Sustainability Science
https://doi.org/10.1007/s11625-023-01432-y

SPECIAL FEATURE: ORIGINAL ARTICLE

Individuals within the Larger System to Support the Energy Transition

To charge or not to charge? Using Prospect Theory to model the tradeoffs of electric vehicle users

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Received: 6 April 2023 / Accepted: 15 October 2023

Abstract
Electric vehicle (EV) users who aim to become flexibility providers face a tradeoff between staying in control of charging and minimizing their electricity costs. The common practice is to charge immediately after plugging in and use more electricity than necessary. Changing this can increase the EV's flexibility potential and reduce electricity costs. Our extended electricity cost optimization model systematically examines how different changes to this practice influence electricity costs. Based on the Prospect Theory and substantiated by empirical data, it captures EV users' tradeoff between relinquishing control and reducing charging costs. Lowering the need to control charging results in disproportionally large savings in electricity costs. This finding incentivizes EV-users to relinquish even more control of charging. We analyzed changes to two charging settings that express the need for control. We found that changing only one setting offsets the other and reduces its positive effect on cost savings. Behavioral aspects, such as rebound effects and inertia that are widely documented in the literature, support this finding and underline the fit of our model extension to capture different charging behaviors. Our findings suggest that service providers should convince EV-users to relinquish control of both settings.

Keywords Smart charging · Electric vehicle · Prospect Theory · Discomfort cost · Direct load control · Prosumer

Introduction

Electric vehicle (EV) users can become flexibility providers if they adapt their charging behavior to electricity market price signals. Charging can be shifted across the time parked, providing the vehicle is charged sufficiently by the time of departure. Instead of EV-users shifting charging manually, providers of smart charging services can facilitate this activity with an optimized charging pattern.

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Smart charging services based on price signals follow a charging pattern that differs from most EV-users. EV-users charge earlier and use more electricity than necessary because of uncertainty (e.g., unpredictable trips), competing interests (e.g., the comfort of not having to plan ahead), and other biases (e.g., range anxiety) (Libertson 2022).

Two parameters of smart charging services allow EV-users to control charging according to their needs. The targeted state of charge (SOC) determines the requested amount of electricity during the charging session. The level of direct load control (DLC) defines the degree of freedom with which the service provider determines the timing of the charging (Gschwendtner et al. 2021; Lehmann et al. 2022). While the target-SOC can be adapted on a daily basis depending on the scheduled trips, the decision about the level of DLC is more fundamental. It is usually made when selecting a smart charging service and is expressed as the right to overrule an optimized charging schedule or immediately charge up to a minimum-SOC (Gschwendtner et al. 2021; Schmalfuß et al. 2015).

Both parameter choices, target-SOC and DLC-level, are based on the EV-users' tradeoff between minimizing

Published online: 25 January 2024

the charging costs and retaining control. How the control parameters correspond to charging cost savings depends on the interplay between charging and price signals. For instance, a request for immediate charging would comply with an optimized charging pattern during periods with high renewable supply.

Successful smart charging services must consider the EV-users' need for control while ensuring certain degrees of freedom for optimizing charging. It is the service provider's challenge to balance these two aspects and gain the EV-user's trust so they relinquish more control (Sloot et al. 2022). This balancing act gives rise to the following research question: "How to balance the need of EV-users to control charging with minimizing their charging costs?".

To answer this question, we tested different control parameters, which reflect the heterogeneous needs for control of EV-users, and analyzed the resulting impact on the charging costs. This was done in three steps: (I) implementing both parameters in the electricity cost optimization to represent the EV-users' needs for control, (II) analyzing the correlation between different control needs and charging costs if both control parameters are adapted consistently (i.e., ranging from a low target-SOC and high DLC to a high target-SOC and low DLC), and (III) analyzing the correlation if only one parameter is adapted. The accepted levels of DLC are based on a vignette survey on smart charging services in Germany ($n = 1116$) (Pelka et al. 2024b). The target-SOCs were taken from a field experiment with German prosumers ($n = 39$) (Gabriel et al. 2022). For step III, this field experiment also provided data about the reduction in the target-SOCs over time due to the service provider's influence. Since no data were available for the change of the other parameters, we combined reversed levels of DLC with the given target-SOCs in a hypothetical scenario.

Answering the above research question bridges the gap between empirical research on acceptable control parameters and energy system models calculating the flexibility potential of cost-optimal charging. We extend the electricity cost optimization of an existing agent-based model (ABM) by adding discomfort costs for relinquishing control over charging. For the latter, we apply the Prospect Theory (PT) of Kahneman and Tversky (1979) to capture EV users' urge to charge immediately and for longer than is needed.

The following literature section (Sect. 2) provides an overview of the control parameters of EV-users and their biases, as well as how charging is implemented in ABM (with and without PT). Section 3 describes how we applied PT to the electricity cost optimization problem in the existing ABM and the underlying data for the model extension. The results section (Sect. 4) presents the changes in the households' charging cost depending on different combinations of the two control parameters. A sensitivity analysis of the other parameters to test the robustness of the results can be found in Appendix E. The results are discussed and conclusions are drawn in Sects. 5 and 6.

Modeling charging behavior

This section describes the literature on charging behavior, including biases and the existing implementations of such behavior in energy system models.

Charging behavior and biases

The literature on EV charging behavior has expanded rapidly over the last few years. The adoption of EVs by new user groups indicates how, where, and when people charge them and may evolve further. After an initial focus on technical charging aspects, empirical insights into behavioral aspects are now also available (Sovacool et al. 2018; Krueger and Cruden 2020). The lack of alternative charging points, such as public charging stations, has resulted in EV-users primarily charging at home. The reported stress due to the lack of charging alternatives has resulted in the widespread practice of always fully charging the battery (Delmonte et al. 2020; Libertson 2022).

Most users charge their EVs when arriving home in the evening (Morrissey et al. 2016). Charging shifts are most acceptable at night (Lehmann et al. 2022). While some research has explored the acceptance of self-executed shifts based on variable tariffs (Delmonte et al. 2020), most studies have examined smart charging services controlled by third parties (García-Villalobos et al. 2014). Constraints set for controlled charging mainly involve technical dimensions of the battery (volume, capacity), the conditions when the EV is plugged in (connection duration, start-SOC), and the requirements for departure (departure time, target-SOC) (Schmalfuß et al. 2015).

