well as the ambient temperature. Inverter efficiencies are modeled using the *PVWATT*[9] model using the yearly peak production to dimension the maximum power of the inverter.

In a second experiment in Section 5.4, we investigate the sensitivity of the PV energy conversion and model only the effect of shadowing and assume otherwise constant efficiencies for PV panels and inverter. The applied workflow is based on [43], but differs in the following key areas:

- We modified the digital terrain model used in [43] by replacing all buildings using the *SwissBuildings 2.0*[10] dataset. This is achieved by rasterization of the 3D vector shapes of the *SwissBuildings 2.0* with the same spatial resolution of 0.5 m of the existing DSM. Thereby, we ensure to use the most recent available rooftop shapes while still modeling the surrounding topography, such as terrain features or vegetation.
- In contrast to calculating long-term mean time series, we calculate the electricity generation for every 30 min for the year 2017 for each building assigned to a BEV user.
- For each building, the ambient temperature of the nearest available weather station is used in the process to model the PV cell efficiencies. The temperature is corrected based on the elevation difference between the building and the weather station and a factor of −0.66 °C per 100 m difference of elevation.[11]

4.4. Photovoltaic potential

By combining the solar irradiation data (cf. Section 3.2) with the geographic data describing the rooftops of participants' houses (cf. Sections 4.3 and 4.5) we compute accurate estimations of the energy that could potentially have been generated using photovoltaic cells on each house.

[9] https://pvwatts.nrel.gov/downloads/pvwattsv5.pdf.
[10] https://shop.swisstopo.admin.ch/en/products/landscape/build3D2.
[11] This value was recommended by the Federal Office of Meteorology and Climatology MeteoSwiss as the vertical temperature gradient.

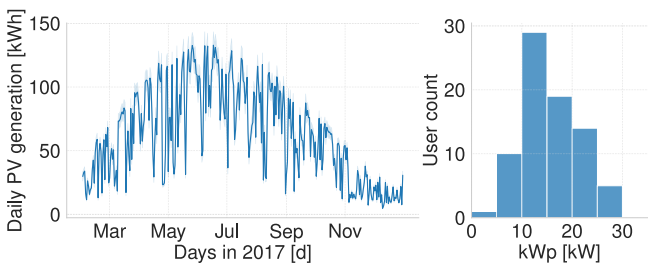

Fig. 5. PV energy generation at homes of study participants. Left side shows the average daily PV generation per participant as well as the 95% confidence interval over the course of the study period. The right side shows the distribution of the peak generation capacity per house.

Fig. 5 shows the average daily PV energy generation of all participants over the course of the study period. It can be seen that the production in winter is a fraction of the one during summer months, that there are occasional days on which the production on all houses drops to values close to zero (mostly days where all of Switzerland is covered by clouds).

4.5. Combination with PV model

We validate each match between home location and building footprint manually in a geographic information system [53] by overlaying recent satellite imagery. 65 of the 78 persons live in single-family homes. We also include 9 users who live in two-family homes and 4 users who live in homes for multiple families with the condition that we could clearly identify the number of households living in this house. For houses with more than 1 household we later divide the PV system size and the generated power by the number of households as if the electricity would be equally shared among all households. The right side of Fig. 5 shows the distribution of the resulting peak generation capacity for all users.

4.6. Smart charging scenarios

In this study we compare four different charging scenarios for the BEV. An overview of these charging scenarios is shown in Fig. 6.

Scenario assumptions

All scenarios assume perfect knowledge of the PV generation as well as the mobility energy demand over the whole study period. These assumptions are justified because the goal of this work is not to present a novel operational smart charging algorithm but to analyze the potential to cover mobility energy demand using residential rooftop PV systems. An overview of existing smart charging algorithms for BEV charging using PV systems was presented in [54]. The temporal resolution of all scenarios with exception of the baseline is one segment in which the car was continuously at home or away from home. As described in Section 3 all users in the study have access to the same BEV with a battery capacity (cf. Section 4.2) of 31.61 kWh. As part of the project all participants installed a private charging station at home; we will assume that all participants have installed a 11 kW charger. In general, we do not explicitly model the plug-in behavior of a user, however, the plug-in behavior was recorded during the study and is implicitly considered in scenario 1. Scenarios 2 and 3 assume that the BEV is able to charge when it is at home.

Baseline scenario: Recorded charging schedule

As a baseline we analyze the actual charging behavior of the BEV owners as it was recorded in the study. The charging of the BEVs in the tracking study is uncontrolled, i.e., if a user plugs in the BEV it immediately starts charging until it is fully charged or unplugged. An example of the recorded charging behavior is shown in Fig. 2.

