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Revenue opportunities by integrating combined vehicle-to-home and vehicle-to-grid applications in smart homes

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HIGHLIGHTS

- Modeling vehicle-to-home (V2H) with linear programming leads to 30% overestimated revenues.
- Indicated V2H revenues for an average German household are around 310 €/a.
- The difference between household electricity price and solar feed-in tariff is most important for V2H revenues.
- Over 90% of V2H revenues are generated in summer months.
- V2G complements V2H very well due to different seasonal profitability.

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ABSTRACT

A smart integration of electric vehicles (EVs) in the future energy system will be crucial in decarbonizing the energy sector. Bidirectional EVs can provide flexibility for the system and generate revenues for the user through multiple use cases. We model both exclusive photovoltaic (PV) self-consumption optimization and the combined usage of PV self-consumption optimization and arbitrage trading for a household with an unmanaged, smart, and bidirectional charging EV in a linear (LP) and mixed-integer linear programming (MILP). Since power flows in a typical household are low, varying non-linear charging and discharging efficiencies of the bidirectional EV in the MILP result in more realistic revenues that are 30% lower than in the LP with fixed efficiencies. For a typical German household using a bidirectional EV for optimizing PV self-consumption, these revenues are about 310 €/a, mostly generated during the summer. Arbitrage trading well complements this vehicle-to-home use case in the winter months, resulting in revenues up to 530 €/a. These significant revenue potentials can lead to more profitable and interactive EVs incentivizing users to change from internal combustion vehicles to electric mobility.

1. Introduction

The electrification of mobility is often considered an essential component in combatting climate change. While CO_2 emissions in the German energy sector have decreased sharply, because of the strong expansion of renewable energies, emissions in the transport sector have remained roughly the same as they were in 1990 [1]. Coupling of the energy and mobility sectors is seen as a major opportunity for reducing emissions in the transport sector, with electric mobility playing a key role [2]. The German government has introduced some subsidies, e.g. for private individuals purchasing electric cars, to increase the share of electric vehicles (EVs) on German roads [3]. Nevertheless, the target of one million registered electric vehicles in Germany by 2020 was missed. A survey by the German Association of Energy and Water Industries found that the high investment costs for an EV are the main argument against switching to electromobility [4]. If the economic viability of EVs could be increased, it would provide an additional incentive for citizens to purchase an electric vehicle.

Here, one possibility is use of bidirectional charging technology. In contrast to unidirectional charging systems, bidirectional charging systems not only allow energy to be drawn from the grid or a generation plant to charge the electric vehicle, but they also allow the energy from the vehicle to be fed back in a smart form. Therefore, during periods of inactivity, the vehicles can also be used in a manner analogous to a stationary battery storage (SBS) [5]. In vehicle-to-grid (V2G) applications,

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Nomenclature

Abbreviations

BCM	Bidirectional Charging Management (project)
BCM	bidirectional charge management
COM	commuter
EV	electric vehicle
EFC	equivalent full cycle
EVSE	electric vehicle supply equipment
GCP	grid connection point
HP	heat pump
LP	linear programming
MILP	mixed-integer linear programming
OH	operating hour
PV	photovoltaic
SBS	stationary battery storage
SoC	state of charge
V2G	vehicle-to-grid
V2H	vehicle-to-home
V2B	vehicle-to-business

Parameters

$b_{EV,dep}$	timeseries if EV is departing
$C_{connected}$	timeseries if EV is connected to the EVSE
$E_{EV,drive}$	EV consumption while driving
m_c	gradient of charging losses
m_d	gradient of discharging losses
n_c	minimum charging losses
n_d	minimum discharging losses
$\eta_{EV,roundtrip,max}$	maximum roundtrip efficiency of EV
$\eta_{SBS,roundtrip}$	roundtrip efficiency of SBS
$p_{el,buy}$	electricity purchase prices for household
$p_{el,buy,v2g}$	electricity purchase prices for V2G
$p_{el,sell}$	feed-in tariff
$p_{el,sell,v2g}$	electricity selling prices for V2G
$P_{EV,l,const,c/d}$	constant charging/discharging losses
$P_{EV,l,const,st}$	constant standby losses of EV and EVSE
$P_{HH,el}$	electrical household demand
$P_{HH,th}$	thermal household demand
P_{PV}	PV generation
SoC_{dep}	minimum SOC at departure
SoC_{safe}	minimum SOC when connected
t	timestep
T	total timesteps
x	start timestep of V2G interval
y	end timestep of V2G interval

Variables

$b_{EV,c}$	boolean variable if EV is charging
$b_{EV,d}$	boolean variable if EV is discharging
E_{EV}	charge level of EV battery
$E_{EV,pub,c}$	public charging energy
$P_{EV,c}$	charging power of EV
$P_{EV,d}$	discharging power of EV
$P_{EV,l,c}$	charging losses of EV
$P_{EV,l,d}$	discharging losses of EV
$P_{EV,l,s}$	standby losses of EV and EVSE
$P_{GCP,in}$	power from grid
$P_{GCP,in,v2g}$	power from grid as V2G process
$P_{GCP,out}$	power to grid
$P_{GCP,out,v2g}$	power to grid as V2G process
$P_{HP,el}$	power consumption of heat pump
$P_{PV,curt}$	curtailment of PV generation
$P_{SBS,c}$	charging power of SBS
$P_{SBS,d}$	discharging power of SBS

bidirectionally chargeable EVs can contribute to grid stability in a system-serving manner [6] while offering economic benefits for EV owners [7].

Similarly, vehicle-to-home (V2H) use cases offer the benefit of optimized use of locally generated renewable energy while also providing revenue opportunities; here some studies have already addressed the profitability of bidirectional charging. Salpakari et al. show that smart and bidirectional charging can save 8–33% of annual electricity costs compared to an unmanaged charging strategy in a household fitted with a photovoltaic (PV) system in Sweden. The additional cost savings from vehicle-to-microgrid are small if battery degradation costs are taken in consideration [8]. Chen et al. study energy use optimization strategies without and with V2H for a household with a PV system in Shanghai, taking into consideration time-varying electricity tariffs with high and low tariff time windows. They show that economic benefits can be achieved for the household in all use cases. PV tariff, weather, and EV driving behavior are the key influencing factors here [9]. Erdinc et al. compare bidirectional charging and unmanaged charging for both V2H and V2G use cases for a household with a small PV system in Portugal, again using time-varying tariffs. In their calculations, they obtain a cost reduction potential of up to 48% by limiting power at peak times and up to 63% for time-variable tariffs by bidirectional charging compared to unmanaged charging [10]. Kataoka et al. evaluate the effect of V2H applications on the economic and environmental performance of a typical household in Japan. They find that V2H can be economically and environmentally more beneficial than SBSs, but results differ between commuters and non-commuters. For future work, they suggest further sensitivity analysis, e.g. regarding the size of EV battery or EV charge and discharge power [11]. The cost-effectiveness of a V2H system in Germany is investigated by Cacilo et al. Yet, no economic evaluation of the vehicle's bidirectional capability, only smart charging, is performed [12]. Keiner et al. analyze smart homes for an average German single-family household including heat pumps (HPs), thermal energy storage systems, SBSs and EVs and find that V2H can assume the role of an SBS [13]. However, they largely focus on different thermal energy storages scenarios and not different EV charging strategies. The above-mentioned studies model fixed charging and discharging efficiencies and thus neglect energy losses resulting from low-powered, ineffective charging and discharging processes in V2H use cases [14]. Further, there is a lack of in-depth research in the literature investigating the influence of different household component set-ups on cost reduction potentials through the use of smart or bidirectional charging EVs.

