Smart Charging and Renewable Grid Integration - A Case Study Based on Real-Data of the Island of Porto Santo

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Abstract. The penetration of battery electric vehicles is increasing. Due to their ability to store electrical power and to shift charging events, they offer a wide range of opportunities with regard to renewable grid integration and lowering the overall CO2 emissions. This is particularly evident for isolated microgrids, such as the Portuguese island of Porto Santo. In this paper, we conduct a data analysis of real-world charging data of 20 electric vehicles operated on the island of Porto Santo. We provide insights into the charging behavior of different users and analyze the opportunity of smart charging for better renewable grid integration using linear optimization models. The data analysis shows that drivers prefer home rather than publicly available charging stations, flexible charging events occur mostly overnight and the charging flexibility of the fleet decreases over the project duration. With regard to make charging more flexible, we can see that smart charging can help to raise the share of electricity generated by renewable energy sources for charging the electric vehicles to up to 33%.

Keywords: Electric vehicles · Vehicle-2-Grid · Grid integration · Smart charging

1 Introduction

All over the world the penetration of electric vehicles (EVs) is increasing. According to the Global EV Outlook [8], the global EV fleet reached a number of 5.1 million units in 2018. An increasing number of EVs comes with challenges and opportunities. Distribution system operators (DSOs) face new challenges in operating their networks, especially in the case of uncoordinated charging during the evening peak hours. On the other hand, smart EV charging strategies can contribute to stabilize distribution grids by supplying energy storage for the integration of volatile renewable energy sources (RES), such as solar or wind

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energy [15]. Additionally, bi-directional charging and Vehicle-to-Grid technologies (V2G) can enable even more benefits in terms of renewable grid integration and grid stabilization.

According to a recently published report [5], there are more than 60 projects involving thousands of EVs and chargers. One of the projects mentioned is the plan to make Portuguese island Porto Santo completely fossil-free by targeting multiple action areas. Within the area of sustainable mobility, a joint project was launched by Groupe Renault and Empresa de Electricidade da Madeira (EEM) with the support and technology of The Mobility House to create a smart electric ecosystem on the island of Porto Santo. Thereby, smart charging of EVs as well as V2G and stationary battery storage systems play an important role. In order to provide better insights on the EV charging behavior, we contribute a comprehensive data analysis of real-world charging data of 20 EVs for a time horizon of six months. Thereby, we also discuss the opportunity of smart charging in the context of vehicle grid integration (VGI). Based on this information, we investigate smart charging potentials to better integrate electricity generated by RES on the island of Porto Santo.

The remainder of this paper is structured as follows: In Sect. 2 we give an overview of related work in the field of VGI on islands as well as data analysis of EV charging data. More information of the Porto Santo project is provided in Sect. 3. Section 4 gives insights into the charging processes and the user behavior. In Sect. 5 we formulate an optimization problem for the maximization of RES usage under consideration of the charging flexibility and user requirements and present respective results. Finally, Sect. 6 concludes the paper with a short summary and an outlook on future work.

2 Related Work

2.1 Vehicle Grid Integration on Islands

The topic of VGI on islands has already been analyzed from different research perspectives. A good overview on island applications of EVs is provided by Gay et al. [7]. The authors review several studies that explore the effect of EV grid integration in terms of V2G services and greenhouse gas emissions on isolated island grids. Additionally, they present a case study for the Caribbean island of Barbados in order to link the principles of V2G services to an existing small island developing state. One of the main findings of the case study addresses the concerns about the impact of EVs on the isolated electricity grids including overloaded distribution feeders and transformers. Possible solutions include smart charging approaches and V2G services where EVs can become a key grid asset. In Pina et al. [12] and Verzijlbergh et al. [16] the potential of EVs on the Portuguese Island of Flores is investigated. Pina et al. [12] present a scenario-based study on the impact of EVs on an isolated island energy system. Under different EV penetration rates and different recharging strategies they investigate the primary energy consumption and CO_2 emissions. The work of Verzijlbergh et al. [16] is focused on the investigation of EVs to support the grid integration of a high share of renewable energy sources on the island of Flores. The authors show that there is a large potential for saving CO_2 emissions compared to diesel generation units and diesel-fueled vehicles. Binding et al. [1] present a platform to optimally integrate EVs on the Danish island of Bornholm. The platform is used to realize the potential of using V2G services in a virtual power plant.

The literature survey reveals that some studies already addressed the grid integration of EVs on islands. However, all approaches have potential for improvement either with regard to the scope or the use of real driving behavior patterns. For instance, Binding et al. [1] uses an agent-based simulation environment to model three different types of EVs (commuter cars, taxis, and family cars); the charging behavior of the EVs is also simulated. In the case of the island of Flores, Verzijlbergh et al. [16] and Pina et al. [12] use a survey of driving patterns to model the driving behavior and charging needs of EVs. In contrast to previous work, this paper present real-word data from a fleet of 20 EVs including plug-in time, plug-out time, charged energy, charging station identification as well as anonymized driver and vehicle identification for the small island of Porto Santo.