Scenario 1: Segment-wise optimization

The first charging scenario, shown in the top left of Fig. 6, optimizes the share of rooftop PV generation used for BEV charging by only shifting the charging schedule within the same segment (cf. Section 4.1 for the definition of segments). In this scenario, the SoC of the BEV at the start and the end of every segment is the same as the reference SoC (SoC_ref) that was recorded for this segment in the case study. We allow, however, to change the charging trajectory (e.g., by deferring charging) between these points. In the example given in Fig. 2 this would mean that the SoC at the beginning and the end of every dark green segment is fixed but we can alter the time when charging takes place in between these points. The purpose of this scenario is to offer a charging schedule that optimizes the consumption of PV energy but remains as close as possible to the recorded data. By that, this scenario implicitly considers the plug-in behavior of a person on a per-segment level as we are only allowed to charge in this scenario when the user also charged in reality.

Scenario 2: Cross segment optimization

The second smart charging scenario, shown in the top right of Fig. 6, implements a greedy approach to maximize the share of PV generation used for the charging of the BEV over the whole study period. Therefore, the BEV in scenario 2 always charges as much as possible using PV power and only takes a minimal amount of energy from the grid to be able to serve the mobility needs of the user. In the example given in Fig. 2 we would be allowed to do any operation as long as we only charge when the user is at home, the maximum charging power is not surpassed and the SoC of the BEV is always greater than 0.

Scenario 3: Storage capacity

In the third scenario we analyze the impact of a commercial home battery storage that is used to buffer the PV power generation. We set the capacity and the maximum symmetric power flow based on a commercial product to 13.5 kWh and 4.6 kW. An overview of the third scenario is shown in the bottom of Fig. 6. The simulation runs as follows: We specify the battery size available. If there is energy generation available from PV, it gets charged to the electric vehicle if it is at home and not full. Otherwise, the generated power is stored in the battery.

The car is charged from either the PV power currently being generated or from the battery. Only if this is insufficient, energy from the power grid gets charged up to the minimum required level to fulfill the mobility requirements.

4.7. Calculation of CO_2 emissions

We evaluate the sustainability of the different scenarios by calculating their relative GHG emissions as CO_2 equivalent. For the comparison we include the GHG emissions of the power used for charging the BEVs, and the emissions generated by the production and the disposal of the rooftop PV and the battery system (scenario 3). We specifically exclude all emissions related to the production and the disposal of the BEV as we only use the calculated emissions to compare the scenarios against each other and the BEVs are the same in all scenarios. All used emission factors were determined in *cradle-to-grave* LCA studies with the exception of the emission factor for the German power mix which is only published based on marginal emissions.

Emission factor for grid charging

The emission factor for the Swiss household consumer mix is published by the Federal Office for the Environment (FOEN) and is 181.1 gCO_2-eq/kWh [55]. While the power generated in Switzerland has considerably lower emissions, much of the Swiss energy is imported (often from Germany) and often stored in one of the many pumped storage power plants to be distributed at a later point in time. The emission factor for Germany is 401 gCO_2-eq/kWh [56] and is significantly higher even though it comprises only direct emissions.