Control by third parties requires measures to guarantee that EV-users retain control of their charging and ensure that their mobility needs are covered. A minimum-SOC that needs to be reached after plugging in the EV is often stated as a key prerequisite for joining smart charging services (Bailey and Axsen 2015; Geske and Schumann 2018; Schmalfuß et al. 2015). The largest class in the survey of Bailey and Axsen (2015) (33% of the participants) not only refuses a deviation from this minimum-SOC but is also willing to pay more for a higher SOC. Willingness to pay for additional driving range (35 to 75 USD per mile) and faster charging (425 to 3250 USD per hour) was also detected by Hidrue et al. (2011). The participants of the field experiment by Schmalfuß et al.

(2015) accepted a minimum-SOC of 30 and 45% of the battery volume. Other empirical research has highlighted an overriding option for the charging shifts (Yilmaz et al. 2021) or an immediate charge button as key features for a smart charging service (Gschwendtner et al. 2021).

Common charging practice 1: charging immediately after plugging in to achieve a certain SOC

These features are in partial conflict with the provision of flexibility. This concerns the general participation in smart charging services and choosing more ambitious control parameters if they participate (e.g., a lower minimum or departure SOC) (Axsen et al. 2017; Sovacool et al. 2018). Even though EV-users were significantly motivated to contribute to grid stability and renewable integration, the survey evaluation of Will and Schuller (2016) ranked safeguarding flexible mobility needs as equally important. Having to plan ahead, and plug in their EVs more frequently, as well as being more dependent and less flexible when driving, creates discomfort (Gschwendtner et al. 2021; Schmalfuß et al. 2015). Despite larger battery volumes, range anxiety and unexpected trips remain the main concerns (Noel et al. 2019; Gschwendtner et al. 2021). EV-users argue that they can decide to share control but not the flexibility they provide since this depends on external factors, such as their working patterns, financial resources, and access to charging stations (Libertson 2022).

Common charging practice 2: charging more than needed and maintaining a certain SOC due to uncertainty or comfort

Prospect Theory and its implementations of charging behavior

Charging immediately and more than needed creates a feeling of comfort. Charging less restricts mobility needs and creates discomfort. PT provides a basis for modeling this non-linear relation between charging and the perceived (dis-)comfort. Following a brief introduction to PT, this section describes how charging behavior and other cases of residential load shifting are modeled with and without PT.

PT and its sloped value function by Kahneman and Tversky (1979) express a diminishing marginal value as subject to deviations from a neutral reference point on which the function is centered. Two parameters shape the marginal value. First, the coefficient lambda λ expresses the asymmetric value assignment of negative (losses) and positive deviations (gains) from the reference point. A loss aversion implies that the discomfort created by a negative deviation is stronger (2 to 2.5 times in the literature) than the comfort of a positive deviation. Referring to common charging practice 1, EV-users with stronger loss aversion charge more electricity immediately than those with lower loss aversion.

Second, the risk attitude exponent alpha α determines the slope of the curve. Alpha values close to 0 express a strong change in the perceived value, corresponding to strongly provoked feelings. Referring to common charging practice 2, these more erratic EV-users require higher electricity prices to accept discharging and offset their strong feelings of discomfort. Alpha values close to 1 represent more even-tempered users and express a more linear relation between the perceived value and the reference point change. This is associated with so-called rational behavior and is more frequently applied in the literature (Klein and Deissenroth 2017; Kahneman and Tversky 1979, 2019a, b).

In the literature on households' load-shifting decisions, a popular, simplified approach to considering such values is to include a fixed discomfort cost parameter in the optimization function. This reflects the effort of enforcing load-shifting measures of flexible appliances (Reis et al. 2019; Gonçalves et al. 2019) or deviations from a desirable state (e.g., lower thermal comfort due to shifted heat pumps) (Tiwari and Pindoriya 2021; Nguyen and Le 2014; Javadi et al. 2021). Yan et al. (2021), Esmaili et al. (2018), and Mao et al. (2018) determine this desirable state concerning EV users' SOC. If the SOC is too low for the upcoming trips, the discomfort costs incite sufficient and foresighted charging. The discomfort costs are implemented in a binary way, i.e., they occur only in the case of uncovered trips. We propose to implement a diminishing marginal value of charged electricity since the uncertainty of unexpected trips does not provide an exact threshold for needed and not needed charged electricity.

In residential energy research, PT is often applied to reflect uncertainty in the availability of resources, such as limited charging infrastructure, weather-dependent renewable supply, and price risks in the energy market. The strategies implemented to handle such uncertainties involve purchasing hedging products of service providers (Bruninx 2021; Yao et al. 2020), using resources earlier under less financially attractive conditions (Liu et al. 2014; Hu et al. 2019; Wang and Saad 2015; Mediwaththe and Smith 2018) or placing more conservative pricing bids (Shuai 2022; Barabadi and Yaghmaee 2019). Charging applications of PT represent risk preferences towards fluctuating prices, range anxiety, and limited charging infrastructure. Despite its fit, PT has not been used so far to examine the common practices of charging immediately and maintaining a certain SOC level.

We investigate this research gap based on a mixture of recently collected empirical data on charging behavior and well-established PT parameters. For instance, Klein and Deissenroth (2017) found that German household PV investments are driven by total revenue and relative change due to regulatory uncertainty.

Materials and methods

This section describes the experimental design, its methods and materials. The latter comprises the existing ABM model with its electricity cost-minimization (Sect. 3.2.1) and our discomfort cost extension based on PT (Sect. 3.2.2), as well as the underlying data (Sect. 3.3).

Experiment design and scenarios

We examine the research question "How to balance the need of EV-users to control charging with minimizing their charging costs?" in three steps: (I) implementing both parameters in the electricity cost optimization to represent the EV-users' control needs, (II) analyzing the correlation between different control needs and charging costs if both control parameters are adapted consistently, and (III) analyzing the correlation if only one parameter is adapted.