2.2 Data Analysis of EV Charging Data

Although EV charging data is sparse, there are some recently published studies about real EV charging or driving behavior patterns available. Lee et al. [9] provide a dynamic dataset of EV charging which includes over 30,000 charging sessions collected from two workplace charging sites in California. The ElaadNL dataset [3,6,13] contains 400,000 events on 1,750 public accessible charging stations distributed over the entire Netherlands. According to Flammini et al. [6] the dataset shows important key figures, such as charge time, idle time, connected time, power, and energy. Chen et al. [2] analyze charging characteristics such as charging time, charging duration and charged capacity on real data from Nanjing, China and derive probability distributions and correlations of these features. Xydas et al. [17] develop a characterization framework for the EV charging demand based on very detailed charging data from the UK. Thereby, the authors develop a data mining model to analyze the characteristics of EV charging demand in a geographical area.

As our literature review shows, there are a few studies available which demonstrate the necessity of real-world data in the EV charging context. We make an important contribution to these works by analyzing the charging data in the Porto Santo project. Since the EV charging dataset of Porto Santo is unique in containing specific, anonymized, driving and vehicle consumption data as well as home and public charging, a more precise analysis of the user behavior is possible. Additionally, the EV charging on Porto Santo has already moved on from uncoordinated charging to enable EV drivers to freely set departure time and state of charge (SOC) that needs to be guaranteed. Therefore, the willingness of EV drivers to charge flexibly can be exploited. The fact that Porto Santo is an island leads to advantages for the data analysis. The grid of Porto Santo is not connected to the outside world, therefore the grid impact and RES share of EV charging can be determined without the difficulties of accounting for the import and export of electricity.

3 Project Porto Santo

3.1 General Information

Groupe Renault and Empresa de Electricidade da Madeira (EEM), the Madeira electricity company, with the support and technology of The Mobility House jointly launched a project to create a smart electric ecosystem on the island of Porto Santo. The aim of the project is to support Porto Santo on its transition of becoming the world's first CO2-free island, to ensure a reliable and intelligent power grid and to avoid cost-intensive grid expansion. The project supports reaching these goals through four action areas: EVs, stationary energy storage, smart charging and V2G charging. The EVs and stationary batteries are used to balance renewable production volatility, which is facilitated by an intelligent smart charging controller and technology.

Porto Santo is a Portuguese island located 43 km northeast of Madeira Island. The island's main economic area, tourism, is characterized by a high seasonality of economic, social and cultural activities which focus on about three months per year. During high season, the population of the 5,000 inhabitants is increased to up to 20,000 by part-time inhabitants and tourists. During these periods, the energy demand is particularly high.

The grid on Porto Santo is a closed system and not connected to Madeira Island. Currently, the electricity demand of 33 GWh (2017) is mainly covered by diesel generators, presenting approximately 85% of the production. The remaining 15% are generated by a solar park of 2 MW and various smaller PV plants, summing up to 0.43 MW as well as a wind turbine of 0.66 MW [4]. The potential for expansion of renewable generation, particularly of photovoltaics, exceeds the energy demand of the island by far.

In a first phase, 20 Renault brand electric vehicles are handed over to public institutions (e.g., police), private companies (such as taxi drivers) and private individuals, who use them for their everyday mobility needs. Out of the 20 EVs, fourteen are Renault ZOE with a battery capacity of 41 kWh and six are Kangoo Z.E with 33 kWh. To make this experience possible for many users, about half of all vehicles change their owners every two months. EV drivers have the possibility to charge their EVs at home (accessible only for one user) and at public (accessible for all project participants) charging stations (total of 33 charging stations). All charging stations are equipped with a controller from The Mobility House and an internet connection. This enables smart charging and monitoring of the charging process. The charging stations are single-phased and have a rated power or 7.4 kW. The uni-directional EV fleet is complemented by two bi-directional Renault EVs with 41 kWh battery capacity and 11 kW charging and discharging power. In terms of costs, home and public charging was free of charge for all users during the considered time horizon.

3.2 Data Sets

The collected, anonymized data contains records of the charging stations' utilization on different levels of granularity. Overall, data for 33 charging stations is available. 8 are publicly available and 25 (including the two V2G enabled stations) are located at private locations.

One part of the data is an aggregated dataset of the entire EVs fleet on Porto Santo. It is available for six months from February 2019 to July 2019 in a timely resolution of 10 s. Every record of this dataset contains the current charging capability, the charged amount of energy as well as the *must* charge value. The charging capability reflects the total possible charging power of all plugged-in EVs in a certain time step.

Smart charging on Porto Santo works under the concept of scheduling. For every charging event exists a schedule determining a minimal SOC, that has to be reached at a specified time. The charging itself is dispatched via a logic preferring renewable energy. However, if this strategy is not able to fulfill the schedule the EV switches into a *must*-charge state, in which the EV immediately charges. Since February 2019 the EV drivers can freely set departure time and goal SOCs via an app. If they do not, the charging station will automatically fall back on a default schedule, which guarantees a SOC of 80% at 7am and 5 or 7pm. As the possibility of monitoring the SOC is only available since August 2019, the schedules always assume that EVs have a SOC of 30% when they plug in at the charging station and dispatch accordingly.