Regarding V2G use cases, there are numerous papers that deal with the revenue potentials of EVs participating in the spot market [15]. Smart charging optimized by electricity prices can reduce charging costs [16,17] and bidirectional charging can further reduce these costs or even generate revenues [18]. None of the studies mentioned deal with V2H use cases complementing arbitrage trading in spot markets. Since arbitrage trading often results in lots of operating hours (OHs) and equivalent full cycles (EFCs) of the battery [19], the temporary replacement by V2H use cases could reduce the battery ageing effect.

In this paper, we address the aforementioned research gaps by modeling V2H use cases exclusively with and without varying charging and discharging efficiencies. This novel evaluation of more realistic modeling of V2H as mixed-integer linear programming (MILP) with varying efficiencies versus modeling of V2H as linear programming (LP) with fixed efficiencies is necessary to assess whether MILP with varying efficiencies is beneficial or even necessary for V2H analyses. For this

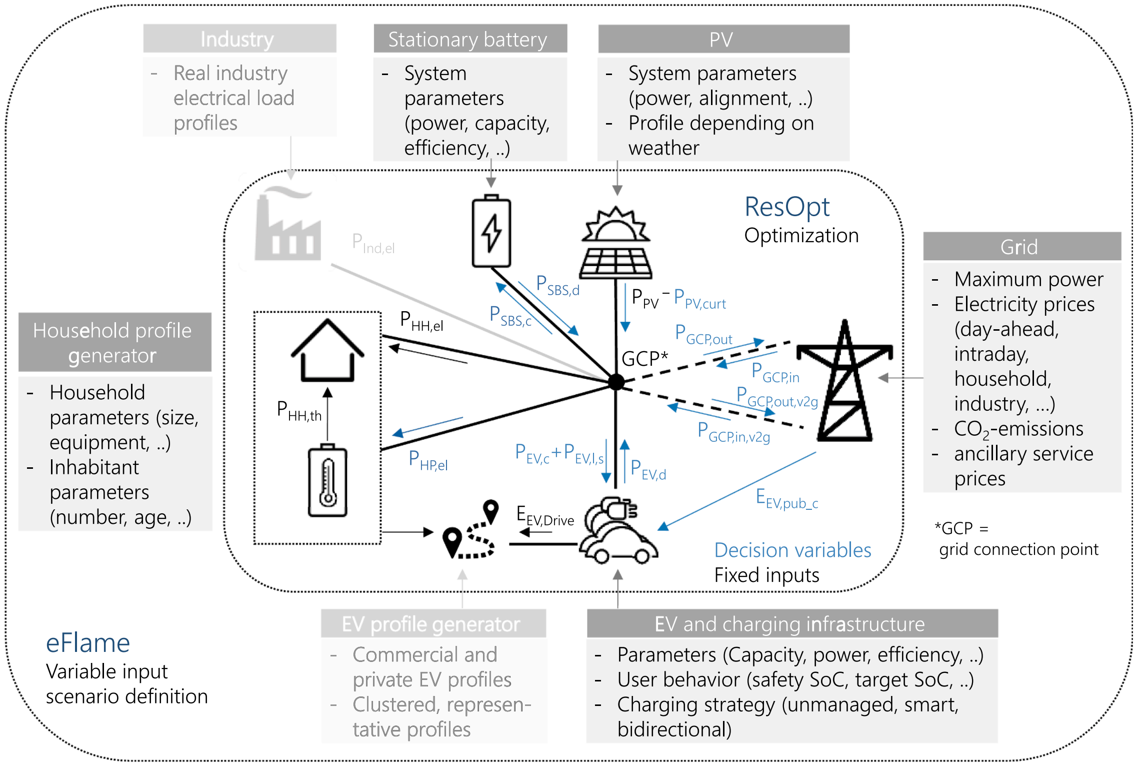

Fig. 1. Schematic representation of the developed optimization model for use cases of bidirectional charging.

purpose, an optimization model is developed that optimizes the electric power flows of a household with the objective of minimizing electricity costs while taking technical restrictions into account. Three different charging strategies are compared regarding household energy flows: an unmanaged charging strategy, a smart charging strategy and a bidirectional charging strategy. The V2H revenue potentials are shown based on the influencing factors of PV size and PV feed-in tariff, household size, household components, EV size, maximum charging power and maximum operating hours. Finally, we model a combined application of V2H and V2G arbitrage trading to show differences and benefits on the electricity costs of a household. This combined, novel modeling of V2H and V2G can realistically combine the seasonally different revenue opportunities of the use cases and shows that a separate modeling of a V2H or V2G use case can underestimate the revenue opportunities. The investigations are embedded in the project 'Bidirectional charging management' (BCM) that analyzes the technical, economic, and regulatory issues of bidirectional charging [5].

2. Methodology

The methodological approach for investigating V2H use cases of bidirectional EVs is divided into two parts: first, we present the optimization model for considering V2H cases exclusively. Then, the combined modeling of V2H and V2G is outlined.

We developed an optimization model in order to assess revenue potential efficiently and accurately in the area of V2H applications. The model determines the best possible charging strategy for one or multiple EVs connected via a grid connection point (GCP) with multiple optional other components. This approach allows a wide range of different analyses, including V2H, V2G and V2B use cases. Fig. 1 shows a schematic of the model structure. As displayed, the model structure *eFlame* (electric Flexibility assessment modeling environment) itself consists of two submodels. Firstly, the household profile generator, where the electrical and thermal consumption of a specific household are modeled based on parameterization of the household and user behavior, modeling as well appropriate EV driving profiles [20]. Secondly, the optimization model *ResOpt* (Residential Optimizer) formulates the objective function and constraints of variable defined components.

The model *ResOpt* comprises several decision variables, the values of which are set for each time step in the course of the optimization: SBS charging $P_{SBS,c}$ and discharging $P_{SBS,d}$, PV curtailment $P_{PV,curt}$, HP demand $P_{HP,el}$, EV charging $P_{EV,c}$, discharging $P_{EV,d}$ and standby losses $P_{EV,l,s}$ as well as power from grid $P_{GCP,in}$ and power to grid $P_{GCP,out}$. For the combined modeling of V2H and V2G use cases (Section 2.2), we integrate the decision variables $P_{GCP,in,v2g}$ and $P_{GCP,out,v2g}$ that represent power from and to the grid that is additionally constrained. A fixed thermal $P_{HH,th}$ and electrical $P_{HH,el}$ household demand is provided as well as the fixed PV generation P_{PV}.

2.1. Modelling of V2H applications with fixed and varying efficiencies

The objective of V2H optimization is to minimize the household's electricity costs, which is expressed in the objective function in Eq. (1). The German household's electricity costs to be minimized consist of the purchase costs $p_{el,buy}$ multiplied by the purchased power $P_{GCP,in}$ minus the feed-in tariff $p_{el,\mathrm{sell}}$ multiplied by the power $P_{GCP,out}$, which is fed into the grid if an electricity generator is present, over all time steps t.

$$min\left(\sum_{t=1}^{T}\left[p_{el,buy}(t)\cdot P_{GCP,in}(t) - p_{el,\mathrm{sell}}(t)\cdot P_{GCP,out}(t)\right]\right) \tag{1}$$

Relevant constrains are implemented for the household's grid connection point, the EV and other optional components. We refrain from a detailed description of the constraints for optional components such as SBS or HP at this point. Most importantly, the power fed into the grid or supplied from the grid must equal the sum of power generated and consumed within the boundaries of the system at any time:

$$P_{GCP,in}(t) - P_{GCP,out}(t) = P_{HH,el}(t) + P_{HP,el}(t) - P_{PV}(t) + P_{PV,curt}(t) + P_{SBS,c}(t) - P_{SBS,d}(t) + P_{EV,c}(t) - P_{EV,d}(t) + P_{EV,l,st}(t) \tag{2}$$

Table 1
Deviation between real and linearized losses and efficiencies for a 11 kW EVSE.