To validate whether the resulting charging pattern of the discomfort cost extension imitates the common charging practices identified in the literature (Sect. 2.1, Step I), we compared one scenario without (*reference* scenario, see Table 1) and one with the discomfort cost extension (*need for control* scenario). In Step II, we compare the differences between the household groups in the *need for control* scenario to examine the impact of varying needs to retain control on the charging costs.

For Step III, we adapt one control parameter of the *need for control* scenario to examine its impact on the charging costs. One control parameter, the target-SOC, was adapted based on empirical app data from a field experiment (*lowered target-SOC* scenario) (Pelka et al. 2024a). Since the data for the other control parameter, DLC-level, do not involve changes over time, we analyzed its impact in an explorative manner by reversely exchanging its values among the groups (*reverse* scenario). For instance, a high DLC-level is (counterintuitively) assigned to households with high control needs.

In each step, the main outcome variable, charging costs per household, is compared between two scenarios or between household groups that differ with regard to their need to control charging. As another outcome variable, we analyze the charging pattern of their EVs to explain cost differences. The outcome variables are calculated using the ABM described in Sect. 3.2. In the ABM, the electricity cost-minimization function is extended by the discomfort cost of having a low SOC. In real life, households control this discomfort level by setting a target-SOC and DLC-level in their smart charging app. We capture their different needs to retain control by integrating both settings as control parameters in the discomfort cost extension.

Model

The modeling is based on an ABM developed by Kühnbach et al. (2022). It consists of a cost-minimization for prosuming agents that are embedded in a simulated German electricity market. To answer our research question, the cost-minimization was extended by the discomfort cost of having a low SOC based on the assumption that EV-users are only willing to pay for the electricity charged if the discomfort of having a low SOC is higher than the electricity costs. The discomfort costs diminish with a higher SOC. Thereby, the two common charging practices from Sect. 2.1, charging immediately and more than needed, are captured in the model. We apply PT to express the diminishing marginal discomfort costs.

Before describing the discomfort cost extension, we outline the relevant parts of the existing cost-minimization model—in particular, the cost-minimization function and the constraints for charging the EV. Further information on the model can be found in Kühnbach et al. (2022). An overview of the variables and parameters is given in Table 4.

Table 1 Scenario overview

Scenario name	Elements of the cost-minimization function		Control parameters differentiated for the groups	
	Electricity cost	Discomfort cost	Target-SOC	DLC-level
1) Reference (electricity cost only)	Applied	Not applied	–	–
2) Need for control (electricity and discomfort costs)	Applied	Applied	Initial target-SOC	*DLC-level*
3.a) Lowered target-SOC, moderate (based on need for control)	Applied	Applied	Lowered target-SOC, moderate	*DLC-level*
3.b) Lowered target-SOC, moderate (based on need for control)	Applied	Applied	Lowered target-SOC, extreme	*DLC-level*
4) Reverse (based on need for need for control)	Applied	Applied	Initial target-SOC	*DLC-level* reverse

Existing electricity cost-minimization function

For each prosumer k, a mixed-integer linear optimization (MILP) is set up to optimize their electricity consumption given the price signal from the electricity market ($p_t^{\text{buying}}, p_t^{\text{selling}}$) and their technical constraints. The objective function, as shown in Eq. (1), minimizes the electricity cost incurred over the optimization period of 1 day. This includes the cost of purchasing electricity and the revenue of selling electricity to the market:

$$\min C_{\text{tot}}^k = \sum_{t=h_{\min}}^{t=h_{\max}} \left(P_t^{k,\text{grid}\to\text{EV}} + P_t^{k,\text{grid}\to\text{EVflex}} + P_t^{k,grid\to hh} + P_t^{k,\text{grid}\to\text{bat}} \right) \cdot p_t^{\text{buying}} - \left(P_t^{k,\text{EVflex}\to\text{grid}} + P_t^{k,\text{pv}\to\text{grid}} + P_t^{k,\text{bat}\to\text{grid}} \right) \cdot p_t^{\text{selling}} \tag{1}$$

The EV-battery is divided into a flexible and an inflexible fraction to meet the constraints of covering the user's mobility demand and enabling demand response. The inflexible fraction of the EV-battery, called EV, is operated to cover the EV-user's inflexible hourly charging profile $P_{EV_{total},t}^k$, which ensures a sufficient SOC on time to cover the upcoming trips (see Eq. (2)):

$$P_{\text{EV}_{\text{total}},t}^k = P_t^{k,\text{grid}\to\text{EV}} + P_t^{k,\text{pv}\to\text{EV}} + P_t^{k,\text{bat}\to\text{EV}} + P_t^{k\text{EVflex}\to\text{EV}} \tag{2}$$

The flexible fraction, called EV-flex, is modeled as a storage unit. This can shift charging to periods of low prices of p_t^{buying} and discharging to periods of high prices of p_t^{selling}. The electricity stored in EV-flex can be used to cover the inflexible charging profile and household energy demand or sold to the market. The stored electricity in time t equals the SOC of the previous hour SOC_{t-1}^{k} plus all power inflows and minus all power outflows (see Eq. (3)):

$$\text{SOC}_t^k = \text{SOC}_{t-1}^k + (P_t^{k,\text{grid}\to\text{EVflex}} + P_t^{k,\text{pv}\to\text{EVflex}} + P_t^{k,\text{bat}\to\text{EVflex}}) \cdot \vartheta_{\text{EVflex,in}} - \left(P_t^{k,\text{EVflex}\to\text{grid}} + P_t^{k,\text{EVflex}\to hh} + P_t^{k,\text{EVflex}\to\text{bat}} \right) \cdot \vartheta_{\text{EVflex,out}} - P_t^{k,\text{EVflex}\to\text{EV}} - P_0^{k,\text{unexpected}} \tag{3}$$

In addition to planned trips expressed by the inflexible charging profile, we implement additional unexpected ones at the level of 20% of the initial SOC. This amount of electricity $P_0^{k,\text{unexpected}}$ is deducted from SOC_t^k in the first hour of the day.