Another dataset contains detailed data records of individual charging events of all EVs for about three months between May, 16th 2019 and August, 6th 2019. This data set contains about 700 charging events each associated with a specific driver id, vehicle id, charging station id, plug-in time and plug-out time as well as the amount of charged energy. This dataset is used i.a. for the determination of individual charging flexibility. In order to be able to analyze the share of electricity generated by RES which is used for charging EVs, Porto Santo's electrical energy generation between January 2018 and August 2019 is also provided.

4 Data Analysis

The data analysis focuses on user behavior and the flexibility it provides in terms of shifting energy consumption towards time periods with a higher share of RES.

4.1 Charging Demand and Electricity Generation

Our analysis of the individual charging events yields that EVs on Porto Santo are often charged at home. Figure 1 shows a boxplot of the number of EVs that are plugged-in at any given hour of the day at home charging stations. EVs are mostly plugged in at home during non-working hours between 11pm and 6am with three vehicles on average at night. The plugged-in vehicles at

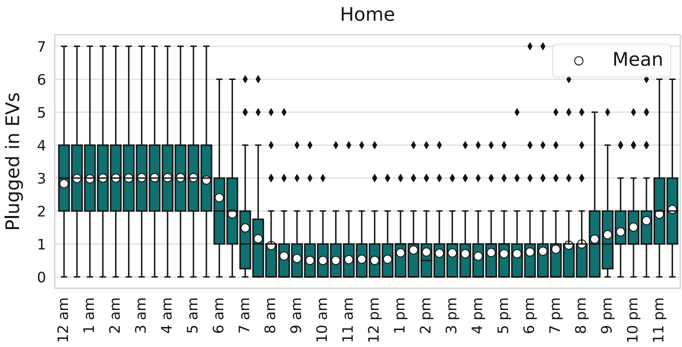

Fig. 1. Plugged-in EVs over clock time at home charging stations in the individual data.

public charging stations do not significantly vary during the day - especially not during working hours. This is contrary to patterns seen in Flanders, Belgium [15]. Reasons are shorter driving distances than in Belgium and that not all public charging stations are installed at sites where people work. In general, public charging events show no significant peaks over the course of a day. We also analyzed differences between weekdays and weekends for both home and public charging events. Both follow the average course apart from the difference that a slightly lower amount of plugged-in vehicles are observable on weekends. On public charging stations the average per day drops from 0.44 plugged-in vehicles on weekdays to 0.31 on weekends and on home charging stations it drops from 1.58 to 1.25, respectively.

In Fig. 2 the capability of the aggregated charging profiles follows the same course as the plugged-in vehicles. This is not surprising since most charging stations have the same rated power of 7.4 kW. Due to scheduling of the charging processes the demand does not follow the expected curve of dumb charging. As shown in Fig. 2, the main demand is between 3 and 7am. The *must* charge course gives insight about the users choice of schedule. Higher amounts of *must* charge indicate that many scheduled departure times are imminent. Judging from Fig. 2 we observe that *must* charge is always high shortly before a default departure time (7am, 5pm and 7pm) is reached. This suggests that many drivers either stuck with the default schedule or chose a very similar one.

The EV charging process shows significant deviations from day to day. The 30-min resoluted capability has a standard deviation of 13.6 kW and can go up to 73 kW. *Must* charge has a standard deviation of 6 kW and demand of 7 kW, both show a maximum of 65 kW. The charging demand is especially noisy in the time frames from 4 to 7am and from 2 to 6pm, with an average standard deviation of 13 kW and 5 kW respectively. During the entire remaining day it remains below 2.5 kW. This suggest that drivers are very likely to charge during these time frames but not necessarily every day. On average every vehicle is only charged every third day.

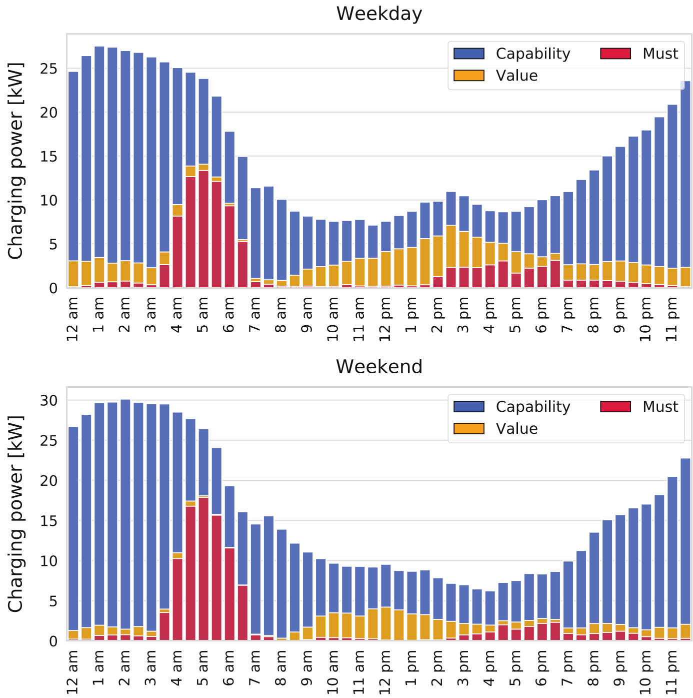

Fig. 2. Charging power over clock time at weekdays and weekends in the aggregated data (overlapping bars).