	Charging process			Discharging process		
Number of intervals	0 (LP)	1	2	0 (LP)	1	2
Maximum deviation of power losses	250 W	42 W	10 W	250 W	55 W	14 W

Standby losses $P_{EV,l,st}(t)$ represent constant losses of the inverter and EV $P_{EV,l,const,st}$, which occur when the EV is connected $C_{connected}(t)$ at the household's charging point (electric vehicle supply equipment, EVSE) and is neither charging $b_{EV,c}(t)$ nor discharging $b_{EV,d}(t)$.

$$P_{EV,l,st}(t) = P_{EV,l,const,st} \bullet [\mathrm{C}_{\mathrm{connected}}(\mathrm{t}) - \mathrm{b}_{\mathrm{EV,c}}(\mathrm{t}) - \mathrm{b}_{\mathrm{EV,d}}(\mathrm{t})] \tag{3}$$

To account for such losses, the connection status $C_{connected}$ (t) (a time series which is 1 if the EV is connected and 0 if it is not connected) and the discrete boolean variables $b_{EV,c}$ (1 if charging, otherwise 0) and $b_{EV,d}$ (equals 1 if discharging, else 0) are used. Thus, standby losses can only be included for MILP.

Another relevant constraint concerns the electric energy stored in an EV at time *t*, which is determined by Equation 4.

$$E_{EV}(t) = E_{EV}(t-1) + [P_{EV,c}(t) - P_{EV,l,c}(t)] \bullet \Delta \mathrm{t} + \mathrm{E}_{\mathrm{EV,pub,c}}(\mathrm{t})$$
$$- E_{EV,drive}(t) - [P_{EV,d}(t) + P_{EV,l,d}(t)] \bullet \Delta \mathrm{t} - \mathrm{P}_{\mathrm{EV,l,const,c/d}} \bullet [\mathrm{b}_{\mathrm{EV,c}}(\mathrm{t}) + \mathrm{b}_{\mathrm{EV,d}}(\mathrm{t})] \bullet \Delta \mathrm{t} \tag{4}$$

Here, energy losses affecting the EV's state of charge (SoC) occur during charging and discharging. Again, to maintain linear programming (LP) optimization, constant losses $P_{EV,l,const,c/d}$ would have to be neglected and charging $P_{EV,l,c}$ and discharging $P_{EV,l,d}$ losses modeled in proportion to charging and discharging power. As the EVSE in the case of bidirectional charging contains an additional inverter converting alternating current (AC) into direct current (DC) if charging and DC to AC if discharging, EVSE losses for bidirectional charging are modeled as variable over time in our work.

For this purpose, we draw on mathematical descriptions of the inverter efficiency deduced in [21], where inverter power losses are expressed as a quadratic function of the corresponding output power. By rearranging the respective equations as described in Appendix A, the inverter losses can be stated as functions of the AC-side power for both charging and discharging processes. As implementation of these non-linear loss functions directly resulted in unacceptably long computation times, we adopted a linear approximation approach. We linearized the power losses equations for charging and discharging by linear regression (method of least squares) as suggested by [22] in a similar context, which results in a linear system of equations:

$$P_{EV,l,c}(t) = m_c \bullet \mathrm{P}_{\mathrm{EV,c}}(\mathrm{t}) + \mathrm{n}_{\mathrm{c}} \bullet \mathrm{b}_{\mathrm{EV,c}}(\mathrm{t}) \tag{5}$$

$$P_{EV,l,d}(t) = m_d \bullet \mathrm{P}_{\mathrm{EV,d}}(\mathrm{t}) + \mathrm{n}_{\mathrm{d}} \bullet \mathrm{b}_{\mathrm{EV,d}}(\mathrm{t}) \tag{6}$$

Here, $m_{c/d}$ is the gradient of the function and $n_{c/d}$ represents the minimum losses at zero power.

By dividing the possible range of charging and discharging power into a number of equally large intervals and applying the method of least squares to each interval individually, the residual sum of squares can be reduced to improve accuracy. Hence, we conducted preliminary simulations to determine a suitable number of intervals for sufficiently high accuracy with acceptable computation time. The resulting deviations obtained when linearizing power losses for zero, one, or two intervals are presented in Table 1 (sum of constant EV losses and varying inverter losses), where zero losses correspond to constant losses. Since respective variations of efficiency are small in any case apart from the simulations with zero intervals, we implemented linearized functions of inverter power losses for both charging and discharging for a single interval $[0; P_{EV,c/d,max}]$ based on real inverter data to limit the complexity of the optimization problem.

Additional constraints are related to the EV's SOC. If an EV is connected at the household's EVSE, the minimum amount of energy, represented by SoC_{safe}, must be reached at all times, which is ensured by Equation 7. Here, $E_{EV,max}$ is the maximum amount of energy to be stored in the EV (i.e. the battery's capacity). Equation 8 guarantees that at the time of departure, which must be set when arriving at the household, a fixed minimum amount of energy, represented by SoC_{dep}, is stored in the EV's battery. To do so, $b_{EV,dep}$ is introduced, which is 1 if *t* is the time of departure. Otherwise, $b_{EV,dep}$ equals 0.

$$E_{EV}(t) \geq SoC_{safe} \bullet \mathrm{E}_{\mathrm{EV,max}} \bullet \mathrm{C}_{\mathrm{connected}}(\mathrm{t}) \tag{7}$$

$$E_{EV}(t) \geq SoC_{dep} \bullet \mathrm{E}_{\mathrm{EV,max}} \bullet \mathrm{b}_{\mathrm{EV,dep}}(\mathrm{t}) \tag{8}$$

Optional features of the model are the limitation of the EV battery's number of EFCs or the EV's OHs per day, which can be used to reduce battery aging or respectively the wear of the EV's power electronics. Equation 9 limits the maximum EFCs (EFC_{max}) and Equation 10 the average maximum OHs per day ($\mathrm{OH}_{max,day}$). Since OHs are related to the boolean variables $b_{EV,c}$ and $b_{EV,d}$, Equation 10 can only be used for MILP.

$$EFC_{max} \geq \frac{\sum_{t=1}^{T}([P_{EV,c}(t) - P_{EV,l,c}(t)] \bullet \Delta t + E_{EV,pub,c}(t))}{E_{EV,max}} \tag{9}$$

$$\mathrm{OH}_{max,day} \geq \frac{\sum_{t=1}^{T}[b_{EV,c}(t) + b_{EV,d}(t)]}{T} \bullet \tag{10}$$

2.2. Modelling of combined V2H and V2G applications

Adding V2G arbitrage trading to the model leads to several adaptions in the objective functions and constraints of the optimization problem. The regulatory framework for arbitrage trading is not yet defined for bidirectionally chargeable EVs at the European Union level [23]. Since power purchased and sold through arbitrage trading by SBS is exempted from multiple duties and taxes [24], we assumed this exemption for V2G such that modeled V2G prices differ from the normal household prices for purchased and feed-in energy. Therefore, the objective function is expanded in Equation 10 by the costs and revenues of the V2G component, considering V2G prices $p_{el,buy,V2G}(t)$ and $p_{el,\mathrm{sell},V2G}(t)$, and V2G power $P_{GCP,in,v2g}(t)$ and $P_{GCP,out,v2g}(t)$.

$$min\left(\sum_{t=1}^{T}\begin{bmatrix} p_{el,buy}(t) \cdot P_{GCP,in}(t) - p_{el,\mathrm{sell}}(t) \cdot P_{GCP,out}(t) + \\ p_{el,buy,v2g}(t) \cdot P_{GCP,in,v2g}(t) - p_{el,\mathrm{sell},v2g}(t) \cdot P_{GCP,out,v2g}(t) \end{bmatrix}\right) \tag{10}$$

The energy purchased $P_{V2G,in}(t)$ and feed-in $P_{V2G,out}(t)$ is added to the power balance of the household grid connection point in Equation 11.