The storage capacity of EV-flex is constrained by Eq. (4):

$$\text{SFL}_{\min}^{k,\text{EVflex}} \le \text{SOC}_t^k \le \text{SFL}_{\max}^{k,\text{EVflex}} \tag{4}$$

The usage of both combined battery fractions is constrained by the maximum charging power $P^{k,\text{evMax}}$ and discharging power as well as the availability of the EV at the home location in hour t ($vsh_{\text{conn},t}^k$), as depicted in Eqs. (5) and (6):

$$P_t^{k,\text{grid}\to\text{EV}} + P_t^{k,\text{grid}\to\text{EVflex}} + P_t^{k,\text{pv}\to\text{EV}} + P_t^{k,\text{pv}\to\text{EVflex}} + P_t^{k,\text{bat}\to\text{EV}} + P_t^{k,\text{bat}\to\text{EVflex}} \le P^{k,\text{evMax}} \cdot vsh_{t,\text{conn}}^k \tag{5}$$

$$P_t^{k,\text{EVflex}\to\text{grid}} + P_t^{k,\text{EVflex}\to hh} + P_t^{k,\text{EVflex}\to\text{bat}} \le P^{k,\text{evMax}} \cdot vsh_{t,\text{conn}}^k \tag{6}$$

50% of the EV-battery capacity is used as a flexible fraction. The target-SOC in the following model extension expresses whether EV-users keep a further share of the flexible fraction permanently charged (e.g., for unexpected trips).

Discomfort cost extension of the cost-minimization function

The marginal value of the charged electricity depends on its contribution to meeting the target-SOC. It diminishes with an increasing SOC. This means that charging an empty EV-battery creates a higher added value than charging an almost full EV-battery. The sloped value function of PT in Kahneman and Tversky (1979) expresses this diminishing marginal value. In our case, the value function as subject to the SOC is centered on the target-SOC ($\text{SOC}_{\text{Ref}}^k$) of the EV-user k as the neutral reference point. If SOC_t^k is lower than $\text{SOC}_{\text{Ref}}^k$, the EV-user perceives discomfort costs at the level of the SOC delta, captured by the discomfort notion. If SOC_t^k is higher than $\text{SOC}_{\text{Ref}}^k$, the EV-user has an increased comfort level, captured by the comfort notion. We extend the cost-minimization function with these two notions in Eq. (7):

$$\min C_{\text{tot}}^k = \sum_{t=h_{\min}}^{t=h_{\max}} [\left(P_t^{k,\text{grid}\to\text{EV}} + P_t^{k,\text{grid}\to\text{EVflex}} + P_t^{k,\text{grid}\to hh} + P_t^{k,\text{grid}\to\text{bat}} \right) \cdot p_t^{\text{buying}} - \left(P_t^{k,\text{EVflex}\to\text{grid}} + P_t^{k,\text{pv}\to\text{grid}} + P_t^{k,\text{bat}\to\text{grid}} \right) \cdot p_t^{\text{selling}}] \cdot (1-\theta^k) - \theta^k \cdot mV_t^k \cdot \begin{cases} (\text{SOC}_t^k - \text{SOC}_{\text{Ref}}^k)^\alpha \cdot vsh_{\text{conn}_t^k} & if\ \text{SOC}_t^k \ge \text{SOC}_{\text{Ref}}^k \\ -\lambda \cdot (\text{SOC}_{\text{Ref}}^k - \text{SOC}_t^k)^\alpha \cdot vsh_{\text{conn}_t^k} & if\ \text{SOC}_t^k < \text{SOC}_{\text{Ref}}^k \end{cases}, \tag{7}$$

where θ^k is the weight assigned to the discomfort cost in relation to the electricity cost for EV-user k. In other words, how willing the EV-user is to compromise on her control need for the benefit of more electricity cost savings. The weight parameter expresses the level of accepted DLC in a reverse manner. A higher weight on the discomfort cost expresses a lower level of accepted DLC (i.e., lower willingness to relinquish control). mV_t^k describes the monetary value, which is assigned to the delta between SOC_t^k and $\text{SOC}_{\text{Ref}}^k$. The parameterization is presented in Sect. 3.3.

The non-linear relation between the charged electricity and discomfort costs is expressed as a mixed-integer non-linear problem (MINLP), consisting of two if-conditions for the comfort and discomfort notions. We decompose the MINLP into optimization constraints based on the BigM method (Cococcioni and Fiaschi 2021); see Appendix B. The large value of BigM combined with a slack variable δ_t expresses the two if-conditions (i.e., whether SOC_t^k is equal to, larger or smaller than $\mathrm{SOC}_{\mathrm{Ref}}^k$, see constraints (B.2) and (B.3)) and the impact of this SOC delta on the discomfort costs (called $\mathrm{utility}_t^k$, see constraints (B.4)–(B.7)).

The relation between the two cost elements in the combined cost-minimization function determines the charging and discharging of the EV-battery. We illustrate this mechanism based on two stylized examples in Appendix C.

Assumptions and data

This section describes how we parameterize the extended cost-minimization using empirical data. Four household groups are distinguished by varying the two control parameters for our comparative analysis, the target-SOC and DLC-level, which capture a household's need to retain control of charging (Sect. 3.3.3). The other parameters of the households' technical equipment (Sect. 3.3.1) and the shape of the diminishing marginal value (Sect. 3.3.2) are the same for all four groups to ensure the comparability of the results.

We base the evaluation on a scenario of the German electricity market in 2030, which was developed and validated by the previous work with this model (Kühnbach et al. 2022). We adopted the individual profiles used here for the inflexible household demand and the configuration of the prosumer's PV and battery systems. From the original 480 prosuming agents implemented by Kühnbach et al. (2022), we selected 80 with EV, PV, and stationary batteries as the target group of this analysis. We applied the same profiles for the inflexible EV and household demand across all groups for comparability. According to the empirical data on control needs in Sect. 3.3.3, the smallest group comprises 9% of households. Therefore, we created a set of seven different profile combinations, which we applied several times for larger groups.

Parameters of the households' technical equipment

The assumptions concerning technical charging aspects were taken from the study by Kühnbach et al. (2022). It is assumed that EVs are only charged at their home location (Scherrer et al. 2019). The average charging power at residential locations is assumed to be 6.2 kW (Gnann and Speth 2021). Assuming an EV-battery of 62 kWh, as in Kühnbach et al. (2022), we assigned half of the maximum storage level to the flexible fraction of the EV-battery (31 kWh). The installed PV capacity of each prosumer is set to 8.1 kWp. A battery of 7.8 kWh and a charging power of 7.8 kWh are assumed for the stationary storage.

