Flexibility Potential of V2G Technology in Switzerland

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***Abstract* – As electric vehicles (EVs) become more widespread, the need for controlled charging technology to mitigate negative impacts on the electricity system becomes increasingly important. This paper explores the potential of controlled EV charging to offer flexibility to the Swiss electrical system by employing a hybrid modeling approach. We utilize a Bass-diffusion model to predict EV market penetration in Switzerland and a binary logistic regression model to associate representative driving profiles with the anticipated EV fleet. The contribution of controlled EV charging to the Swiss electrical supply is then investigated using quadratic mixed integer programming. The results show that controlled EV charging and vehicle-to-grid (V2G) can significantly minimize residual load fluctuations, reducing load peaks by approximately 5% in 2025 and 11% in 2030.**

***Index Terms* – Electric vehicles, Vehicle-to-Grid, Controlled charging, Load smoothing, Bass-diffusion model**

INTRODUCTION

The Swiss Federal Council predicts that final energy consumption will decrease by 2050 due to efficiency gains, particularly in the transport sector where highly efficient EVs are projected to decrease final energy use by 40% in 2050 compared to 2019 [1]. However, the widespread adoption of EVs combined with the electrification of heating and industrial applications will increase electricity consumption in such a scenario. Furthermore, the capacity for electricity imports could be restricted from 2025 onwards due to the failed negotiations about an electricity market agreement between Switzerland and the EU [2]. Without an outline for such an agreement, the future integration of Switzerland into the European energy market is currently uncertain.

Moreover, Switzerland is undergoing significant changes in electricity generation as the country gradually phases out nuclear power and shifts to renewable energy sources (RES) [3]. While hydroelectric generation has traditionally supplied most of Switzerland's electricity, due to climate change, less precipitation will be stored as snowpack in the mountains, and hence the seasonal production of hydroelectric generation will likely shift in the future [4]. Therefore, the domestic electricity generation from additional RES sources is planned to be gradually increased, with photovoltaics showing particular potential [5]. However, due to the high volatility of RES generation, integrating them on a large scale into the electricity system requires additional flexibility options.

Despite increasing electricity demand, electric mobility has the potential to offer substantial flexibility for the electricity system by controlling the charging process. When EVs are integrated into the electricity grid as storage assets, whereby charging and discharging flows are bidirectional, it is often referred to as Vehicle-to-Grid (V2G). Numerous papers have examined the impacts of V2G. For instance, authors in [6 - 8] investigated the revenue potential of V2G, while researchers in [9, 10] adopted a system perspective to analyze the load-smoothing potential of V2G technology. However, only a limited number of studies have specifically addressed V2G within the Swiss context. The authors in [11] modeled the interplay of V2G with other storage technologies in Switzerland. More recently, [12] explored various electricity market effects of V2G in Switzerland by extending a large-scale energy system model. Neverteless, these studies take a more generalized approach to modeling the EV fleet and do not incorporate adopter behavior as detailed when estimating the load-shifting potential of EVs.

Hence, this paper introduces a methodology that assesses the flexibility potential of EVs in Switzerland based on representative mobility data that reflects user behavior. More precisely, our approach maps representative mobility data onto projected EV fleets, which then serve as input for a load-smoothing optimization model to assess the load smoothing potential of V2G technology in Switzerland. The paper is structured as follows: First, we introduce the developed methodology, which consists of three interconnected sub-models. Next, we present the results and discuss our findings, highlighting key insights. Lastly, we draw conclusions from our investigation.

METHODOLOGY

The developed methodology comprises a Bass-diffusion model, a binary logistic regression model, and a quadratic mixed integer optimization model. We present these submodels in the following more detailed.

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A. Bass-diffusion model

Following the approach in [13], we employed a Bass-diffusion model to analyze EV diffusion in Switzerland. This model is widely used for estimating new product adoption in emerging markets. Equation (1) represents the cumulative adoptions up to time t, with innovation coefficient p and imitation coefficient q generating diffusion values. The market potential is denoted by *m,* and t indicates the specific year. The model predicts future fleet sizes annually since the start year t_0, where $t - t_0 = 0$.

$$N(t) = m\,\frac{1 - e^{-(p+q)(1-t_0)}}{1 + \frac{p}{q} e^{-(p+q)(1-t_0)}} \tag{1}$$

To estimate the values of p and q of the model adoption, a non-linear least square algorithm was applied to historical data on EV sales [14] and future governmental targets [15]. Based on our analysis, we developed and modeled three different EV ramp-up scenarios. The base-case scenario has been derived from the Swiss government's target of achieving a 50 % EV market share by 2025. In addition, we developed an optimistic and a pessimistic scenario, which varied the targeted EV market share in 2025 by +/- 15 percentage points. The model parameters for the different scenarios can be found in table 1.