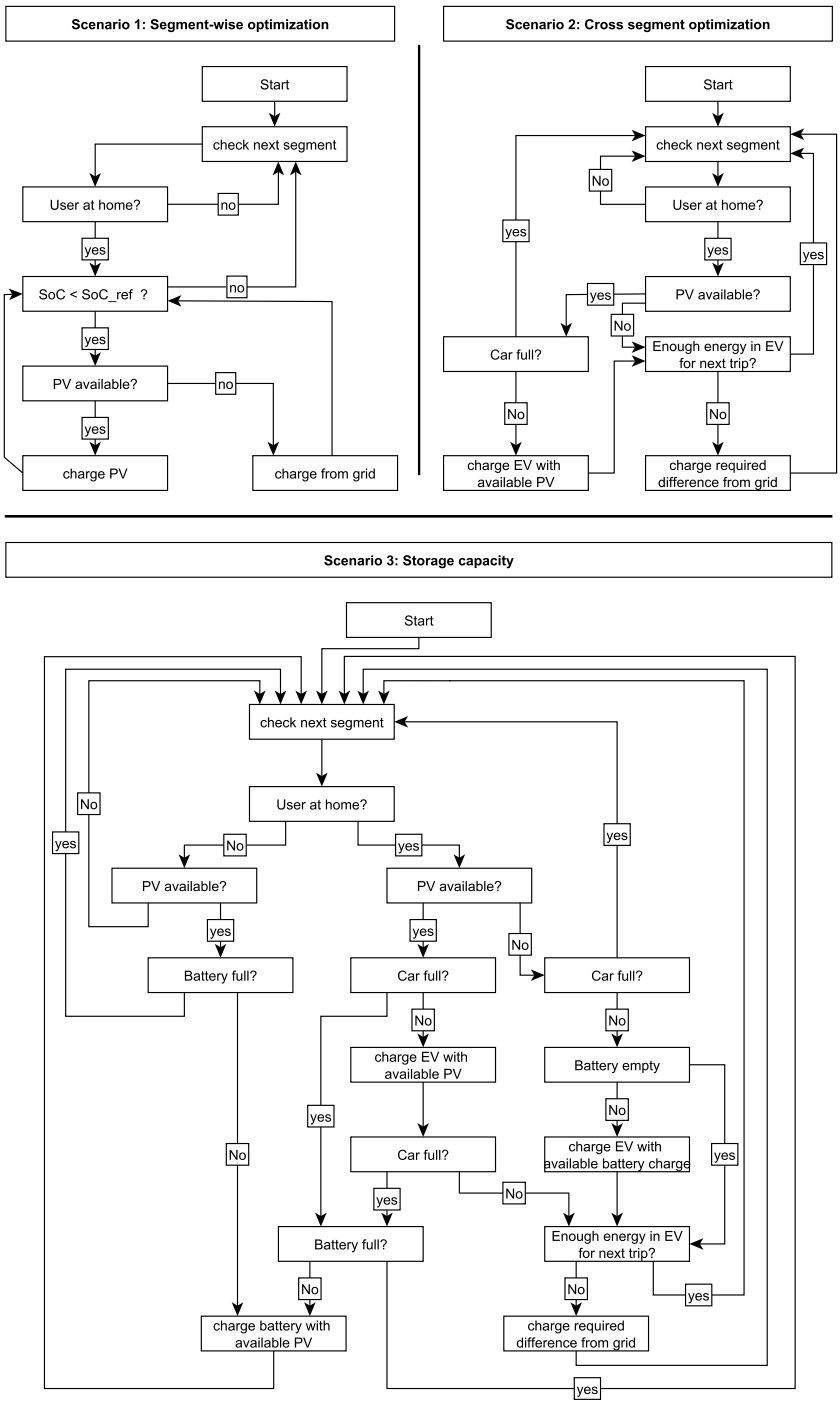

Fig. 6. Flowcharts representing the charging logic of the different scenarios (top left: scenario 1 segment-wise optimization, top right: scenario 2 cross-segment optimization, bottom: scenario 3 cross-segment optimization with battery).

Emission factor for PV charging

Even though PV power generation is considered a clean source of energy, it is not carbon free [57] and its cradle-to-grave emission factors are controversially debated as they can strongly vary depending on the assumptions taken on production techniques [58]. The 2014 study from Nugent and Sovacool [58] reported an average emission factor of 49.91 gCO_2-eq/kWh but noted that large-scale PV generation facilities are generally more efficient than rooftop PV systems. We assume an emission factor of 53.6 gCO_2-eq/kWh as this was reported by a recent study with a very similar use case to ours [59]. The factor is in line with the study of Nugent and Sovacool [58] and another recent study [60] that reported average values ranging between 30 gCO_2-eq/kWh and 80 gCO_2-eq/kWh depending on the panel technology. We further omit emissions stemming from the hypothetical need of additional infrastructure (such as a distribution grid expansion) and system management losses as they are expected to only have a minor impact [60].

Emission factor for home storage

For the home storage we use a capacity specific emission factor of 76.1 $kgCO_2$-eq/kWh as it was reported for a recent lithium-ion battery (lithium cobalt phosphate) [61]. We follow [59] and assume a lifetime of 5000 cycles and an average usage of 1 cycle per day which results in

an average lifetime of 13.7 years. To correctly account for the battery related emissions over the study duration, we calculate the average weekly emissions of the battery. A battery with a capacity of 13.5 kWh has then average emissions of 1.44 $kgCO_2$-eq per week.

5. Results

We calculate the detailed mobility energy demand and the rooftop PV generation potential for all users using the steps described in Section 4 and simulate a detailed charging schedule for each of the four charging scenarios presented in Section 4.6. In this section, we analyze the potential to cover the mobility energy demand using rooftop PV generation, the development of this coverage ratio over time, and the impact of the PV generation on the GHG emissions stemming from mobility. In the end of this section, we further analyze the sensitivity of the results to roof size, overall BEV usage and panel efficiency.