Weekends have an overall lower charging energy demand. On average the daily energy demand is 100 kWh, while it is only 87 kWh on weekends. Figure 2 shows that the overall course of charging differs mostly in the morning peak from 3 to 7am and in the afternoon 2 to 5pm. The morning peak is considerably higher while the mostly freely charged afternoon peak is almost non existent. This would suggest that at weekends even less charging events occur during the day, however this contradicts the findings from the individual data, where plug in number decreased uniformly over the entire weekend.

Figure 3 shows the average electricity generation over clock time. The average share of RES in the investigated time period between January and June 2019 is 15.1%. In the winter the wind and PV generation are almost equal. In the summer PV generates about four times as much electricity than wind. Thus, over the course of a year most of the renewable energy is generated by PV and the amount of total RES generation is very low during nighttime. As the charging strategy aims at maximizing the RES share, this leads to delayed charging of all users that arrive after sunset. However, since most users stuck with the default schedule demanding 80% SOC at 7am, the charging stations have to switch into *must* charge mode at around 4am to fulfill the schedule. This explains the high demand during 3 and 7am in Fig. 2.

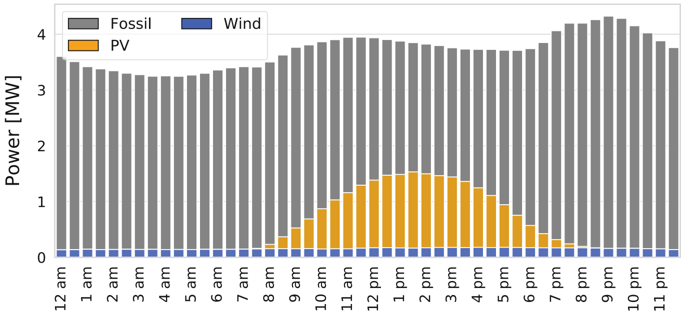

Fig. 3. Electricity generation over clock time for spring 2019 (stacked bars).

Most users stuck with their default schedule. Therefore overnight charging events are very flexible. However, it is problematic that the share of renewables is lowest exactly in this time frame. The desynchronized behavior of the charging capability and the renewable energy generation is a major obstacle in achieving a high share of RES for the EV charging on Porto Santo. Thus, the current charging strategy in Porto Santo has a substantial impact by increasing the RES proportion of charging to 16.4% even though the favored overnight plug-in times do not match the PV production.

4.2 User Behavior and Charging Flexibility

A measure for the flexibility of charging events (or any other flexible load) is the *time flexibility* [10,11,14]. The time flexibility ϕ is defined as the maximum amount of time the charging energy can be shifted. It is calculated according to Eq. 1 by the difference between the total plugged-in duration $\Delta t_{\text{plugged-in}}$ in h and the time it would take to charge the required energy amount E_{req} at the maximum power rate $P_{\max}$.

$$\phi = \Delta t_{\text{plugged-in}} - \frac{E_{\text{req}}}{P_{\max}} \tag{1}$$

Figure 4 shows the distribution of the user behavior metrics of individual charging events: a) charged energy, b) plugged-in duration and c) the time flexibility. Figure 4c) shows that most public charging events have less than three hours of time flexibility. In general, the public charging events show significantly less time flexibility than those at homes. At home the available time flexibility differs greatly between the different cars. While the group of ZOEs has a higher median of 4 h, the Kangoos have one peak at 9 h of time flexibility and another peak at 1 h. Similar distributions can be seen for the plugged-in durations. The mean charging energy is significantly higher for the ZOEs, which suggests a correlation with the battery size. Figure 4d) shows that charging events at home are more numerous than in public. Interestingly many drivers only frequent either