Table 1: Estimated Parameters of Bass-diffusion model

Scenarios	p	q	Std. Dev. p	Std. Dev. q	R2
Optimistic	2.3E-05	0.506	5.3E-06	0.014	0.970
Base-case	1.0E-04	0.396	3.3E-05	0.020	0.926
Pessimistic	3.2E-04	0.301	1.4E-04	0.028	0.847

B. Binary-logistic regression model

To model the charging behavior of EV users, it is necessary to predict which car users will adopt EVs. Consequently, we employed a binary logistic regression model, building upon prior work [16], to predict EV adoption probabilities according to individual user characteristics. A Swiss e-mobility study identified age, income, and residence status as key factors affecting the purchase decisions of prospective EV adopters [17]. Utilizing these factors, we estimated the variables of a binary logistic regression model to determine the likelihood of EV adoption based on the specified user characteristics. Equations (2) and (3) present the estimated logistic regression model:

$$P(y_n = 1) = \frac{1}{1 + e^{-z}} \tag{2}$$

$$z = -0.0311x_1 + 1.0916x_2 + 0.0.7273x_3 + 0.6725 \tag{3}$$

The dependent variable y_n represents the probability to which a car user n would shift to an EV. x_1 represents the independent variable "age", which has a negative coefficient, meaning that younger users are more likely to shift to an EV. x_2 depicts the residence status (0: tenant, 1: owner) which has a positive coefficient, meaning that owners are more likely to shift to EV. x_3 3 represents the income (0: smaller than CHF 7'000.-, 1: greater than CHF 7'000.-) and is positive as well, meaning that users with higher incomes are more likely to adopt electric mobility.

We calculated the adoption probability for each mobility profile within a representative Swiss mobility survey [18]. This probability mapping allows the allocation of mobility profiles to the projected EV fleet, prioritizing trip profiles with higher adoption probabilities. Despite the dataset primarily consisting of conventional vehicle users, their behavioral patterns were assumed to remain unchanged upon transitioning to EVs.

Utilizing the assigned mobility profile information, parking profiles for the EV fleet were derived by examining the arrival and departure times, as well as destinations, of Swiss motorists. With the assumption that parked EVs can charge at home or work with 11 kW and that users consistently plug in their vehicles upon arrival, aggregated load profiles for the Swiss EV fleet in the case of uncontrolled charging were generated.

C. Load-smoothing optimization model

To investigate the impact of controlled charging, a quadratic mixed integer optimization model, inspired by [9] and [19], was developed. With this model, we investigate the load smoothing potential of unidirectional and bidirectional controlled charging strategies in Switzerland. The objective (4) of the developed model is to minimize the residual load fluctuations for every hour $t \in T$ of the analyzed day by dispatching the charging and discharging flows $p_{t,n}^{PEV}$ of every grid-connected EV $n \in N$. The parameter $p_t^{residual}$ refers to the residual load in hour $t \in T$ and P^{target} represents the average residual load in hour $t \in T$ without EVs during a day. The input data of the optimization model can be divided into two categories: data describing the vehicles and mobility patterns and data describing the state of the electricity system, including RES generation and demand. The former data was generated using the sub-models presented earlier. The latter data were obtained from time series data in the TYNDP22 National Trends scenario [20]. Thereby, the residual load was calculated by subtracting the RES generation from the electricity demand. The RES generation was forecasted by scaling historical data for Switzerland's PV, wind, and run-of-river production from 2021 to expansion targets for 2025 and 2030. The demand time series were corrected by subtracting the average daily electricity demand of the EV fleet demand to avoid EV demand duplication. Thereby, the electricity demand was calculated assuming a consumption of 21 kWh/100km and a daily driving distance of 23.9 km. Imports have not been included in the residual load calculation to reflect the possible future restrictions resulting from a failed electricity market agreement.