Table 2
Relevant parameterization of elements connected to the household.

Element	Parameter	Value	Additional Input
Household	$\sum P_{HH,el}$	3800 kWh (yearly)*	Load profile*
	$\sum P_{HH,th}$	9000 kWh (yearly)*	Load profile*
Grid	$p_{el,buy}$	29.9 ct/kWh [26]	
PV system	$P_{PV,max}$	5.5 kWp***	Generation profile****
	$\sum P_{PV}$	6200 kWh (yearly)	based on [28]
	$p_{el,sell}$	11.6 ct/kWh [27]	
EV	$P_{EV,c,max}$	11 kW**	Driving profile*
	$P_{EV,d,max}$	11 kW**	
	$E_{EV,max}$	60 kWh*****	
	$\eta_{EV,roundtrip,max}$	85%**	
	Annual mileage	10,000 km*	
	EV consumption (including charge losses)	22 kWh/100 km**	
EV user	User type	Non-Commuter	
	SoC_{safe}	30%**	
	SoC_{dep}	70%**	
SBS	$P_{SBS,c,max}$	2.8 kW	
	$P_{SBS,d,max}$	2.8 kW	
	$E_{SBS,max}$	5.5 kWh******	
	$\eta_{SBS,roundtrip}$	88%	
HP	$P_{Hp,el,max}$	5 kW [29]	
	Coefficient of Performance	3.45 [30]	

*Average load value, annual driving, load profile and driving profile are output from household profile generator [20] and provided in supplementary material.
**Based on specifications of BCM project [5].
***Calculated by usable roof space multiplied by specific energy 0.15 kWp/m^2 [31].
****Provided in supplementary material.
*****E.g. Volkswagen ID.3 Pro [32] / Opel Ampera-e [33].
****** Capacity and power of SBS based on PV power [34].

$$P_{GCP,in}(t) - P_{GCP,out}(t) + P_{GCP,in,v2g}(t) - P_{GCP,out,v2g}(t) = P_{HH,el}(t) + P_{HP,el}(t) - P_{PV}(t) + P_{PV,curt}(t) + P_{SVS,c}(t) - P_{SBS,d}(t) + P_{EV,c}(t) - P_{EV,d}(t) + P_{EV,l,st}(t) \tag{11}$$

In contrast to a SBS, bidirectionally chargeable EVs consume electricity by driving and thus charging and discharging energy do not balance. Since V2G electricity prices will only be exempted from multiple duties and taxes if the same amount of purchased energy is fed back into the grid at a different time, we add constraints to the V2G powers in Equation 12. The purchased energy $sum\left(\sum_{t=1}^{T}\left[P_{GCP,in,v2g}(t)\right]\right)$ equals the fed-in energy $sum\left(\sum_{t=1}^{T}\left[P_{GCP,out,v2g}(t)\right]\right)$ divided by the maximum V2G roundtrip efficiency $\eta_{EV,roundtrip,max}$, because losses of a V2G roundtrip are included in the exemption from additional electricity charges [24]. The roundtrip efficiency refers to the charging and discharging efficiency of the bidirectionally chargeable electric vehicle (from AC to AC). The timeframe of the power equation $t = x$ to y can be set variable depending on the regulatory framework of the considered household.

$$\left(\sum_{t=x}^{y}\left[P_{GCP,in,v2g}(t)\right]\right) = \left(\sum_{t=x}^{y}\left[P_{GCP,out,v2g}(t)\right]\right) \Big/ \eta_{EV,roundtrip,max} \tag{12}$$

To ensure that the purchased and fed-in energy is associated with the EV and not a different component of the household, we add Equations 13 and 14. Purchased energy $P_{GCP,in,v2g}(t)$ has to be lower than charged electricity $P_{EV,c}(t)$. In addition, fed-in energy $P_{GCP,out,v2g}(t)$ must be lower than discharging of the EV $P_{EV,d}(t)$.

$$P_{GCP,in,v2g}(t) <= P_{EV,c}(t) \tag{13}$$

$$P_{GCP,out,v2g}(t) <= P_{EV,d}(t) \tag{14}$$

Finally, considering a household with PV generation leads to possibilities of misuse when V2G energy is exempted from duties and taxes. In such a case, PV energy could first be charged into the EV and later be discharged into the grid as a V2G process (duties and taxes exemptions). As the EV is allowed to purchase the corresponding amount of energy described in Equation 12 as a V2G process, such an EV could purchase energy at a different time which would replace purchases of energy at household electricity prices. In this way, as much PV energy as desired can be fed through the EV into the grid in order to purchase the corresponding amount of energy at much lower prices at a different time. To prevent this effect, only V2H or V2G may be performed within a set period. Equations 15 and 16 constrain the optimization problem for a V2G time frame. If boolean variable b_{V2G} is set to 0 for a time interval t $=$ x to y, V2G is not allowed. If b_{V2G} is set to 1, discharged energy of the EV must be fed to the grid and is not allowed to be fed to the household. Thus, V2H self-consumption optimization is not allowed for the respective time interval.

$$P_{GCP,out,v2g}(t) <= b_{EV,v2g} \bullet \mathrm{P}_{\mathrm{EV,d,max}} \tag{15}$$

$$P_{EV,d}(t) \leq P_{GCP,out,v2g}(t) + (1 - b_{EV,v2g}) \bullet \mathrm{P}_{\mathrm{EV,d,max}} \tag{16}$$

with $b_{EV,v2g} = [0, 1]$ for time interval t $= x$ to y

3. Results

Every scenario study includes three EV operation strategies: unmanaged charging, smart charging, and bidirectional charging. Revenues of a bidirectional or smart charging strategy are always compared

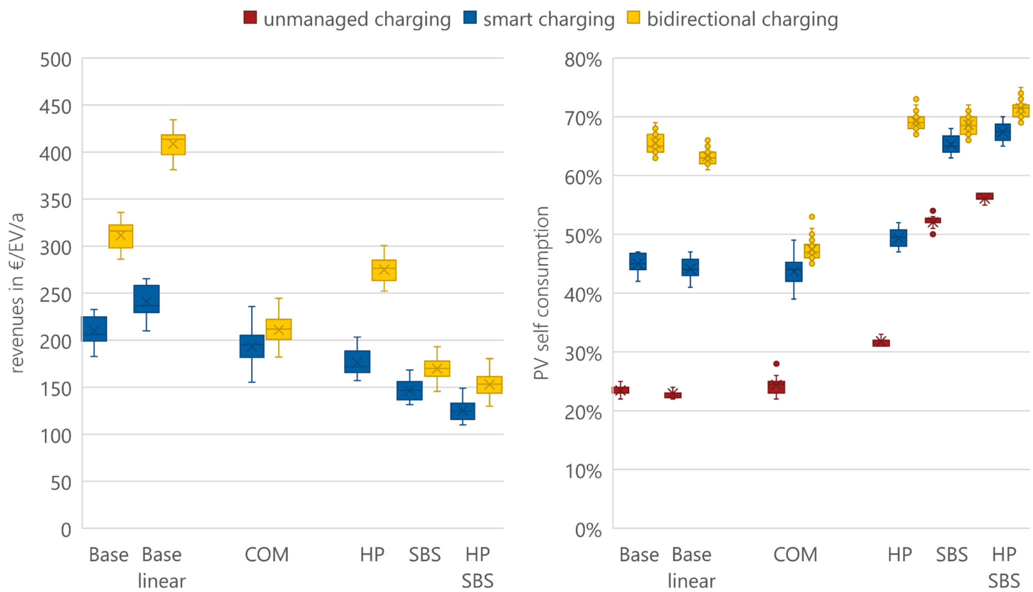

Fig. 2. Revenues and PV self-consumption for base MILP scenario in comparison to base linear scenario, commuter scenario COM and added components scenarios HP, SBS, and HP SBS.

to the reference of unmanaged charging.