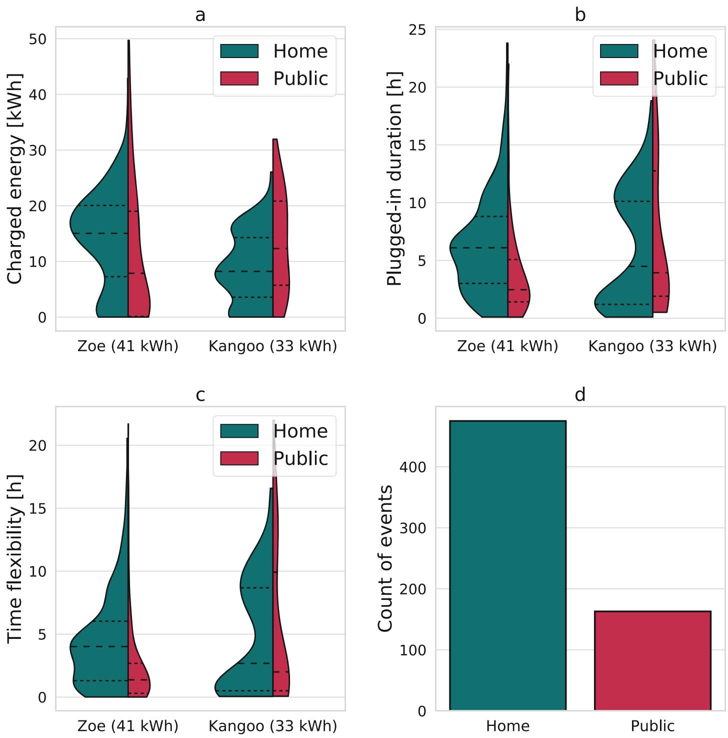

Fig. 4. Distribution of metrics for charging events in the individual data. Divided up by station and vehicle kind. The dashed line with longer dashes is the median, the lines with shorter dashes represent quartiles.

public or home stations. Out of the 24 in the data set only 7 frequented both types of charging stations.

The different users show very individual behavior. In Fig. 5 plug-in and plug-out times of all the events of the individual charging events data set are displayed in a bubble plot. The size of the bubbles reflects the charged energy and some users are highlighted by colors. The cloud on the lower right are the overnight charging events whilst the cloud in center stretching to the top right consists of intraday events. The composition of these two clouds differs. Public charging events make up for 25.5% of the intraday events and only for 11.5% of the overnight events.

Some users, like user 4 shown in blue, behave according to a consistent pattern, while many others, like user 8 shown in green, are hard to predict. Nonetheless some overall patterns become clear. Firstly, the duration of intraday events is shorter than five hours in 84% of the cases. The duration of overnight charging events differs greatly, however they almost always plug out between 6 and 9am. Secondly, in the intraday case charging energy increases very distinctly with longer plugged-in durations, while the charging energy is more uniformly

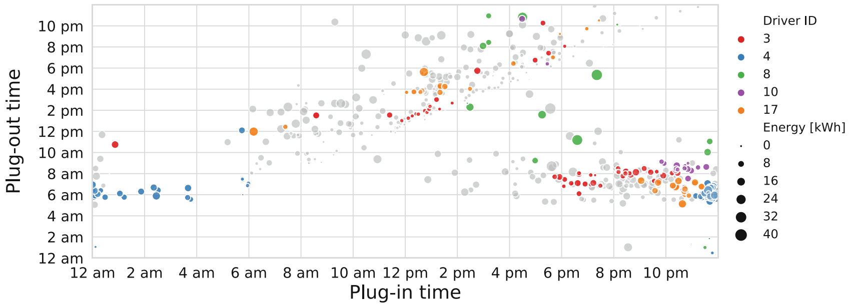

Fig. 5. Scatter plot of charging events over start and stop clock time. Some driver IDs are highlighted.

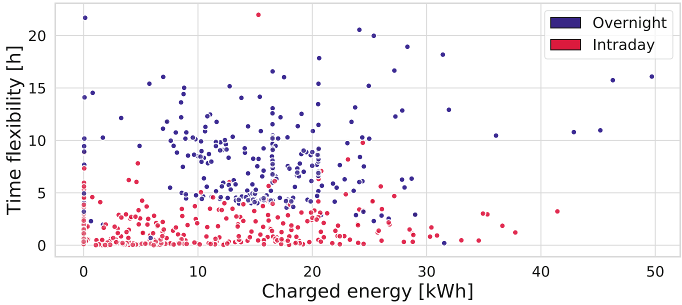

Fig. 6. Scatter plot of time flexibility over charged energy per charging event.

distributed in the overnight case. This is confirmed by the Bravais-Pearson correlation coefficient between the charging energy and plugged-in duration. For intraday events it is 0.6 while it is 0.37 overnight. This suggests that most intraday events are terminated soon after the energy demand has been supplied.

Summarizing, the primary time frame for flexible charging is overnight. A plot of the time flexibility over the charged energy in Fig. 6 shows this very clearly. This observation strengthens the challenge mentioned in Sect. 4.1, that flexible charging options are desynchronized with RES generation.