5.1. Coverage of mobility energy demand using rooftop PV generation

All scenarios were implemented as Python 3 scripts.[12] following the procedures outlined in Section 4 The main result of this work is a detailed juxtaposition of mobility-induced electric energy requirements (stemming from individual motorized transport) and potential (local, i.e., on an individual's home's rooftop) generation using photovoltaics under the assumption of different smart charging scenarios.

Fig. 7 shows a histogram per scenario for the overall coverage ratio per user for the full study duration. The coverage ratio is defined as the total energy charged from rooftop PV divided by the total energy charged by the BEV. Additionally, the average coverage ratio over all users is given in the title of each scenario. As expected, the coverage ratio is increasing with increasing complexity of the scenarios. The baseline scenario represents the charging behavior of the users as it was recorded in the study. The evaluation of this scenario shows that uncontrolled charging results in a very low coverage of the mobility demand with rooftop PV generation of only 15%. These results are lower than the reported self-consumption of the total household load in combination with a plug-in electric vehicle [20] or the self-consumption reported in a case-study that looked at shared BEVs in a microgrid [62]. However, already shifting the charging within individual at-home segments increases the coverage ratio by 41%. This is rather surprising given that the overlap between sunny hours and when the car is at home is thought to be comparatively low. Scenario 2 represents a theoretical upper boundary on how much of the individual's mobility behavior energy demand could be covered by PV generation under the assumption of perfect forecast of the upcoming PV generation and the mobility behavior. The results of scenario 2 show that 32 users could theoretically cover more than 95% (height of the last bin) and the others substantially more than 50% of their mobility energy demand by PV generation based on their own roofs. Scenario 3 follows the same charging strategy and assumptions as scenario 2 but uses an additional home energy storage to buffer energy generated by PV if possible. In this scenario almost all users can cover their demand by 100%; while this is very high, the difference to scenario 2 is small.

5.2. Coverage ratio over time

Fig. 8 shows a different view on the results. Here, we plot the cumulative sum of the energy that was used by the cars against the net energy generated (and utilized) by PV. In this graph the two lines through the origin $x = y$ and $x = -y$ represent the case when only PV generation or only energy from the grid was used to charge the BEV. The graph is based on the data of all study participants and was sorted by time before creating it. The total energy used, drawn on the x-axis, is therefore monotonic over time and can be seen as a proxy for temporal progression. This graph shows again that scenario 2 and scenario 3 are close to optimal over the whole study period, as opposed to the baseline charging strategy which is close to the worst-case scenario. Both, the baseline scenario and scenario 1 show a hump in the second half of the graph which is already a hint for the (expected) influence of seasonality on the PV generation and therefore on the results.

Fig. 9 shows the distribution of the coverage per week per user for every scenario. In this graph the seasonality effect is clearly visible. In all scenarios except for scenario 3 coverage is higher during the sunny months. Fig. 9 could support the assumption that the coverage ratio is increased due to the higher generation during the summer months which could also lead to the assumption that the result mostly depends on the roof size and the installed generation capacity. This question is further investigated in Section 5.4.

5.3. Effect on CO_2 emissions

We calculate the average CO_2 emissions of each user on a weekly basis. Therefore, we multiply the sum of the weekly energy usage per user with the emission factors discussed in Section 4.7. For the used power we distinguished between energy used from the grid and energy used from the rooftop PV system. For scenario 3 the emissions of the battery are added as a constant factor each week, PV generation that was temporarily stored in the battery is accounted for in the rooftop PV emission factor. Fig. 10 shows the average emissions over all users for the different scenarios. The left side of the Figure shows the results for the Swiss electricity mix. It demonstrates that there is a significant potential of saving CO_2 emissions. For the comparably clean Swiss power mix, every user would save on average 2.93 $kgCO_2$-eq per week for scenario 1, 4.11 $kgCO_2$-eq per week for scenario 2, and 3.13 $kgCO_2$-eq per week for scenario 3 in comparison to the baseline scenario. Further, the graph shows that already scenario 1 has a significant potential to save emissions when compared to the baseline. We can also see that the battery in scenario 3 is not able to amortize its initial emissions with higher PV usage which leads to weekly average emissions that are often higher than those of scenario 1.

The right side of Fig. 10 shows the same analysis for the German power mix. The result follows a similar trend but the absolute difference in emissions is larger. For the comparably emission-heavy German power mix, every user would save on average 7.29 $kgCO_2$-eq per week for scenario 1, 10.78 $kgCO_2$-eq per week for scenario 2, and 10.63 $kgCO_2$-eq per week for scenario 3 in comparison to the baseline scenario. Furthermore, it shows that scenario 3 now achieves lower emissions than scenario 1 and also lower CO_2 emissions than scenario 2 in early spring and late autumn. The higher difference in emissions between power from the grid and the rooftop PV generation allows for a better amortization.