3.1. Input data and set-up of average household scenario

To evaluate the economic viability of the use case 'self-consumption optimization' by bidirectional electric vehicles, a medium-sized single-family house (150 m2 living space) is defined, which is subsequently referred to as the base scenario. Table 1 shows the main characteristics of the household and potential additional components. These optional components include a PV system, an EV, a SBS and a HP. Table 2 shows the parameterization of these components, additional input for their modeling, and the associated references. Prices and profiles are based on data from the year 2018.

Concerning the household profiles, Appendix B shows that 20 discrete profiles are sufficient to represent average revenues of a household class. Therefore, 20 profiles are used below, having on average the characteristics shown in Table 2. We focus on EVs that are used by non-commuters, since approximately 75% of EVs in Germany are non-commuting EVs [25], but show the revenues for a commuting EV as a sensitivity in chapter 3.2.

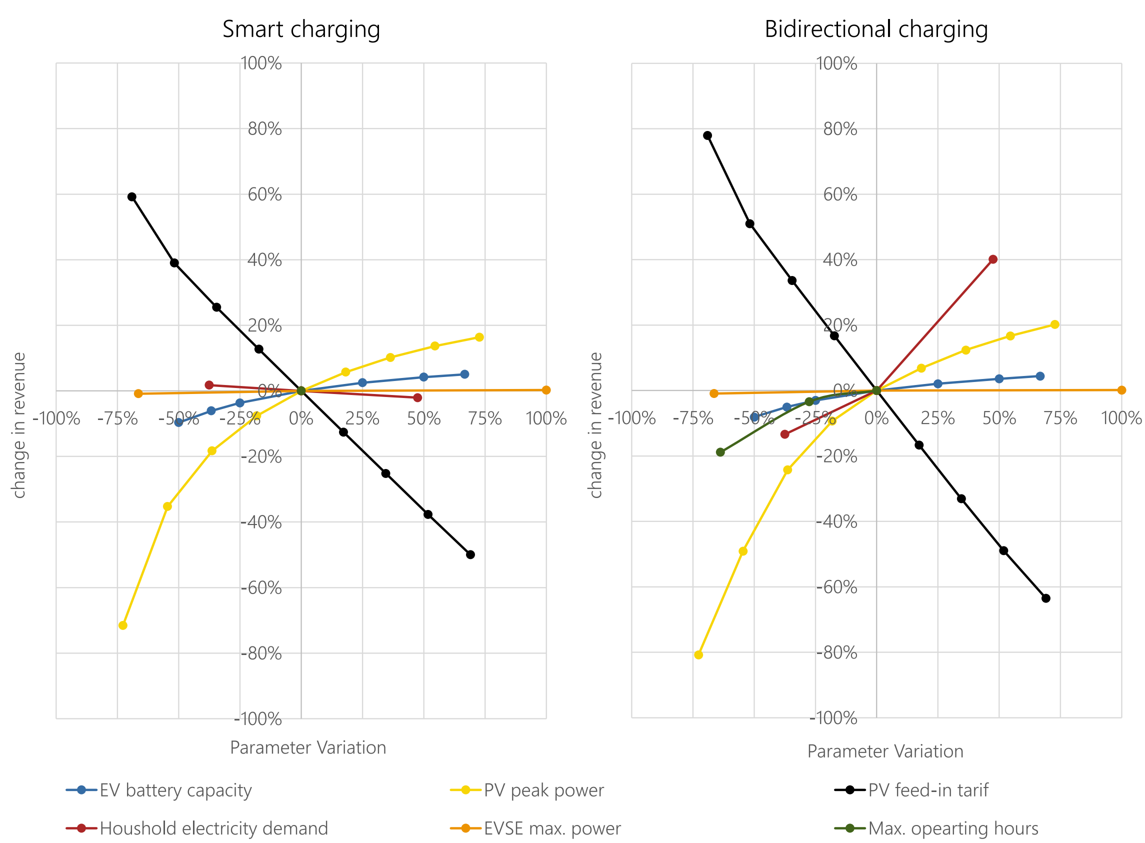

Fig. 3. Parameters influencing revenues of V2H use cases for smart and bidirectional charging EVs.

Table 3
Revenues, operation hours and EFCs for bidirectional operating strategy of the EV.

Scenario		V2H base	V2H base + V2G	V2H base + V2G max. 10 OHs/day	V2H base + V2G max. 5 OHs/day
Average revenues in €/a	Total	310	530	510	410
	V2H	310	300	300	270
	V2G	-	230	210	140
EFCs/a		50	320	250	130
OHs/d		6.9	12.5	10	5

3.2. Revenues for V2H operation

Various sensitivity calculations are evaluated to assess the benefits of bidirectionally chargeable EVs for household owners. Fig. 2 compares the revenues and PV self-consumption of smart and bidirectional charging strategies for the base scenario to the linear base scenario (LP optimization with constant efficiencies), the commuter EV scenario 'COM' and scenarios with the additional components HP and SBS.

Additional revenues for the base scenario are around 210 €/a for a smart charging EV and around 310 €/a for a bidirectionally chargeable EV. These revenues represent cost reductions of 25% to 36% compared to a household with an unmanaged charging EV. Self-consumption of electricity from the PV system increases on average from 23% for unmanaged charging to 45% for smart charging and 65% for a bidirectionally chargeable EV. This improved use of cheaper PV energy rather than energy from the grid leads to higher revenues and a higher degree of autarky.

The 'Base linear' scenario shows a similar PV self-consumption increase, but significantly higher revenues for both smart and bidirectional charging compared to the base scenario. Since the household power demand and the PV power are both below 1 kW in 90% respectively 73% of all timesteps, where a varying inverter efficiency would drop significantly, the fixed efficiency of the EV's charging and discharging leads to a higher utilization with much lower losses. A more detailed description of the resulting differences in charging and discharging behaviour between fixed and varying efficiency is provided in Appendix C. PV self-consumption in the linear base scenario is slightly lower than in the non-linear base scenario due to lower charging and discharging losses. The diverging revenues of around 100 €/a for a bidirectionally chargeable EV compared to the base scenario (divergence of 32%) show that for our considered use case, it is not valid to model a LP with fixed efficiencies. Therefore, all of the following results are based on a MILP optimization with a varying efficiency for charging and discharging of the EV.

In the commuter EV scenario 'COM', we model a commuter EV instead of a non-commuter EV in the household. The average annual mileage increases from 10,000 km/a to 20,000 km/a and the average availability of the EVs at the charging point decreases from 91% to 67%. For smart charging EVs, the average commuter EV generates only slightly lower revenues compared to the revenues of the smart charging EV in the base scenario. The lower availability of the commuter EV is compensated by the higher EV consumption that leads to more possibilities of smart charging. In contrast, the bidirectionally chargeable, commuting EV generates revenues that are about 100 €/a lower than the non-commuting EV's revenues. The lower availability of the commuting EV during the day leads to fewer opportunities of charging PV electricity. Therefore, the PV electricity is used for consumption of the EV, but not for discharging to the household.

Adding additional smart components to the household leads to lower revenues for managed EV operation strategies, since these components also use the cheaper PV energy to optimize the household's electricity costs. In these scenarios, the reference case of unmanaged EV charging is already much more efficient than in the base scenario leading to a lower revenue potential of bidirectionally chargeable EVs. In scenario HP, the heat pump can be operated flexibly such that part of the low-cost PV electricity is used for heat generation. In particular, the battery storage in the SBS scenario acts similarly to the bidirectional electric vehicle, such that the revenue potential there is even more limited. The combination of these additional smart components in the household then provides the lowest revenue potentials. The impact on revenue potential is in turn linked to the level of self-consumption of the solar energy for the different EV operating strategies. With additional smart components in the household, a higher self-consumption is already apparent with unmanaged charging of the EV, such that the possible increase is limited.