Another challenge is the overall development of the approximated time flexibility $\hat{\phi}$ of the entire EV fleet during the pilot project since the introduction of free schedule choice. This flexibility is approximated with Eq. 2, on the basis of Eq. 1, for weekly intervals. The plugged-in duration is substituted by the duration of a week Δt_{week} and the maximum power rate is substituted by the average capability of the EV fleet $\bar{P}_{\text{cap}}$ (see Sect. 3.2). In this context the required energy E_{req} is the total demand of the EV fleet during the week.

$$\hat{\phi} = \Delta t_{\text{week}} - \frac{E_{\text{req}}}{\bar{P}_{\text{cap}}} \tag{2}$$

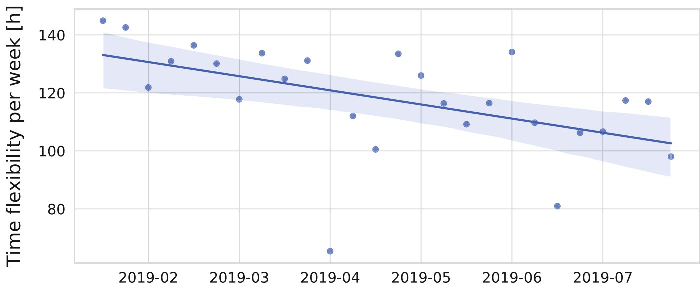

Fig. 7. Flexibility of charging since the implementations of individual schedules. Estimated from the aggregated data in weekly intervals.

Table 1. Variable definition overview

Symbol	Description
t	Model time
T	Length of the optimization horizon
Δt	Time step length
P_t^{RES}	Electricity generated by RES at time step t
P_t^{total}	Total electricity generation at time step t
P_t^{charge}	Total charging power at time step t
E^{real}	Total charging demand
$P_t^{\max}$	Maximum charging power rate

As shown in Fig. 7, the trend of $\hat{\phi}$ is downwards. The graph shows weekly decline in flexibility since February 2019 (beginning of the evaluation). This means that people tend to plug in less with ongoing project time, which arises the question of suitable incentives to foster plugging-in the vehicle whenever possible to increase the available charging flexibility.

5 Optimization

To analyze the optimal integration of RES into the EV sector of Porto Santo three different optimizations have been carried out. All basic definitions are summarized in Table 1.

5.1 Methodology

All three optimizations share the same mathematical structure which is given in Eq. 3a to Eq. 3c. They only differ in the input dataset and the optimization horizon. The objective is to maximize the RES share of the charged energy. Equation 3a shows the objective function. Additionally the maximum power rate ($P_t^{\max}$) at every time step must not be exceeded (Eq. 3c), discharging is not allowed and the energy demand (E^{real}) in a given time period T must be fulfilled (Eq. 3b). The time step length Δt is always 15 min.

$$\begin{aligned}
\underset{P^{\text{charge}}}{\text{maximize}} \quad & {E^{\text{real}}}^{-1} \cdot \sum_{t \in T} \left(\frac{P_t^{\text{RES}}}{P_t^{\text{total}}} \cdot P_t^{\text{charge}} \cdot \Delta t \right) && \text{(3a)} \\
\text{subject to} \quad & \sum_{t \in T} (P_t^{\text{charge}} \cdot \Delta t) = E^{\text{real}}, && \text{(3b)} \\
& 0 \leq P_t^{\text{charge}} \leq \; P_t^{\text{max}}, \qquad \forall t \in T && \text{(3c)}
\end{aligned}$$

Optimization (Opt.) 1 and 2 are calculated on the aggregated dataset. In this context P_t^{max} describes the capability and E^{real} the sum of the energy demand of the entire EV fleet in T. The Optimization is not carried out over the entire data set at once, but in separate time segments of fixed length. Opt. 1 and 2 only differ in their choice of segmentation. Opt. 1 is carried out in day long segments ($T = 24h$) allowing energy shift between night and day. As discussed in Sect. 4 the two most distinct time frames of charging are intraday and overnight. This is represented in Opt. 2, in which the periods are divided into two groups: intraday for the time frame between 7am to 7pm and overnight from 7pm to 7am (with $T = 12h$).

Both Opt. 1 and 2 only take the behavior and demand of the entire EV fleet into consideration neglecting individual constraints. To determine the impact off this approximation a third approach (Opt. 3) is implemented with the data set of the individual charging sessions. This data set is already segmented by event. Thus in Opt. 3, the time period T is the time frame between plug-in and plug-out time, E^{real} is the actual charged energy of that event and P_t^{max} refers to the maximum charging rate of the station and is therefore constant.

The results of Opt. 2 show an idealization of the current user behavior thus an overestimation of the energy constraint. The energy of charging events can be shifted between 7pm to 7am and between 7am and 7pm. Especially the intraday events on Porto Santo have a duration shorter than 12 h. The results of Opt. 1 would require a significant change in the user behavior. The EVs would need to be plugged-in both in public and at home. Opt. 3 shows the best integration possible with the current behavior.

5.2 Results

The share of RES during the evaluation period was 15.1%. In this first project phase, the fleet was charged with 16.4% without considering forecasts. The slightly higher share is already a significant improvement compared to a scenario where EVs are charged immediately after plug-in, since the high share of overnight charging correlates with a low RES share on Porto Santo. However, Opt. 1 shows a high increase in the RES integration. In total, the share of RES can be increased from 16.4% in the real case to 26.5%. Opt. 2 reaches 20.1%.