5.4. Sensitivity

To provide insights into the reasons for the coverage variance between users, we analyze the influence of the roof size, the total energy demand, and the overall efficiency of the PV system.

Influence of PV system size and charging demand

Intuitively we would expect that it is easier to cover the mobility energy demand if a study participant has a large rooftop PV system or if she does not use the car very often. However, our analysis suggests that the influence of these factors is rather small.

To test the influence of these factors we run a regression analysis for each scenario using the average yearly coverage ratio per person as dependent variable and the PV system's peak power and the total mobility energy consumption as independent variables.

[12] All code used for this project can be accessed via https://github.com/mie-lab/rooftop-PV-EV-charging.

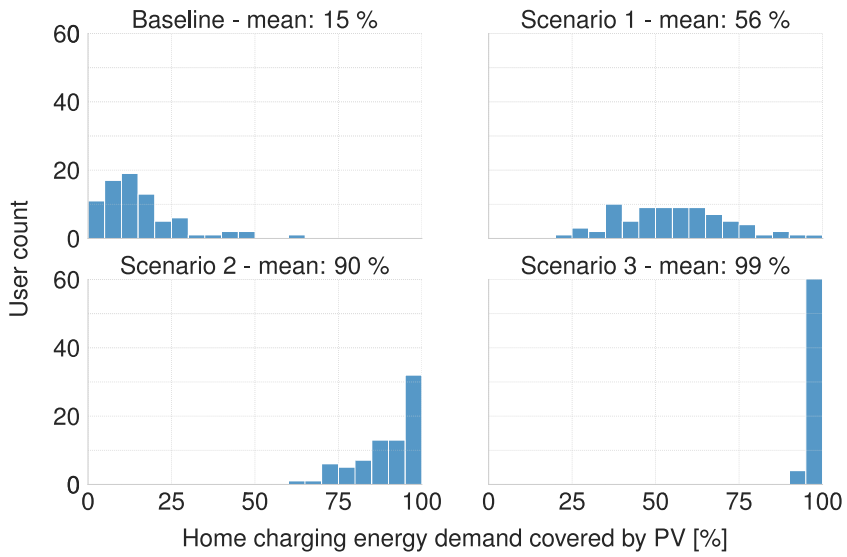

Fig. 7. Share of energy (required for mobility) generated by local rooftop PV for each user in all scenarios over the full study duration.

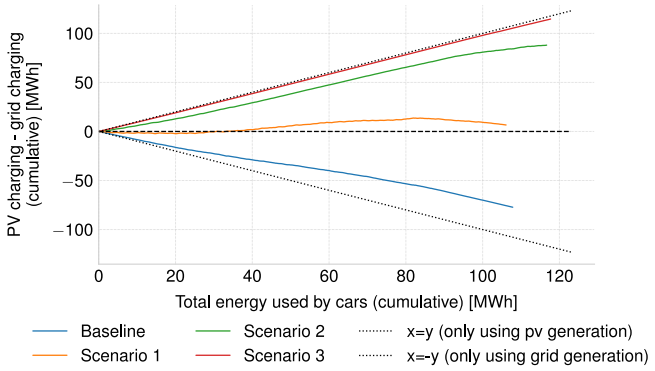

Fig. 8. Energy sources (rooftop PV or the grid) for the (cumulative) energy demand of BEVs for each scenario.

Table 1
Results of the regression analysis examining the correlations between total energy demand for mobility resp. peak PV power and PV coverage ratio.

	Demand		PV peak power		R^2
	Coef. $\frac{[\%]}{kWh}$	p	Coef. $\frac{[\%]}{kWp}$	p	
Baseline	−4.94E−03	2.40E−02	4.68E−01	4.73E−02	0.10
Scenario 1	−1.10E−02	2.20E−04	6.29E−01	4.42E−02	0.19
Scenario 2	−9.00E−03	3.83E−08	1.93E−01	2.16E−01	0.33
Scenario 3	−1.44E−03	2.55E−05	7.07E−02	4.04E−02	0.23

The results of this analysis are shown in Table 1. Total energy demand and PV system size are below the 5% significance level for all scenarios except for the PV peak power for scenario 2. However, the rather low R^2 values suggest that these factors can only partially explain the result of the analysis. A more detailed look at the regression coefficients further reveals that the linear relationship might be significant, but for the baseline scenario as well as scenarios 2 and 4 its influence is rather low as a change of several hundreds of kWh in yearly demand or a change of several kWp in PV system size are necessary to change the coverage value by 1%. This can be also seen in the scatter plots shown in Fig. 11, where it is visible that neither the total yearly electricity demand of the BEV nor the size of the PV system can explain a substantial part of the variance.