$$\min \sum_{t \in T} \left(\sum_{n \in N} \left(p_{t,n}^{PEV}\right) + p_t^{residual} - P^{target} \right)^2 \tag{4}$$

s.t.

$$\sum_{t \in T} p_{t,n}^{PEV} \; T_{t,n,x}^{plug,x} = E_{n,x}^{demand} \; \forall n, x \tag{5}$$

$$CL_{t,n} = CL_{0,n} - E_{t,n}^{consumed} + \left(p_{t,n}^{PEV} * T_{tn}^{plug}\right) \quad \forall t, n \; with \; t = 0 \tag{6}$$

$$CL_{t,n} = CL_{t-1,n} - E_{t,n}^{consumed} + \left(p_{t,n}^{PEV} * T_{t,n}^{plug}\right) \quad \forall t, n \; with \; t \neq 0 \tag{7}$$

$$CL_{t,n} = CL_n^{max} \; \forall n, t \; with \; t = \; t_{n,X}^{departure} \tag{8}$$

$$0 \leq CL_{t,n} \leq CL_n^{max} \; \forall t, n \tag{9}$$

$$-11 \; \leq p_{t,n}^{PEV} \leq 11 \; \forall t \; with \; m_n^{V2G} = 1 \tag{10}$$

$$0 \leq p_{t,n}^{PEV} \leq 11 \; if \; m_n^{V2G} = 0 \; \forall n, t \tag{11}$$

$$m_n^{V2G} \in \{0,1\} \tag{12}$$

Equation (5) ensures that the electricity demand $E_{n,x}^{demand}$ required for charging the battery is satisfied for each charging event x and vehicle n. Hereby, the parameter $T_{t,n,x}^{plug,x}$ refers to the time vehicle n is plugged in at home or at work during charging event x and hour t. The constraints in (6) and (7) track the charging level $CL_{t,n}$ of the battery for each vehicle n and hour t by subtracting the consumed energy $E_{t,n}^{consumed}$ during hour t as well as the charged or discharged energy $p_{t,n}^{EV}$. It is assumed that the EVs are charged to $CL_{0,n}$ at hour $t = 0$. Equation (8) ensures that the battery is fully charged at the hour of the first departure $t_{n,X-1}^{departure}$ and after the last charging event of the previous day $X - 1$. Equation (9) ensures that the charging level stays within the bounds of zero and the maximal battery capacity CL_n^{max}. Equations (10) and (11) limit the charging and discharging power $p_{t^h,n}^{PEV}$ to +/- 11 kW if an EV is V2G capable ($m_n^{V2G} = 1$) and to + 11 kW otherwise ($m_n^{V2G} = 0$). Finally, (12) defines the binary variable m_n^{V2G}, indicating whether a vehicle is bidirectional capable or not.

RESULTS

In recent years, the adoption of EVs has been on the rise in Switzerland, with an outlook of further increase in the future. According to the results of the developed diffusion model, between 461,000 and 707,000 EVs are expected to be on Swiss roads by 2025, increasing to between 1,372,000 and 2,068,000 by 2030. Although the current diffusion of EVs is in its initial stages, the model predicts that the adoption rate will accelerate. Depending on the scenario, it is estimated that the whole Swiss car fleet of 4.6 million vehicles will be replaced by 2042 (optimistic scenario), by 2046 (base case scenario), or by 2050 (pessimistic scenario). The resulting forecasted yearly EV fleet sizes can be found in Figure 1.

The aggregated battery capacity of the EV fleet was determined by assigning representative trip profiles and vehicle classes to the Swiss EV fleet. The aggregated battery capacity of the Swiss EV fleet is forecasted to range from 26 GWh to 40 GWh in 2025, and between 78 GWh and 118 GWh in 2030, depending on the scenarios considered. In

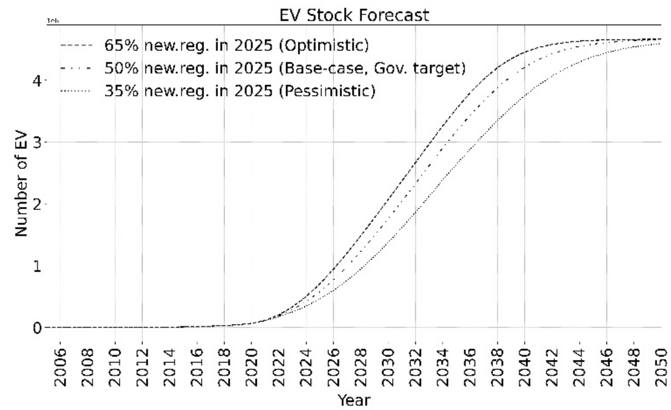

Figure 1: Diffusion of EVs in Switzerland

comparison, the total existing hydro storage capacity in Switzerland summates to 8,880 GWh [21].