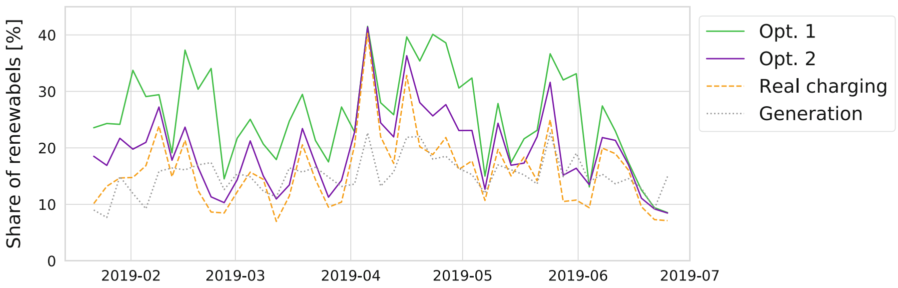

Fig. 8. Share of RES for two optimal cases, the real case and the generation over the project duration. Averaged over 3 and a half days.

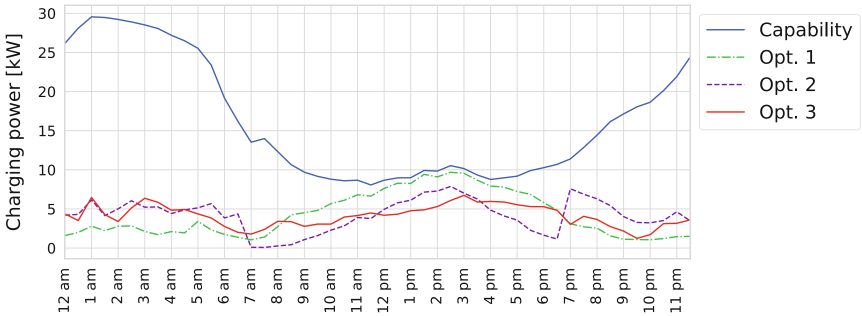

Fig. 9. Charging power over clock time for each optimization case.

Figure 8 shows the renewable share of the charged energy over the project duration.

The current charging strategy mostly follows this baseline with short but significant advantages in certain time frames, like in the first quarter of April. Perfect dispatch with separation of night and day charging, represented by Opt. 2, would increase the size of these positive windows.

The biggest opportunity for higher RES integration lies in removing the barrier between intraday and overnight charging. Figure 8 shows that Opt. 1 leads to an overall strong improvement compared to the real charging case. Figure 9 shows the daily average dispatch of all scenarios. It becomes clear that the main advantage of Opt. 1 lies in the higher integration of PV, since most charging gets shifted to daytime. As PV generation is also highly predictable on a daily basis, this advantage should therefore be transferable to the real world.

In order to realize this, strong incentives to plug-in the vehicle at day and at night should be established. However, Opt. 1 and 2 overestimate the results as they neglect the constraints from individual users. The optimization based on the real user behavior, Opt. 3, is an upper bound for the effectiveness of smart charging strategies that do not impact user comfort. Due to missing data, it is only calculated for a shorter time frame. However, it shows a very similar RES

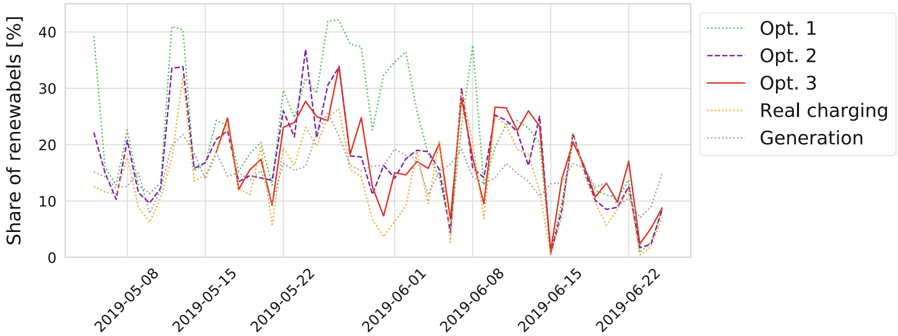

Fig. 10. Share of RES for each optimal cases, the real case and average in generation over the Project duration. Average over single days.

integration as Opt. 2 (see Fig. 10). Opt. 2 can predict the more precise Opt. 3 with a coefficient of determination (R^2) of 0.75. The share of RES from Opt. 3 is at 18.3%. For comparison in the same time frame Opt 2. has a RES share of 18.2%. This shows that the methodology of Opt. 2 is able to estimate Opt. 3 well. The fact that Opt. 3 and Opt. 2 have almost the same results shows that for the current scenario on Porto Santo, smart charging strategies are limited to an increase of the RES share of about 5% points (or 33%) compared to the RES proportion in the power grid. As long as the driver behavior does not change, e.g., by means of the introduction of variable charging costs or new incentice schemes like gamification or financial remuneration, a full usage of the high PV peaks will remain limited.