Influence of overall PV system efficiency

In addition to the sensitivity to PV system size and total energy demand, we tested the influence of varying the overall PV system efficiency. We therefore repeated the main experiment 24 times and calculated the coverage ratio for every user for all scenarios assuming a fixed PV system efficiency that varies its efficiency between 6% and 29%. The overall system efficiency here is defined as the ratio of generated power and incoming solar irradiation (see also Section 4.3). Fig. 12 shows the average coverage value over all users and its 95% confidence interval. The average coverage ratio grows quickly for low panel efficiency values and slowly saturates for efficiency values between 10% and 16% depending on the scenario.

A close look reveals that the uncertainty of the estimated mean slowly grows with growing panel efficiency for scenario 1 and 2 while it shrinks for scenario 3 and 4. This indicates that the scatter of the coverage values increases for the first two scenarios while it decreases for the others. Scenario 1 and 2 preserve the original mobility and plug-in behavior, the increase of the scatter in the data shows that there are some users who can better take advantage of the increased generation while others cannot, e.g., because they rarely plug-in their BEV. Scenario 3 and 4 optimize the PV usage with the mobility demand as the only boundary condition. In this case the only distinction between users are their usage patterns and an increased generation will lead to an increased coverage for all users that cannot yet fully cover their BEV's demand.

6. Discussion

6.1. Potential of home charging of EVs

The evaluation of the real-life charging schedules shows that there is a great potential to cover the mobility energy demand using rooftop PV generation. However, the results also show that uncontrolled greedy charging (as it is mostly the case at the moment) leads to almost worst-case results in terms of coverage (cf. Fig. 9). The results from scenario 1 demonstrate that it is theoretically possible to increase the average coverage ratio by 41% without requiring any change in the behavior of the BEV owner (e.g., to always plug in the BEV). These results could be achieved by two simple adjustments to smart charging algorithms: Restrict the maximum charge to the available PV generation as long as sunlight is available and do not fully charge the BEV during the night to have the possibility to take advantage of the sunlight in the morning hours.

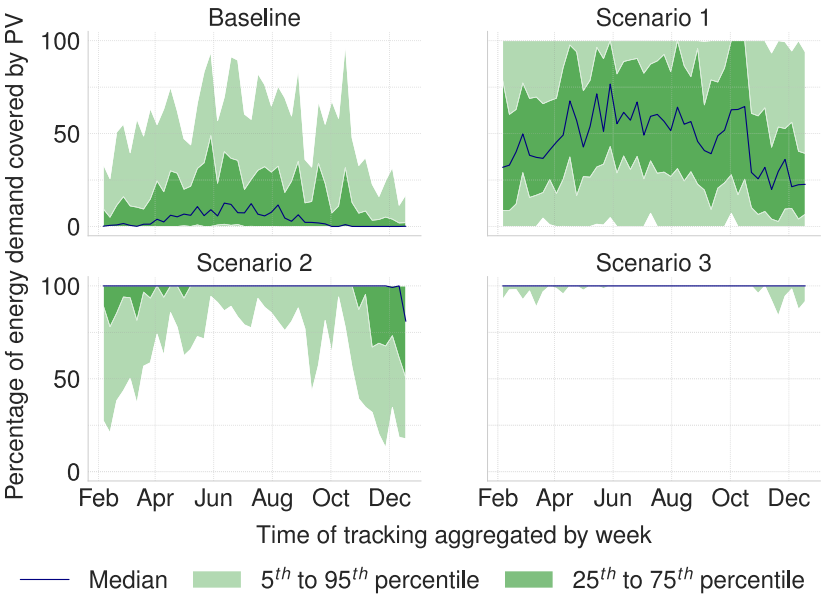

Fig. 9. Shares of energy produced by rooftop PV for each user over the duration of the study period.