Parameters influencing the diminishing marginal value

Parameters influencing the diminishing marginal value are alpha and lambda, as well as the monetary value of being able to drive. Alpha and lambda are set to well-established values (see Table 2) proposed by Kahneman and Tversky (1979) and confirmed by other scholars, such as Klein and Deissenroth (2017).

Since empirical evidence is missing for the monetary value, we randomly assigned electricity market prices based on the assumption that EV-users are willing to pay these prices for charging and that they reflect the monetary value of being able to drive. The randomization expresses the time-dependent value of being able to drive, ranging from urgent (e.g., need to go to the hospital) to flexible trips (e.g., grocery shopping).

Table 2 Behavioral parameters for calculating the discomfort cost

Group (sorted from EV-users with the lowest need for need for control to one with the highest)	Group size	Parameters influencing the diminishing marginal value (identical for the groups)			Parameters expressing the need to retain control of charging (differentiated for the groups)				
		Alpha	Lambda	Monetary value	DLC-level	Initial target-SOC	Lowered target-SOC, moderate	Lowered target-SOC, extreme	DLC-level reverse
	#	–	–	[EUR/kWh]	–	[kWh]	[kWh]	[kWh]	–
G1	7	0.88	2.25	Random assignment based on electricity prices	0.211	9.3	7.7	0	0.844
G2	27	0.88	2.25		0.422	17.2	14.2	0	0.633
G3	39	0.88	2.25		0.633	26.7	22.1	1.9	0.422
G4	7	0.88	2.25		0.844	31	25.7	18.6	0.211

Parameters expressing the need to retain control of charging

We varied the parameters expressing the need to retain control of charging among the four household groups. We used the empirical data collected from German EV-users in a field experiment ($n = 111$) of the Horizon 2020 project NUDGE (H2020 NUDGE 2023) for the target-SOC and data from a vignette survey ($n = 1.116$) of a German research project for the DLC-level. We applied the data set to the larger sample, the vignette survey, for the assignment of the 80 model agents into the four household groups.

The vignette survey asked 1116 current or prospective owners of flexible technologies (in particular, EVs, heat pumps, or stationary batteries) to rate the likelihood of using four services facilitating the optimization of their flexible technologies on a 5-point Likert scale. We conducted a linear regression based on the likelihood of using a service that forces them to relinquish control with the need to retain control as a regressor. The β-coefficient of the need to stay in control ($\beta = 0.221$) combined with the 5-point Likert scale for usage likelihood (excluding the middle response) creates the DLC-level for the four groups (see Table 2).

For the assignment to the four household groups, two smaller groups (9% respectively) represented the extreme need for control and extreme indifference to control based on the sample that responded "very unlikely to use" or "very likely to use". The two more moderate household groups correspond to the 19% who were unlikely to use it and the 35% who were likely to use it (also excluding the middle response). Further information on the vignette survey is provided in Pelka et al. (2024b).

In the Horizon 2020 project NUDGE field experiment, 39 out of the 111 prosuming participants own a controllable EV and use a smart charging app that automatically optimizes their charging based on the target-SOC and other parameters. Information on the charging optimization is displayed in the app to encourage users to set a lower target-SOC (Gabriel et al. 2022). Other studies based on this field experiment have shown that such information led to a significant reduction in electricity costs (Pelka et al. 2024a; Burkhardt et al. 2022).

However, only a small sub-group of eight participants frequently interacted with the app and adapted their target-SOC. We focused on this group to extract the initial target-SOC, its average, and extreme reduction. The quantiles of the minimum target-SOCs were applied as an extreme case. For the moderate case, we deducted the standard deviation of 17% of the values from the initial target-SOCs. Appendix D explains how the target-SOCs of the field experiment were transformed into model parameters.

Matching the resulting parameters in Table 2 with the scenarios in Sect. 3.1, we combined the DLC-level and initial target-SOC in the *need for control* scenario. For the scenarios testing the adaptation of one parameter, we replaced the initial SOC with the lowered target-SOC or the DLC-level with its reversed version.

Changes in the households' charging costs due to their charging practices

The results section is structured by the three steps taken to answer the research question "How to balance the need of EV-users to control charging with minimizing their charging costs?". Section 4.1 compares the *reference* (assuming EV-users optimize based only on electricity cost) with the *need for control* scenario (also including discomfort costs). It shows whether including discomfort costs captures the common charging practices of charging immediately and for longer than needed (Step I). Section 4.2 compares the four household groups of the *need for control* scenario and analyzes how their varying need to retain control influences their charging cost (Step II). The two control parameters are set consistently to represent the group's high or low need for control. Subsequently, we change one control parameter of the *control need* scenario to explore its individual impact (Step III). Section 4.3 shows how changes to the target-SOC influence charging costs, and Sect. 4.4 shows how changes to the DLC-level influence these costs.

For all steps, we first report the interplay between price signals, control needs and charging patterns. Second, we examine the resulting charging costs and pay particular attention to the weighted average prices during charging and discharging and the average SOC.

Capturing common charging practices in the charging optimization control parameter

The *reference* scenario demonstrates an optimized charging pattern based purely on electricity costs: The early morning hours with low prices are used to charge the EV-battery with electricity from the market (Fig. 1). As the price peaks for the first time in the day, electricity is sold to the market. During the daytime, self-consumption from the PV system is maximized, and electricity from the grid is used to fill the remaining EV and stationary battery capacity in expectation of a high-price period in the evening. In the evening, both the stationary battery and the EV-battery cover the electricity demand as far as possible, avoiding purchasing expensive electricity from the market.