Thus, without accounting for any potential advancements in battery capacities, it is estimated that EVs could provide a storage capacity equivalent to 1.3 % of today's total hydro storage capacity in Switzerland using the optimistic scenario for 2030.

Figure 2 depicts the parking profile for an average workday of the Swiss EV fleet in the year 2025. Since parking profiles exhibit minimal variation across different years, no additional parking profiles are presented. The results show that a majority of the EV fleet, approximately 95 %, is parked throughout the day. However, during typical commuting hours from 7 am to 8 am and 5 pm to 6 pm, the share of parked vehicles drops to around 85 %. The profiles show that EV users tend to park their vehicles at home and work for the majority of the day, indicating potential opportunities for load-shift applications.

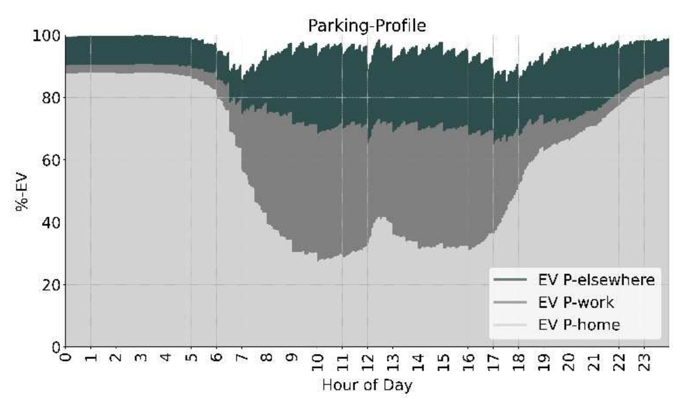

Figure 2: Parking profile of Swiss EV fleet for an average work day in 2025

Figure 3 shows the derived charging profiles in the case of uncontrolled charging EVs. Considering the very similar driving pattern of the EV users in 2025 and 2030, the shape of the load profile for every scenario of the EV fleet in 2025 and 2030 is similar, differing only in the order of magnitude of the load. The charging profiles have two load peaks that correspond with typical commuting times in the morning and