Other relevant factors potentially influencing revenue potential include:

- EV battery capacity
- Maximum power of EVSE
- PV peak power
- PV feed-in tariff
- Household size
- Maximum OHs of EV and EVSE

Fig. 3 shows the effect of parameter variation on the revenue potential for smartly and bidirectionally chargeable EVs. The use case of self-consumption optimization is highly sensitive. In particular, the design of the PV system has a strong impact on the revenues. A large PV system with a low feed-in tariff generates significantly higher revenues through both smart and bidirectional charging of an electric vehicle. The parameterization of the EV and the EVSE has much less effect. In this case, larger designs cause no or only small increases in revenue. As for the EV, the selected capacity in the base scenario is sufficient to exploit the major part of revenue potentials for the fixed household and PV configuration. The small effects of the EVSE are related to the configuration of the household in the base configuration (maximum PV feed-in 4.5 kW, maximum demand household 7.7 kW). An EVSE of 22 kW instead of 11 kW has no effect on revenues. In contrast, the household size has a large impact on the revenue potential for bidirectionally chargeable EVs, since a larger household with higher demand power enables more efficient discharging of the EV.

Additionally, we evaluate a limitation of the resulting OHs of the bidirectionally chargeable EV reducing the impact on battery ageing and the additional load on power electronics. OHs of the bidirectionally chargeable EV in the base scenario without limitation are around 6.9 h/d compared to 0.7 h/d for the unmanaged charging EV. EFCs are less affected and increase only by 18 EFC/a from 34 to 52 EFC/a for the bidirectionally chargeable EV. Since OHs are much more affected than EFC, we present constrained OHs per day to show the effect of limited usage on revenues. A reduction of OHs by 64% to 2.5 h/d results in a moderate revenue reduction of 19%. EFCs of the battery then reduce from 52 EFC/a to 41 EFC/a.

Lastly, for a maximum revenue estimate, we examine a household that has the best suited configuration of each of the analyzed parameters. An average annual household demand of 5900 kWh is combined with a 9.5 kWp PV system, which receives a feed-in tariff of 3.6 ct/kWh, and an EV with a battery capacity of 100 kWh. This household set-up receives revenues of 835 €/a for a bidirectionally chargeable EV and revenues of 390 €/a for a smart charging EV, showing the maximum potential revenues for the use case self-consumption optimization.

3.3. Revenues for combined V2H and V2G operation

Since self-consumption optimization achieves more profits when more PV energy is generated, V2H is more useful in summer times than in winter times. To benefit from the bidirectionally chargeable EV in the best possible way, we model a combined use of V2H and V2G arbitrage trading. For explained regulatory reasons, the EV is not allowed to optimize self-consumption and arbitrage trading at the same time. Instead, the optimizer can switch the use case of the bidirectionally chargeable EV daily.

For arbitrage trading, we use German day-ahead market prices from

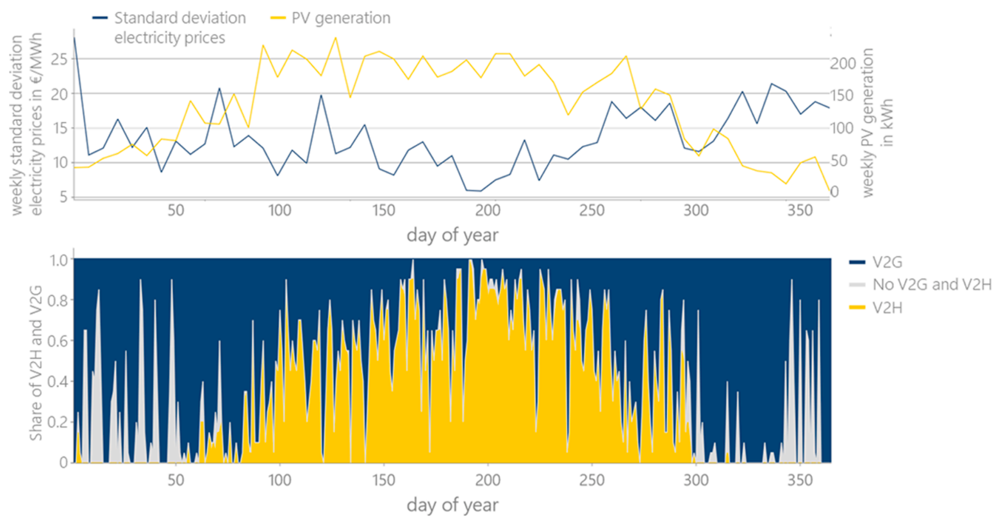

Fig. 4. Daily share of households using V2H and V2G correlated to weekly standard deviation of electricity prices and weekly PV generation.

2018 [35] matching the parameterization of the other components. Duties and taxes for purchased energy are not added to the electricity prices, because the regulatory framework for bidirectionally chargeable EVs is not yet fully defined. The revenues shown are thus an upper estimation.

Table 3 compares potential revenue of a combined optimization of V2H and V2G with and without restricted OHs to the revenues of the base V2H scenario. Revenue potentials of unrestricted, combined V2H and V2G increase by 220 €/a (plus 71%) compared to the base scenario, while EFCs increase by 270 EFCs/a and OHs by 5.5 OHs/d, meaning a significant additional load for the EV's battery. Limiting the maximum OHs to 10 h/d barely reduces revenues. In this case, EFCs are reduced by 70 EFCs/a relative to the unconstrained scenario, which is still an increase of 200 EFCs/a compared to the base V2H scenario. Limiting the maximum OHs to 5 h/d leads to revenues, which are 100 €/a higher than for the base scenario, yet 120 € lower than for the unrestricted combined scenario. Here, the EV usage is reduced significantly (only 70 EFCs/a more than the base scenario).

The generally increased revenues show that V2G arbitrage trading represents a very good complement to V2H use cases. To further analyze the combination of these use cases, Fig. 4 shows the share of daily usage of V2H and V2G for the evaluated 20 households in the restricted optimization by 5 OHs/day as well as the weekly standard deviation of electricity prices and the weekly PV generation. The usage of V2H correlates to the PV generation that is the highest from April to September. In contrast, the daily standard deviation of day-ahead prices does not vary on a seasonal basis, meaning that daily arbitrage trading is on average equally profitable in summer and winter times. Therefore, V2G complements V2H in winter times. Since Fig. 4 shows the OHs restricted optimization, there are days on which no V2G and V2H is used, which are days of low revenue potential.

4. Discussion on results and limitations

Our results show that smartly and bidirectionally chargeable EVs can reduce a household's electricity costs significantly by optimizing the self-consumption of PV energy. Profits of the V2H use case are highly sensitive to components of the household and their parameter variations. While the design of the EV and EVSE has a small impact on the revenues of the use case, the higher the maximum PV power and the lower the PV feed-in tariff, the more profitable V2H is. Our simulations show revenues of about 300 €/a for a typical German household with varying efficiencies (MILP). Potential cost reductions for households with bidirectionally chargeable EVs in a scenario best fitted for maximum revenues go up to 830 €/a, while households with smart charging EVs reach a maximum cost reduction of 390 €/a. Furthermore, we show that commuting EVs are not well suited for bidirectional self-consumption optimization but should rather only use smart charging. The average revenues indicated in this paper are slightly higher than revenues in the literature relating to V2H [8,11,13]. However, we show that revenues related to smart and bidirectional charging EVs are strongly sensitive to parameterization of household components.