In contrast, the *need for control* scenario shows how the discomfort cost extension distorts the optimized charging pattern and captures the common charging practice: EV-users

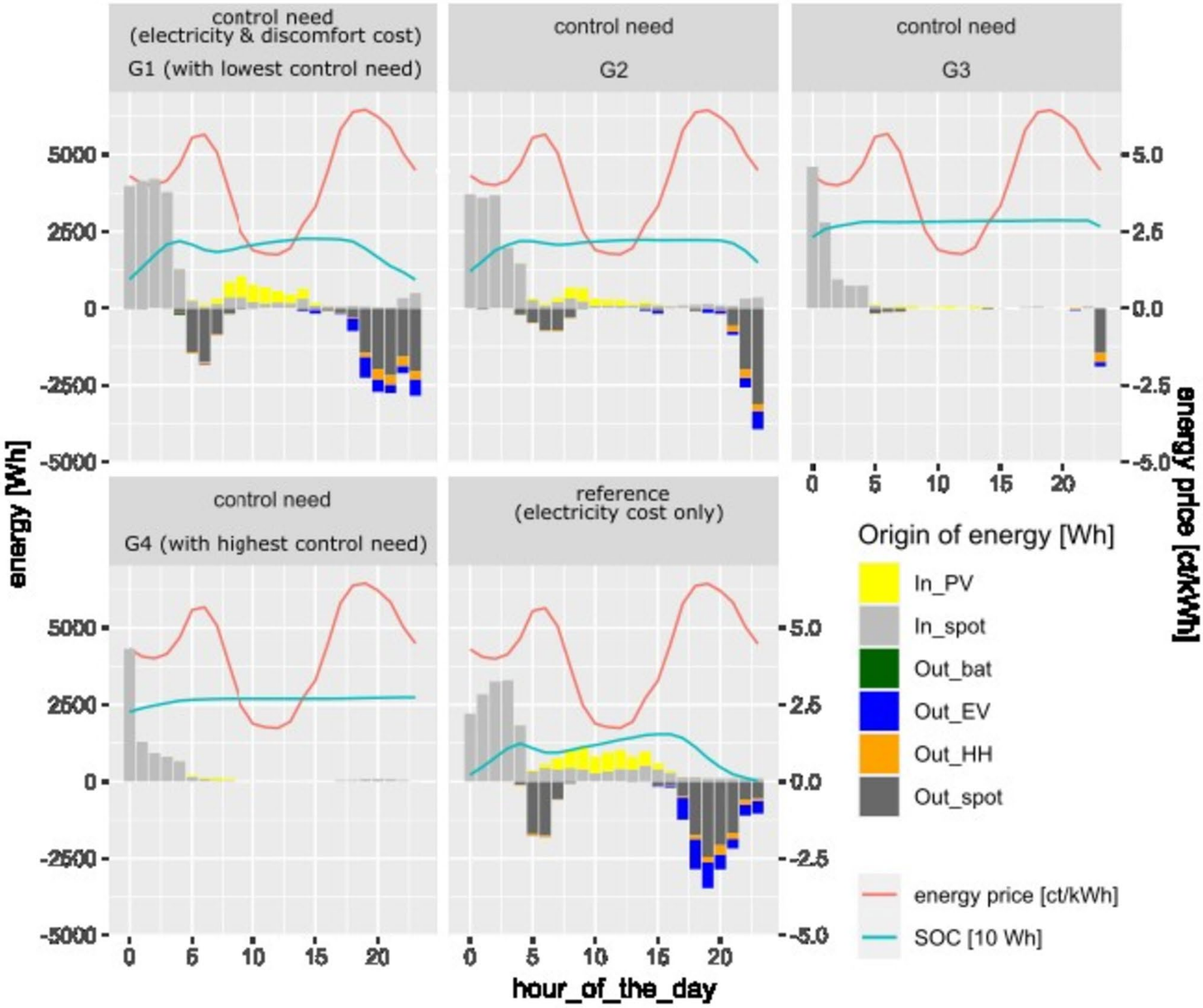

Fig. 1 Average in- and outflows of the EV-battery over 24 h for scenario *control need*, distinguished by sources (In_[…] = charged electricity from […], Out_[…] = discharged electricity provided to […], spot = electricity spot market, bat = stationary battery, EV = inflexible charging demand, HH = inflexible household demand), the SOC values in Wh are divided by 10 to fit the primary *x*-axis

charge earlier (common charging practice 1), realize a higher SOC, and maintain this during the day (common charging practice 2) (Fig. 1).

Effects of different needs to control the charging

Comparing the household groups with different needs for control in the *need for control* scenario reveals how an increased need restricts their response to electricity price signals and the local electricity demand. Conversely, a lower need for control offers households financial benefits since this leads to disproportionally large cost savings. We elaborate on these findings, referring to the four household groups, which range from group 1 (G1) with the lowest control needs (i.e., low target-SOC and high DLC) to group 4 (G4) with the highest control needs (i.e., high target-SOC and low DLC).

EV-users' price responsiveness decreases with an increasing need to control charging. EV-users in G1 and G2 with lower control needs charge larger amounts of electricity during low-price periods and discharge more during high-price periods than G3 and G4, which have higher control needs (Fig. 1). The lack of price responsiveness in G3 and G4 is especially apparent for charging during the first hours of the day and for discharging during the last hours of the day. These groups charge during the high-price periods of the first hours to immediately reduce the discomfort of having a low SOC. Because of their already