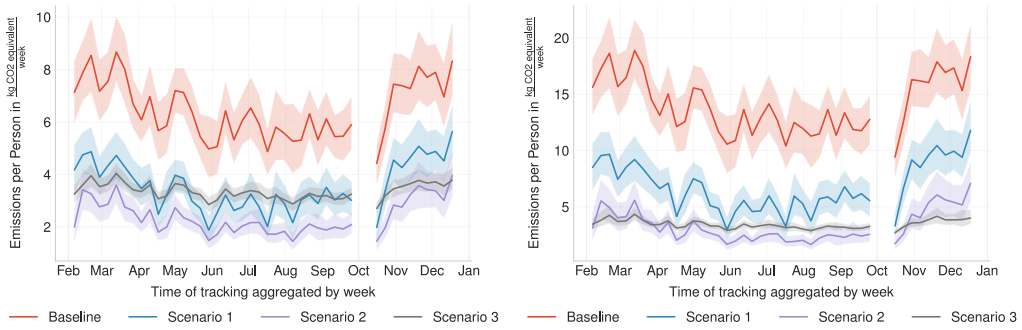

Fig. 10. Average greenhouse gas emissions stemming from electric mobility for all users. On the left side, a typical Swiss power mix is assumed, on the right side a German power mix (only the direct emissions considered for Germany). Two weeks in October affected by missing data are excluded. Uncertainty intervals show the 95% confidence interval of the mean.

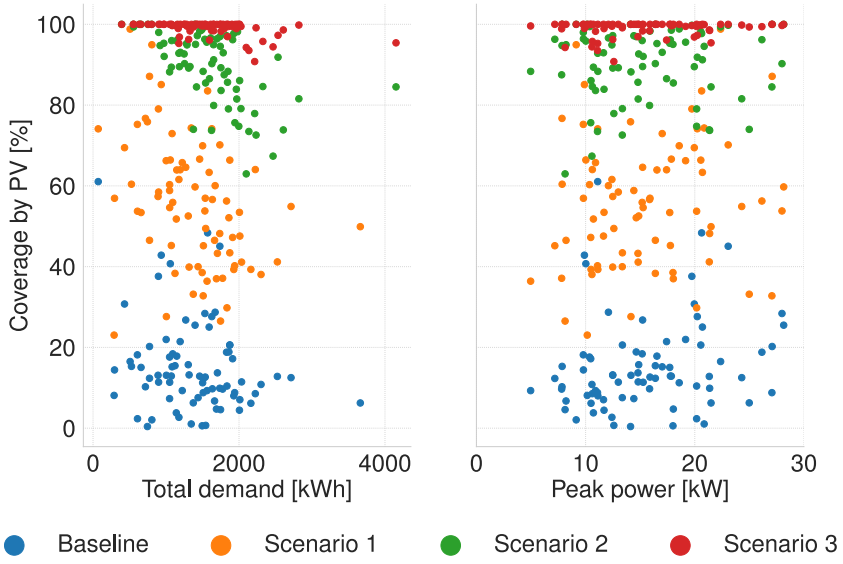

Fig. 11. Analysis of correlation between total energy demand for mobility resp. peak power production on individual rooftops and energy coverage by PV power. In blue, the baseline scenario is shown, in orange scenario 1, in green scenario 2 and in red scenario 3.

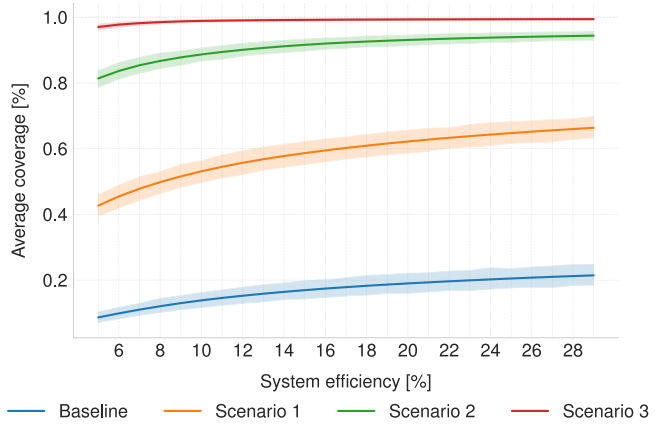

Fig. 12. Average coverage value as a function of the overall PV system efficacy. The graph shows the average over all users per scenario and the 95% confidence interval.

Scenario 2 shows that almost all BEV owners could fully cover their mobility energy demand using rooftop PV generation. In practice it will be hard to achieve these values as it requires good forecasts of the PV generation and the individual mobility energy demand. In this study the results of scenario 2 are already close to optimal which could lead to the conclusion that the installation of an additional home battery storage is unnecessary. However, the design of a good charging strategy that relies on uncertain forecasts becomes significantly easier with the possibility of buffering the energy. This consideration could thus justify the installation of a home battery system.