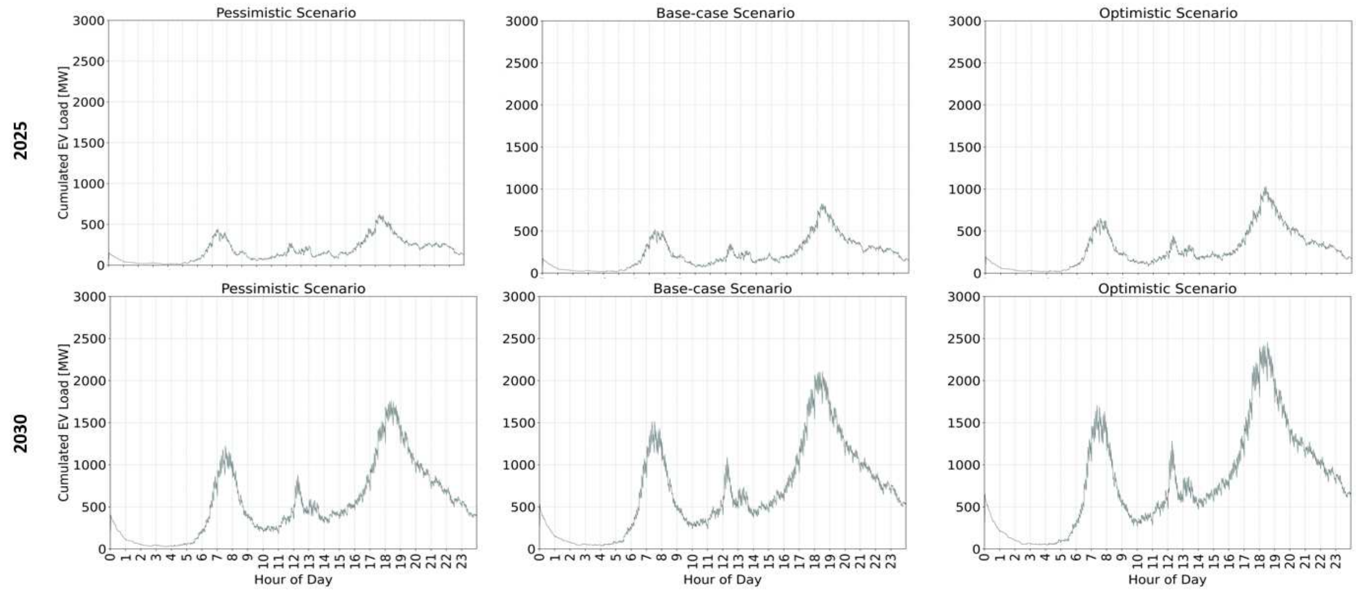

Figure 3: Charging profiles in case of an uncontrolled charging EV fleet

evening. The total load of the morning peak reaches between 400 MW and 600 MW in 2025 and between 1,200 MW and 1,700 MW in 2030. The larger evening peaks reach between 600 MW and 1,000 MW in 2025 and between 1,750 MW and 2,450 MW in 2030. To put it into perspective, the grid load reaches a maximum of 6,600 MW considering a low-demand summer day and 13,400 MW for a winter day with high electricity demand [20].

Table 2: Electricity charged in MWh totally, directly, and flexibly charged per day

				2030		
		Direct	Flexible	Total	Direct	Flexible
Optimist	6457	448	6009	18426	1185	17241
Base-case	5203	370	4388	15703	1004	14699
Pessimist	4111	289	3822	12575	802	11773

The energy demand of the EV fleet in case of uncontrolled charging can be estimated by integrating the load curve over time. Specifically, the area under the load curve represents the amount of energy used by EVs for charging. For the 2025 EV-fleet scenarios, the total energy charged during the day ranges from 4.1 GWh to 6.5 GWh, while for the 2030 scenarios, the energy charged ranges from 12.6 GWh to 18.5 GWh. In light of the projected electricity consumption in Switzerland of approximately 239.3 GWh per day in 2025 according to evaluations based on [20], the EV fleet's daily consumption represents approximately 3% of the total electricity demand. In the optimistic EV-fleet scenario for 2030, this percentage increases to 7% of the total daily electricity demand. Previous research by the authors in [22] demonstrated that electric vehicle (EV) drivers in Germany require a minimum range of approximately 120 km before being willing to participate in load-shifting. By incorporating these range requirements into our analysis, we found that between 92% and 94% of the energy charged can be considered flexible and utilized for load-shifting purposes. Table 2 displays the total energy charged, along with the corresponding subtotals of energy that must be charged directly to fulfill range requirements and the energy that can be charged flexibly.

The developed quadratic optimization model has been used to investigate the possibility of smoothing residual load by dispatching EV charging processes in a manner that minimizes fluctuations in the residual load for 2025 and 2030. We applied the optimization model for a working day in the winter months, which features a high residual load caused by low electricity supply from RES (cold dark lull) coupled with high electricity demand. In addition, we investigated various fleet compositions, where the share of bidirectional vehicles was up to 20% of the total EV fleet, while the remainder of the fleet used unidirectional charging control. The load curves resulting from the base-case scenario for the analyzed years and fleet compositions are displayed in Figure 3, while the other scenarios can be found in the Appendix. The plots also feature load curves for an uncontrolled charging EV fleet, providing a reference for the improvements achieved through the optimized controlled charging EV fleet.

The results show that uncontrolled EV charging amplifies the residual load peaks observed on the investigated winter day, as the load peaks generated from uncontrolled EV charging overlap with the residual load peaks caused by other consumers. Specifically, in 2025, the morning and evening peaks increase by 300 MW and 200 MW respectively. In 2030, with a larger EV fleet, the morning and evening peaks rise between 700 MW and 900 MW for the base-case scenario.