By comparing results modeled as MILP with varying efficiencies to modeling with fixed efficiencies (LP), we found that it is highly important to model V2H use cases for bidirectional charging as MILP with varying charging and discharging efficiencies. Since for V2H applications only low charging and discharging powers are needed due to low household power demand and low PV system generation power, in reality low charging and discharging efficiencies occur at many times. Thus, modeling with a fixed efficiency (LP) led to revenues that are over 30% higher than the more realistic results of MILP, which is why we recommend to model V2H use cases exclusively with varying efficiencies.

All revenues presented are based on the German regulatory framework. However, through the sensitivity analyses, detailed conclusions can be drawn about V2H revenue potentials in other countries. The sensitivity analyses show that the difference between household electricity price and feed-in tariff is the most important influencing factor. According to Fig. 3, a higher feed-in tariff of almost 20 ct/kWh results in 60% lower revenues, i.e. approx. 120 €/a for an average household. In a country with a price spread between household electricity price and feed-in tariff of 10 ct/kWh, these strongly reduced revenues can be expected. Similar conclusions can be drawn with regard to the country-specific revenues for V2G applications, which we discuss in detail in [19]. In this way, the detailed findings of the sensitivity analyses can be transferred very well to the conditions in other countries.

With the novel combined modeling of the use cases self-consumption optimization (V2H) and arbitrage trading (V2G), we show that the two use cases are highly complementary in terms of potential revenues. Since the V2H use case is strongly dependent on the PV generation, cost reduction options are high during the summer months. V2G arbitrage trading, where revenues do not alter significantly over the course of a year, can thus make greater use of the bidirectionally chargeable EV in the wintertime, resulting in an increased utilization of the vehicle. Dependent on the permitted usage of the EV, revenues of the base scenario increase from a maximum of 220 €/a to 530 €/a. As this increase shows, our more complex yet more realistic modeling highlights the great economic potential of combined V2H and V2G. As implementing multiple use cases at a time is likely to become common for EV users in the near future, our results show the future perspective of such multi-use-implementation for greater flexibility and higher revenues.

OHs and EFCs of the EV's battery increase for V2H use cases, but far less than for arbitrage trading [19]. We show that limited use of the EV of 2.5 h/d still generates high V2H revenues, which are only 19% below the unconstrained revenues. Comparing these limited OHs of around 900 h/a and EFCs of 41 EFC/a to currently warrantied lifetime values for battery and power electronics in automotive applications, which are around 10,000 OHs [36] and up to 5,000 EFCs [37,38], additional OHs are more critical than additional EFCs, but V2H is still suitable as a use case for EVs. In this context, we want to emphasize the trade-off that although V2G arbitrage trading can generate significant additional revenues, it also leads to significant additional OHs and EFCs.

For the arbitrage trading, modeled electricity prices for selling and purchasing energy are equal. Depending on the regulatory framework there might be some additional duties and taxes for purchased energy, making the use case less profitable. Therefore, the presented revenues for arbitrage trading in the day-ahead market are to be interpreted as an upper bound of revenues. For a more detailed revenue estimation of arbitrage trading in European electricity markets, we refer to Kern et al. [19].

Finally, an economic evaluation of V2H and V2G use cases must include the additional investment costs of a bidirectional EVSE. To bring the presented revenue potentials into perspective for both present and future circumstances, we roughly estimate the economic viability of V2H by including additional annual costs via the annuity method [39]. Currently, there are only few offers for bidirectional EVSEs suitable for on low-volume production, resulting in high investment costs of around €6,000 [40]. The medium-term cost projections of experts in the BCM project for such an EVSE are around €2,000 [5]. Assuming an EVSE lifetime of 15 years [41], an interest rate of 3.5% [42] and unmanaged charging EVSE costs of €599 [43] leads to additional annual costs of the bidirectional EVSE of currently 469 €/a and medium term 122 €/a. A comparison with the V2H revenues of the typical German household of 310 €/a shows that V2H will most probably not be economical for this household at current costs but is likely to become profitable in the medium term. However, this is only a rough estimate and other additional costs should also be quantified for a more solid prediction, such as the installation costs of the bidirectional EVSE and potential additional costs for the bidirectional vehicle.

5. Conclusions

Vehicle-to-home (V2H) use cases and a combination of V2H and vehicle-to-grid (V2G) use cases can be highly beneficial for electric vehicle (EV) users. We provide a detailed description of the modeling and input data, that allows readers to reconstruct the revenues for these use cases. The major findings of our study are:

- Indicated revenues for an average German household are around 310 €/a for bidirectional charging and 210 €/a for smart charging compared to an unmanaged charging EV, increased to 830 €/a and 390 €/a respectively for a maximum revenue estimation.
- Revenues of V2H use cases should consider varying charging and discharging efficiencies in a mixed-integer linear programming, since modeled fixed efficiencies in a linear programming led to 30 % higher revenues and an unrealistic charging/discharging behavior.
- Revenues of bidirectionally chargeable EVs are highly case-sensitive depending on the composition of a household. The dimensioning of the photovoltaic system and the household size are more decisive than the size of the EV.
- Smart additional components in a household, such as heat pumps and stationary battery storages, significantly limit the revenues of a smartly chargeable or bidirectionally chargeable EV.
- V2G arbitrage trading works well with V2H self-consumption optimization because arbitrage trading revenues do not depend on the time of the year, while V2H primarily generates revenues during the summer.
- Combined use of V2H and V2G leads to maximum additional revenues of 220 €/a, but increases operating hours of the EV by more than 5 h/d and equivalent full cycles (EFCs) by as much as 270 EFCs/a.

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CRediT authorship contribution statement

Timo Kern: Conceptualization, Methodology, Investigation, Formal analysis, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Patrick Dossow:** Conceptualization, Writing – review & editing, Investigation. **Elena Morlock:** Methodology, Visualization.

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 A

A key element of the presented model development is the varying efficiency of the charging and discharging process depending on the respective power. In the case of bidirectional charging, losses are neither constant nor directly proportional to the charging or discharging power due to the additional inverter at the charging point. Thus, we describe the derivation of the relevant equations for the MILP in detail. According to [21], power losses of an inverter P_l consist of a constant self-consumption v_{const}, voltage losses at diodes and transistors v_l that are proportional to the output power, and quadratic power-dependent losses caused by ohmic loss resistances v_q. As the efficiency of the inverter η is the ratio of output power P_{out} to input power P_{in}, we formulate the following equation:

$$\eta = \frac{P_{out}}{P_{in}} = \frac{P_{out}}{P_{out} + P_l} = \frac{P_{out}}{P_{out} + v_{const} + v_l \cdot P_{out} + v_q \cdot P_{out}^2} \tag{A.1}$$

We express the efficiency for charging η_c and discharging η_d as a function of the AC-side power. For charging, AC-power before the inverter is converted into DC-power. Thus, P_{in} equals $P_{AC,c}$ and P_{out} equals $P_{DC,c}$. We express $P_{DC,c}$ as a function of $P_{AC,c}$ (Equation A.2) to derive Equation A.4. For discharging, directions are reversed, such that P_{in} equals $P_{DC,d}$ and P_{out} equals $P_{AC,d}$ resulting in Equation A.3 and A.5.