6 Conclusion

This research work addressed the introduction of EVs on the Portuguese island of Porto Santo that aims to become the world's first CO_2-free island. To support the achievement of the objectives, Groupe Renault and Empresa de Electricidade da Madeira (EEM) with the support and technology of The Mobility House, jointly launched a project to create a smart electric ecosystem on Porto Santo. In this work, we gained interesting insights of the charging behavior of different user groups on Porto Santo driving 20 EVs for a six-month period. Thereby, we also studied the opportunity of flexible charging by introducing three linear optimization models. Results showed, that smart charging strategies on Porto Santo can help to increase the RES share to 33% compared to the RES proportion in the grid.

As we proceed, we intend to include more real-world data after the Porto Santo project is finished. In parallel, we will start working on a holistic model for the energy system of Porto Santo in order to conduct a scenario-based study for Porto Santo's transition towards the first CO2-free island. For the operations on Porto Santo, forecasts and optimization should be added to the smart charging logic in a second project phase. Furthermore, incentive schemes for more frequent and longer plug-in events may be developed and their influece on the user behavior may be analyzed.

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References

1. Binding, C., et al.: Electric vehicle fleet integration in the danish edison project - a virtual power plant on the island of bornholm. In: IEEE PES General Meeting, pp. 1–8 (2010)
2. Chen, Z., Zhang, Z., Zhao, J., Wu, B., Huang, X.: An analysis of the charging characteristics of electric vehicles based on measured data and its application. IEEE Access **6**, 24475–24487 (2018)
3. Develder, C., Sadeghianpourhamami, N., Strobbe, M., Refa, N.: Quantifying flexibility in EV charging as DR potential: analysis of two real-world data sets. In: 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), pp. 600–605 (2016)
4. Empresa de Electricidade da Madeira (EEM): Internal report (2018)
5. Everoze Partners Ltd. and EVConsult: V2G Global Roadtrip: Around the World in 50 Projects - Lessons learned from fifty international vehicle-to-grid projects (2019)
6. Flammini, M.G., Prettico, G., Julea, A., Fulli, G., Mazza, A., Chicco, G.: Statistical characterisation of the real transaction data gathered from electric vehicle charging stations. Electric Power Syst. Res. **166**, 136–150 (2019)
7. Gay, D., Rogers, T., Shirley, R.: Small island developing states and their suitability for electric vehicles and vehicle-to-grid services. Utilities Policy **55**, 69–78 (2018)
8. International Energy Agency: Global ev outlook 2019 - scaling-up the transition to electric mobility (2019)
9. Lee, Z.J., Li, T., Low, S.H.: ACN-data: analysis and applications of an open EV charging dataset. In: Proceedings of the Tenth ACM International Conference on Future Energy Systems, pp. 139–149. e-Energy 2019, Association for Computing Machinery, New York (2019)
10. Nakahira, Y., Chen, N., Chen, L., Low, S.: Smoothed least-laxity-first algorithm for ev charging. In: Proceedings of the Eighth International Conference on Future Energy Systems. p. 242–251. e-Energy 2017, Association for Computing Machinery, New York, NY, USA (2017)
11. Neupane, B., Šikšnys, L., Pedersen, T.B.: Generation and evaluation of flex-offers from flexible electrical devices. In: Proceedings of the Eighth ACM International Conference on Future Energy Systems, e-Energy 2017, pp. 143–156. ACM, New York (2017)
12. Pina, A., Baptista, P., Silva, C., Ferrão, P.: Energy reduction potential from the shift to electric vehicles: the flores island case study. Energy Policy **67**, 37–47 (2014)
13. Sadeghianpourhamami, N., Refa, N., Strobbe, M., Develder, C.: Quantitive analysis of electric vehicle flexibility: a data-driven approach. Int. J. Electr. Power Energy Syst. **95**, 451–462 (2018)
14. Schlund, J., Pruckner, M., German, R.: FlexAbility - modeling and maximizing the bidirectional flexibility availability of unidirectional charging of large pools of electric vehicles. In: Proceedings of the Eleventh ACM International Conference on Future Energy Systems. e-Energy 2020. ACM, New York (2020)

15. Van Roy, J., Leemput, N., Geth, F., Büscher, J., Salenbien, R., Driesen, J.: Electric vehicle charging in an office building microgrid with distributed energy resources. IEEE Trans. Sustainable Energy **5**(4), 1389–1396 (2014)
16. Verzijlbergh, R.A., Ilić, M.D., Lukszo, Z.: The role of electric vehicles on a green island. In: 2011 North American Power Symposium, pp. 1–7 (2011)
17. Xydas, E., Marmaras, C., Cipcigan, L.M., Jenkins, N., Carroll, S., Barker, M.: A data-driven approach for characterising the charging demand of electric vehicles: a UK case study. Appl. Energy **162**, 763–771 (2016)