The implementation of unidirectional controlled charging for EVs leads to a slight increase of the residual load peaks in the evening of approximately 100 MW in 2025 and 250 MW in 2030. This is due to the charging process being shifted to times when the residual load is below the target load. Notably, the load smoothing potential increases significantly when

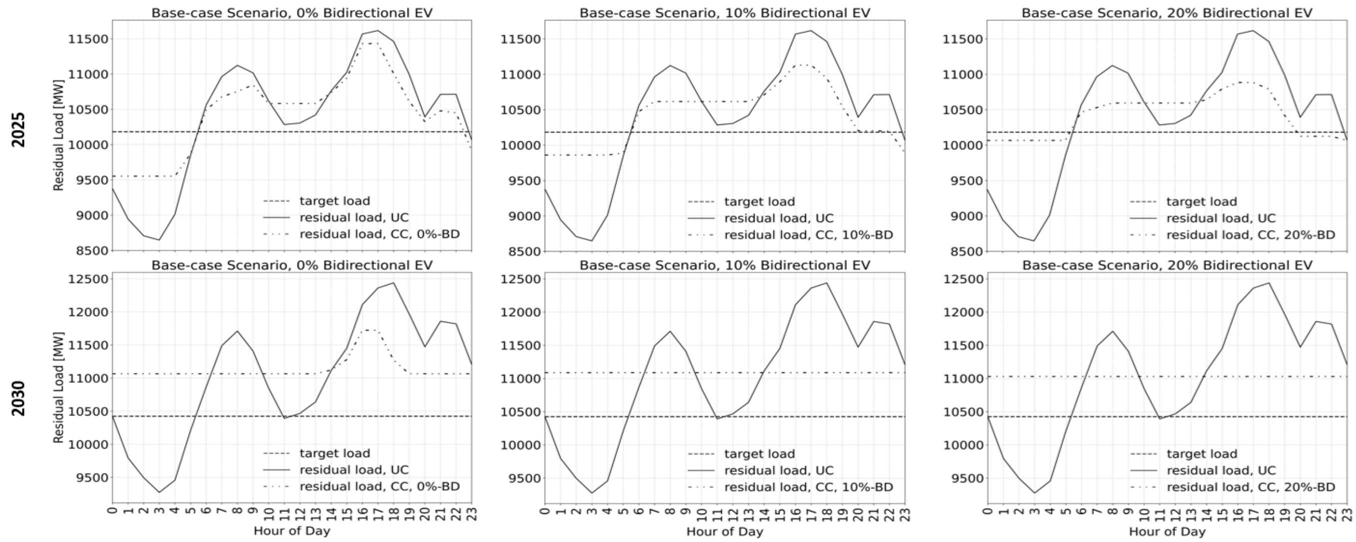

Figure 4: Impact of uncontrolled- and controlled charging on the residual load

considering unidirectional controlled charging with a larger EV fleet in 2030. This can be attributed to the larger amount of charging energy, that can be shifted in order to smooth the residual load.

When 10 % and 20 % bidirectional EVs in the fleet are considered, the results reveal a reduction in peak residual loads and an improvement in smoothing behavior. Specifically, incorporating 20 % bidirectional EV, the reduction of the evening peak ranges between 550 MW and 850 MW in 2025 and between 1,350 MW and 1,500 MW in 2030. In comparison, today's largest Swiss pumped storage power plant Linth-Limmern has an installed power of 1,520 MW. The required power from controllable power plants or imports to cover the residual load during the evening peak could be reduced by 4.7 % to 7.3 % in 2025 and by 10.9 % to 11.6 % in 2030 when 20% bidirectional EVs are incorporated.

Some limitations of the results and future work directions are discussed here. The Bass-diffusion model used does not take into account potential policy changes that might moderately impact EV adoption. Furthermore, the developed binary logistic regression model includes only three factors, which somewhat limits its explanatory power. Prior studies, such as those by [16] and [23], have considered factors like technology affinity, green party preferences, and car usage frequency to improve accuracy. However, these variables were not incorporated in the datasets employed in this paper.

Regarding controlled charging, we assume that all EVs participate in load-smoothing-oriented controlled charging. In practice, not all vehicles may have the necessary hardware (e.g., suitable wallbox), and EVs could be used in other scenarios, such as vehicle-to-home, where charging patterns align with household electricity consumption and RES generation. As a result, slightly higher shares of bidirectional vehicles might be needed to achieve the results of this analysis in real-world settings. For future work, the assumptions made in this study about the share of vehicles participating in controlled charging and plug-in probability could be reconsidered.