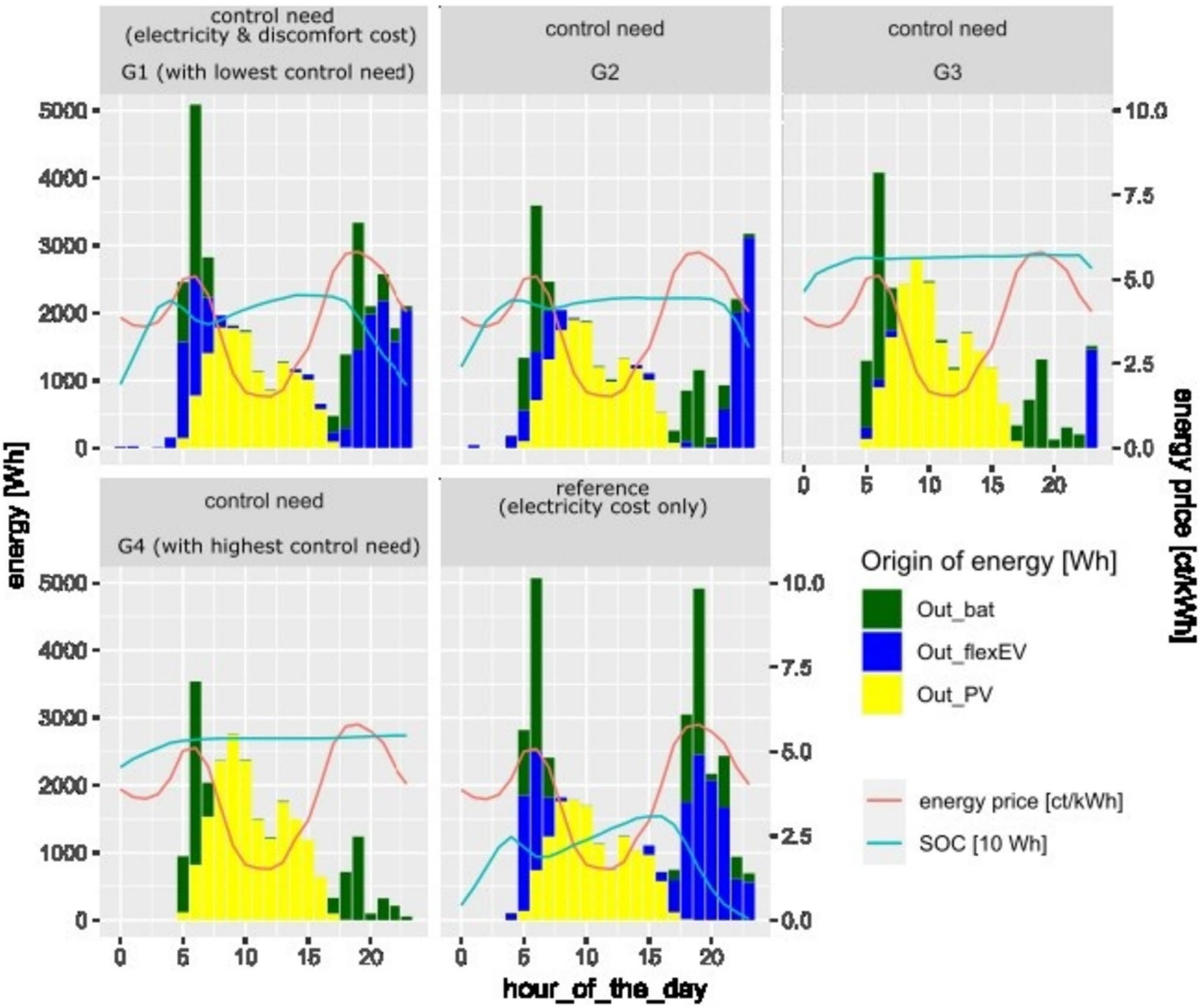

Fig. 2 Average market supply within 24 h, distinguished by sources (bat = stationary battery, EV-flex = EV-battery, PV = PV system), the SOC values in Wh are divided by 10 to fit the primary *x*-axis

full EV-battery, they sell their self-generated electricity to the market during the midday price drop instead of consuming it themselves (Fig. 2). During the evening price peak, they opt for increased comfort and decide to maintain the high SOC level up to the last hours of the day instead of selling the stored electricity.

For G1 and G2, they balance the discomfort of a low SOC level (such as G3 and G4) with realizing cost savings (such as the cost-optimal *reference* scenario). In particular, they decided to spread the charging over the first hours of the day and the discharging over the last hours of the day.

Restricting the usage of the EV-battery as a flexibility source results in a more frequent usage of the stationary battery to cover the inflexible demand during price peaks. For instance, while the stationary battery only covers 4% of the inflexible EV demand in the cost-optimal *reference* scenario, it covers 26–27% for G3 and G4. Figure 2 shows the cost-optimal usage of the stationary battery in the *reference* scenario. For G3 and G4, the simultaneity of inflexible demand and price peaks does not allow the stationary battery to sell its electricity during the price peaks.

As illustrated in Fig. 3, the less price-responsive charging pattern of the groups with a higher need to retain control leads to increased charging costs. The average monthly charging cost between the groups ranges between 0.45 EUR for G1 and 16.03 EUR for G4. Comparing the changes in the control parameters to changes in the charging costs reveals a disproportional development. EV-users can save on average 1.5 EUR per lowered target-SOC by switching from the

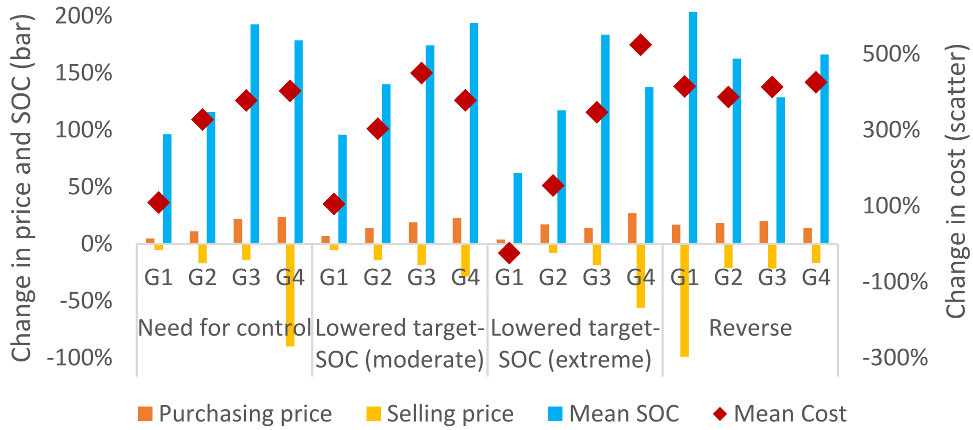

Fig. 3 Changes in charging costs and underlying factors for all scenarios compared to the reference scenario (electricity cost only)

control parameters of G2 to those of G1. In contrast, they only save 0.3 EUR per lowered target-SOC when switching from G4 to G3 or G3 to G2.