$$P_{DC,c} = \mathrm{P}_{AC,c} - \mathrm{P}_{l,c} = P_{AC,c} - \left(v_{const,c} + v_{l,c} \cdot P_{DC,c} + v_{q,c} \cdot P_{DC,c}^2\right) = \frac{-\left(\mathrm{v}_{l,c} + 1\right) + \sqrt{\left(v_{l,c} + 1\right)^2 - 4 \cdot v_{q,c} \cdot \left(v_{const,c} - P_{AC,c}\right)}}{2 \cdot v_{q,c}} \tag{A.2}$$

$$P_{DC,d} = \mathrm{P}_{AC,d} + \mathrm{P}_{l,d} = P_{AC,d} + \left(v_{const,d} + v_{l,d} \cdot P_{DC,d} + v_{q,d} \cdot P_{DC,d}^2\right) = \frac{-\left(\mathrm{v}_{l,d} - 1\right) + \sqrt{\left(v_{l,d} - 1\right)^2 - 4 \cdot v_{q,d} \cdot \left(v_{const,d} + P_{AC,d}\right)}}{2 \cdot v_{q,d}} \tag{A.3}$$

$$\eta_c = \frac{P_{DC,c}}{P_{AC,c}} = \frac{-\left(\mathrm{v}_{l,c} + 1\right) + \sqrt{\left(v_{l,c} + 1\right)^2 - 4 \cdot v_{q,c} \cdot \left(v_{const,c} - P_{AC,c}\right)}}{2 \cdot v_{q,c} \cdot \mathrm{P}_{AC,c}} \tag{A.4}$$

$$\eta_d = \frac{P_{AC,d}}{P_{DC,d}} = \frac{2 \cdot v_{q,d} \cdot \mathrm{P}_{AC,d}}{-\left(\mathrm{v}_{l,d} - 1\right) + \sqrt{\left(v_{l,d} - 1\right)^2 - 4 \cdot v_{q,d} \cdot \left(v_{const,d} + P_{AC,d}\right)}} \tag{A.5}$$

Based on these equations, we express the inverter power losses of charging and discharging as a function of the respective AC-power (Eqs. (A.6) and (A.7)). These equations constitute the basis for the linearization described for implementation in this work.

$$P_{l,c} = \mathrm{P}_{AC,c} - \mathrm{P}_{DC,c} = P_{AC,c} - \frac{-\left(\mathrm{v}_{l,c} + 1\right) + \sqrt{\left(v_{l,c} + 1\right)^2 - 4 \cdot v_{q,c} \cdot \left(v_{const,c} - P_{AC,c}\right)}}{2 \cdot v_{q,c}} \tag{A.6}$$

$$P_{l,d} = \mathrm{P}_{DC,d} - \mathrm{P}_{AC,d} = \frac{-\left(\mathrm{v}_{l,d} - 1\right) + \sqrt{\left(v_{l,d} - 1\right)^2 - 4 \cdot v_{q,d} \cdot \left(v_{const,d} + P_{AC,d}\right)}}{2 \cdot v_{q,d}} - \mathrm{P}_{AC,d} \tag{A.7}$$

Appendix B

To determine the number of profiles for a representative mapping of a household group, a number of profiles is randomly drawn from a maximum of 150 profiles. This is done 10,000 times per number of profiles. The calculated mean values of these 10,000 draws are compared to the mean value of the 150 profiles and the maximum deviation of these mean values is displayed in Fig. B1. The deviations of the mean revenues are a maximum of 5% for 20 profiles, which is tolerated as a maximum deviation. Therefore, in the following, all studies are based on 20 randomly drawn, discrete household profiles.

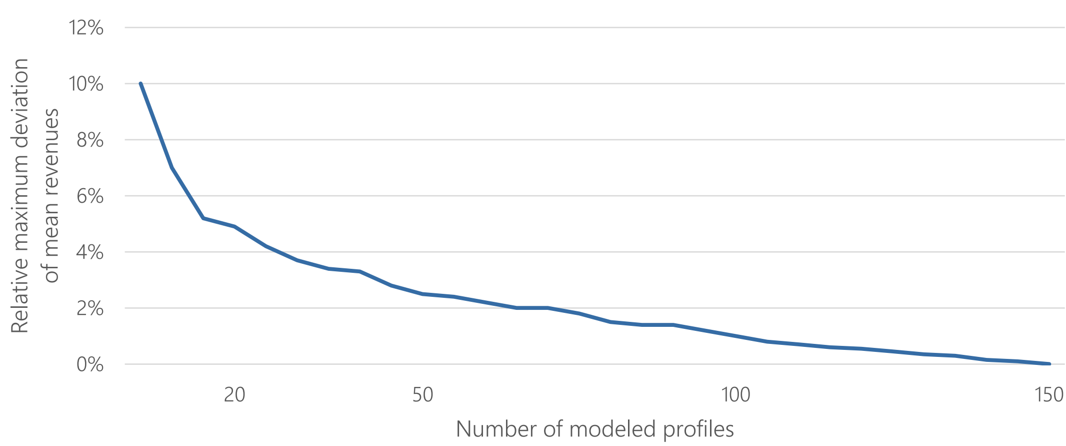

Fig. B1. Relative maximum deviation of mean revenues in dependance on number of modeled profiles.

Appendix C

Fig. C1 shows the power flows at the GCP for a typical summer day. Power in the direction of the GCP is shown as positive. This includes EV discharging, PV generation and grid supply. Power flowing away from the GCP is shown as negative. This includes EV charging, household demand and grid feed-in (electricity supplied to the grid). For LP with fixed efficiency, household demand is balanced by EV discharging at night. For MILP with varying efficiencies, household demand is mainly balanced by grid supply, because the discharging efficiency of the EV is too low for these small power demands.

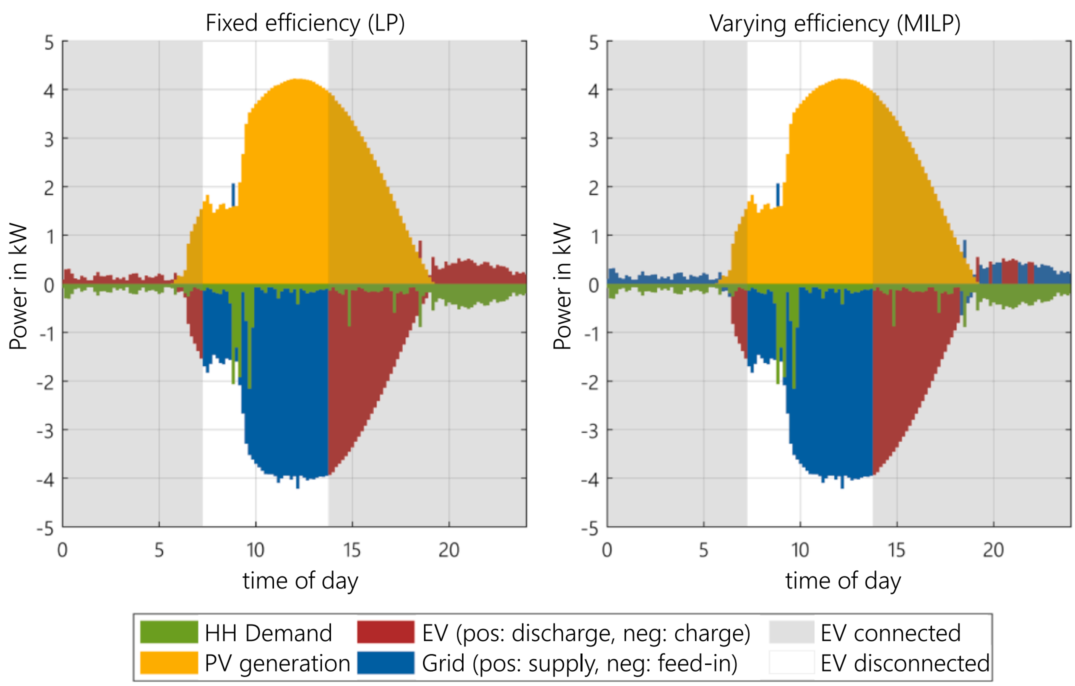

Fig. C1. Power flows at the GCP for a typical summer day.

Appendix D. Supplementary data

Household_data: electrical and thermal consumption, PV generation, and driving profile in 10-minute time resolution for 20 households. Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.118187.

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