Conclusion

This analysis provides insights into the potential of EVs to provide flexibility in Switzerland's future electricity system. Specifically, the analysis has disclosed that with many EVs being parked most of the day, most of the charging processes can be shifted in time without limiting the user in their range requirements. Moreover, the importance of controlled charging systems was emphasized, as uncontrolled charging can exacerbate peak loads during typical morning and evening peak hours. The research indicates that, if EVs charge uncontrolled, peak loads increase by approximately one Gigawatt per 700,000 EVs, representing a significant burden for the electricity system.

As EV fleets have a high installed charging power but comparatively low aggregated storage capacity, EVs are well suited for short-term storage and less suited for seasonal storage applications. The application of the developed optimization model demonstrated the considerable load leveling potential of both unidirectional controlled charging and V2G technologies. Bidirectional charging, as seen in V2G, provides greater flexibility potential to an EV fleet compared to unidirectional controlled charging alone. However, as the size of the EV fleet increases, most of the load leveling can already be achieved by shifting unidirectional charging processes to off-peak hours, and the additional flexibility from V2G may not be fully utilized. Thus, it might not be necessary to equip the entire future EV fleet with V2G technology. In this case study, a maximum fleet share of 20% bidirectional vehicles was sufficient to smooth the load to a nearly static level.

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APPENDIX

Table A-1: Evening residual load peak reduction with controlled charging and V2G

	2025, 10% BD			2030, 10% BD		
[MW]	**Tot. Red.**	**Red. UD**	**Red. BD**	**Tot. Red.**	**Red. UC**	**Red. BD**
Optimistic	550	200	350	1,350	750	600
Base-case	500	150	350	1,300	650	650
Pessimistic	350	100	150	1,200	500	700
	2025, 20% BD			**2030, 20% BD**		
[MW]	**Tot. Red.**	**Red. UD**	**Red. BD**	**Tot. Red.**	**Red. UC**	**Red. BD**
Optimistic	850	100	750	1,500	850	650
Base-case	700	75	625	1,450	750	700
Pessimistic	550	50	500	1,350	550	800

Table A-2: Morning residual load peak reduction with controlled charging and V2G

	2025, 10% BD			2030, 10% BD		
[MW]	**Tot. Red.**	**Red. UD**	**Red. BD**	**Tot. Red.**	**Red. UC**	**Red. BD**
Optimistic	500	350	150	500	500	0
Base-case	450	300	150	550	550	0
Pessimistic	400	200	200	600	650	50
	2025, 20% BD			**2030, 20% BD**		
[MW]	**Tot. Red.**	**Red. UD**	**Red. BD**	**Tot. Red.**	**Red. UC**	**Red. BD**
Optimistic	550	350	200	600	500	100
Base-case	500	300	200	600	550	50
Pessimistic	450	200	250	600	650	50