6.2. Potential of rooftop PV to decarbonize transport

Even though BEV have lower GHG emissions than fossil fuel dependent ICEVs, their emissions depend strongly on the technologies used for power generation. The analysis of the average CO_2 emissions in the different scenarios reveals the large potential that the combination of rooftop PV generation and BEVs offers for the decarbonization of individual mobility. The reduction potential depends on the emission intensity of the energy mix available to the consumer, which means that the reduction potential becomes lower over time with the ongoing progression of the decarbonization of the energy sector. The impact of home-charging might be reduced if a BEV can be charged using PV at the workplace [63] (e.g., if a person can charge her BEV using PV at the workplace, the BEV might be almost full when returning home).

6.3. Potential of rooftop PV and BEVs for increased grid stability

The stability of the distribution grid is an important factor that has to be considered during the expansion of PV generation as well as during the roll-out of BEVs. It is realistically feasible to cover a large portion of the mobility energy demand using the own rooftop PV generation and by that residential roof-top PV might be able to lower the grid impact of BEV charging. However, the inverse might not be true as for PV the critical point is the peak in the middle of the day where BEVs are usually not available at home.

6.4. Limitations

Due to the employed methods and because of the used datasets the results of this study are subject to several limitations.

The movement data used to estimate the BEV demand is entirely sourced from Switzerland, a country that is known for its excellent transportation and public transportation infrastructure. The transfer of the results to countries with differing infrastructure might be limited due to the impact that available infrastructure has on BEV demand.

Furthermore, the developed methodology cannot be used to directly derive operational smart charging algorithms due to the assumptions taken (see Section 4.6). Most notably, we are assuming the availability of perfect forecasts for mobility energy demand and the available solar generation. The results therefore present an upper limit of the achievable performance of an operational smart charging algorithm.

Lastly, we are not considering seasonal effects for the calculation of the CO_2 emission factor for grid charging in Switzerland, but simply use the yearly average. This might lead to an overestimation of the CO_2 emission factor for grid charging in summer and an underestimation in winter.

7. Conclusion

In this work we presented a detailed case study as a contribution to the open question to what extent BEV owners can be self-sustainable using rooftop PV generation. To answer this question, we combined the detailed mobility data records from 78 BEVs in combination with a detailed model of the BEV owners' roofs to estimate the potential rooftop PV generation.

Our results show that currently deployed uncontrolled greedy charging strategies (baseline scenario) lead to a very low coverage factor of only 15% on average over all BEV users. Very simple adjustments without changing mobility or plug-in behavior (scenario 1) can already greatly increase this to an average coverage of 56%. We argue that these values could be easily reproduced in practice by currently feasible smart charging algorithms if they charge slower and limit their charging intake to the currently available PV generation, and if they do not fully charge during the night in order to take advantage of the morning hours.

We further showed that the upper boundary of the coverage with and without additional home battery storage over all users is on average 90% and 99% respectively without restricting a person in their mobility. The degree to which these values can be achieved in practice will depend strongly on the quality of mobility demand and generation forecasts. Considering these uncertainties, it could be that the home battery storage will provide a more significant advantage than it does for the theoretical upper boundary.

No matter the charging schedule scenario, all of them greatly increase the consumption of rooftop generated PV which significantly reduces the emissions from driving the BEV. This highlights the large potential that rooftop PV power generation has to accelerate the BEV based decarbonization of the transport sector.

Future work should investigate smart charging algorithms that consider the goal of maximizing the usage of rooftop PV energy as it is cheaper and more sustainable for the user. Very high self-consumption rates for BEV charging will only be achievable if sufficiently good predictions of the energy demand of the BEV are available. However, reliable predictions of individual mobility behavior which induces the mobility demand are still an open problem and should be tackled in the future.

CRediT authorship contribution statement

H. Martin: Conceptualization, Methodology, Software (Mobility data and scenarios), Data curation, Writing – original draft, Visualization. **R. Buffat:** Conceptualization, Methodology, Software (PV Model), Writing – original draft. **D. Bucher:** Conceptualization, Methodology, Writing – original draft, Visualization. **J. Hamper:** Conceptualization, Software (scenarios). **M. Raubal:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. PV panel parameters

Manufacturer	Schüco
Model	SPV 170-SME-1
N_P	1
N_S	72
V_{OC0}	44 V
I_{SC0}	5.15 A
V_{MP0}	35 V
I_{MP0}	4.86 A
$\alpha_{I_{SC}}$	0.055
$\beta_{V_{OC}}$	−0.37
T_{ref}	45 °C
A_{cell}	125.0 ∗ 125.0 mm
A_{panel}	1580.4 ∗ 808.4 mm

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