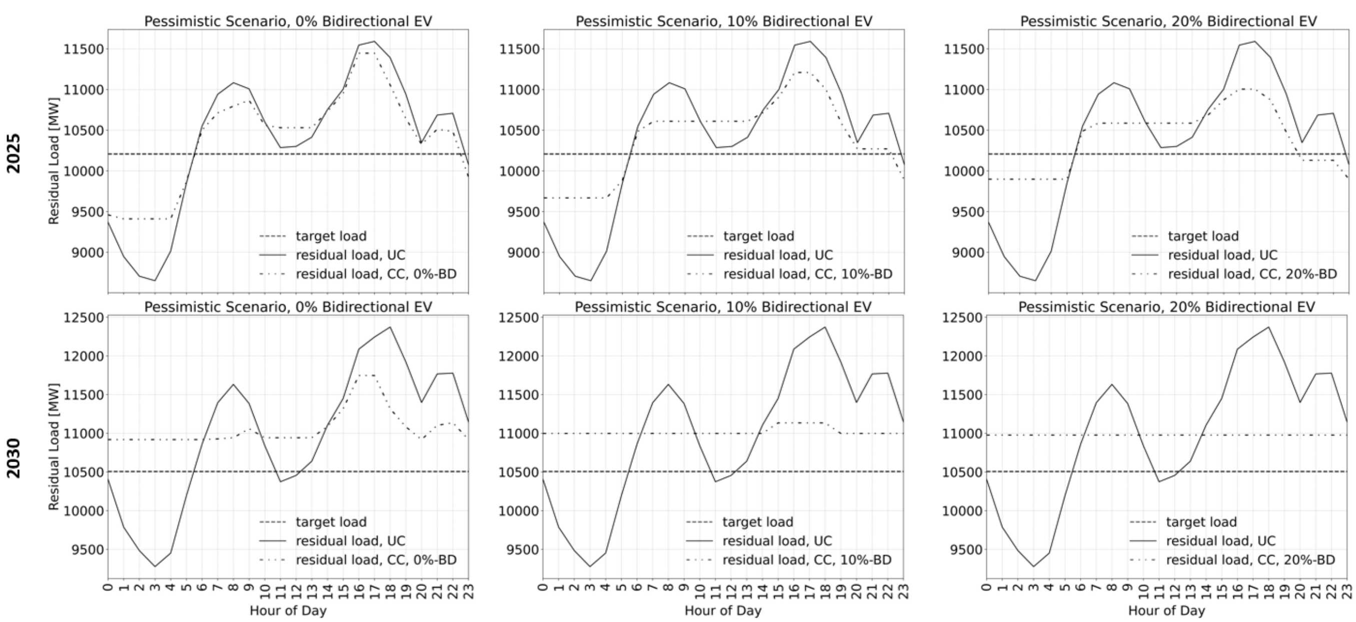

Figure A-1: Impact of uncontrolled- and controlled charging on the residual load, pessimistic scenario

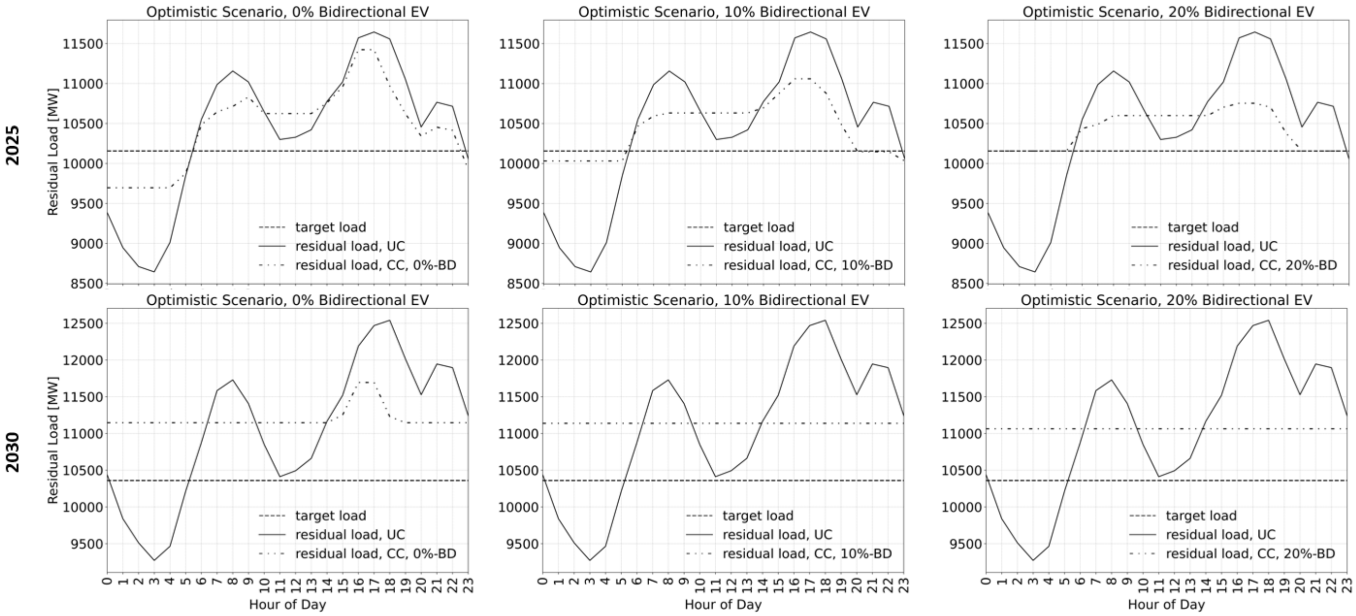

Figure A-2: Impact of uncontrolled- and controlled charging on the residual load, optimistic scenario