We can identify how the different groups realize cost savings in their weighted average prices and average SOC. Compared to G3 and G4, G1 and G2, with lower control needs, are able to exploit the price spreads and realize additional revenues when charging and discharging the EV-battery. This practice results in an average SOC above their target-SOC. In contrast, the discomfort-driven charging of G3 and G4 during the morning price peak leads to high purchasing prices (up to 43.84 EUR/MWh) and a radical drop in the selling price (up to 5.63 EUR/MWh).

Overall, more relaxed control parameters result in greater charging cost savings. To what extent the low costs of G1 are due to its low target-SOC or its high DLC-level is explored in Sect. 4.4.

Effects of reducing the target-SOC

The following analysis tests the impact of reducing the target-SOC (compared to the *need for control* scenario) while the other control parameter, the DLC-level, remains the same. The results indicate that the highest cost savings result from a lower target-SOC combined with a high DLC-level. If a lower target-SOC is combined with a low DLC-level, the EV-user creates additional comfort (and electricity costs) by charging more than targeted. We first elaborate on the savings in the case of an extreme target-SOC reduction (i.e., a complete reduction to 0 kWh for G1 and G2, a 93% reduction for G3 and 40% for G4), followed by a moderate target-SOC reduction (i.e., 17% per group).

G1's higher DLC-level leads to higher relative cost savings than G2. With a reduction of 7.05 EUR on their average monthly charging costs, G1 has the second-highest absolute and the highest relative savings per reduced target-SOC (i.e., 0.76 EUR /target-SOC). G2, which displays the largest target-SOC reduction (17.2 kWh), has the highest absolute cost savings, a reduction of 9.22 EUR, and the second-highest relative savings (i.e., 0.54 EUR/target-SOC). The lower target-SOC allows both groups to charge more during the later morning hours with falling prices and discharge more during the evening price peak. Due to its higher DLC-level, G1 can align the discharging with the highest prices. In contrast, G2 delays discharging for a few hours to minimize the remaining time with a lower SOC (see Fig. 4).

Remarkably, G4's reduction of 12.4 kWh leads to an average monthly cost increase of 6.45 EUR (see Fig. 3). Since G4 charges more electricity during the first hours of the day (see Fig. 4) and reaches the target-SOC faster, it creates additional comfort by charging the EV-battery more than targeted. Lowering the target-SOC combined with a low DLC-level leads to (uncontrolled) surplus charging and increases costs.

The slightly increased price responsiveness due to the moderate target-SOC reduction leads to minor cost savings (see Fig. 3). The largest difference compared to the *need for control* scenario is for G3, whose monthly charging cost even increases by 3.82 EUR. G3's low DLC-level only allows the EV-battery to discharge at the end of the day. Although this charging strategy successfully decreases discomfort costs over the last hours, it requires additionally charged electricity at the beginning of the following day (see Fig. 5). Optimization periods longer than 1 day are expected to reduce the particularity of discharged electricity at the end of the optimization period.

Effects of increasing the levels of direct load control

The previous section demonstrated that additional degrees of freedom for one control parameter, the target-SOC, result in the greatest cost savings if they align with a similar degree of freedom in the other parameters, the DLC-level. We used a hypothetical scenario that reversed the values of both parameters to assess how varying both control parameters impacts

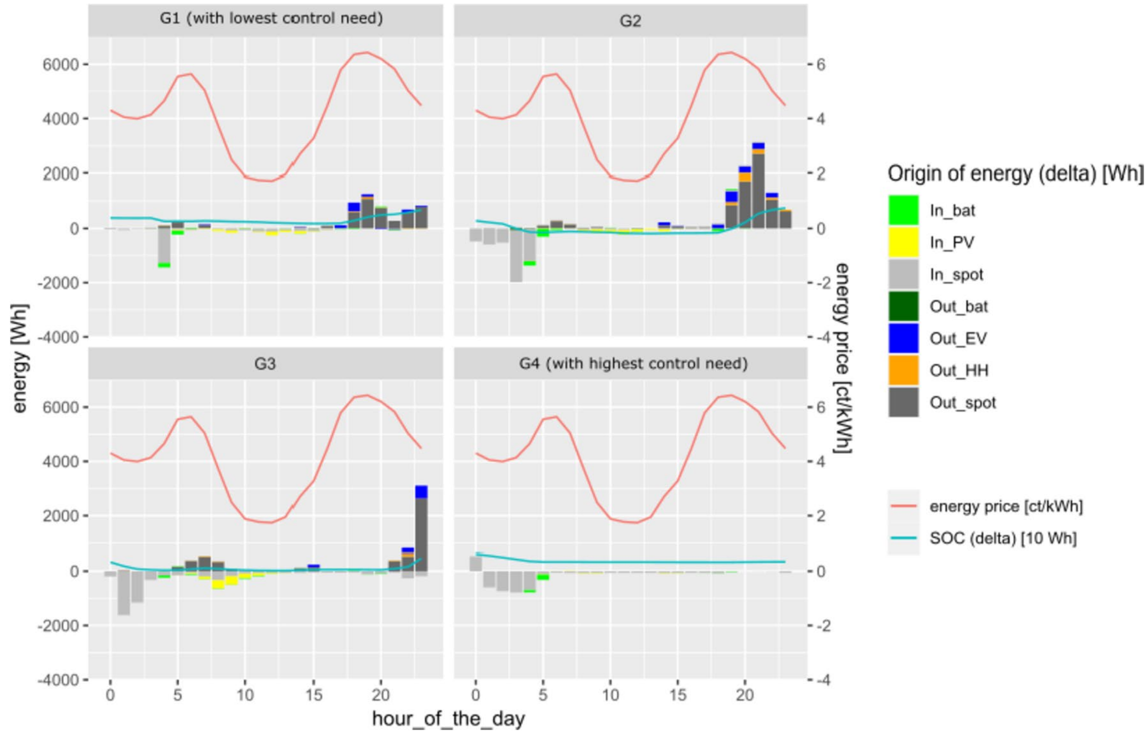

Fig. 4 Delta calculation between scenarios lowered target-SOC (extreme) and need for control for the in- and outflows of the flexible EV-battery from different sources. Negative values correspond to higher values in need for control than in the lowered target-SOC, and vice versa. The SOC values in Wh are divided by 10 to fit the primary x-axis

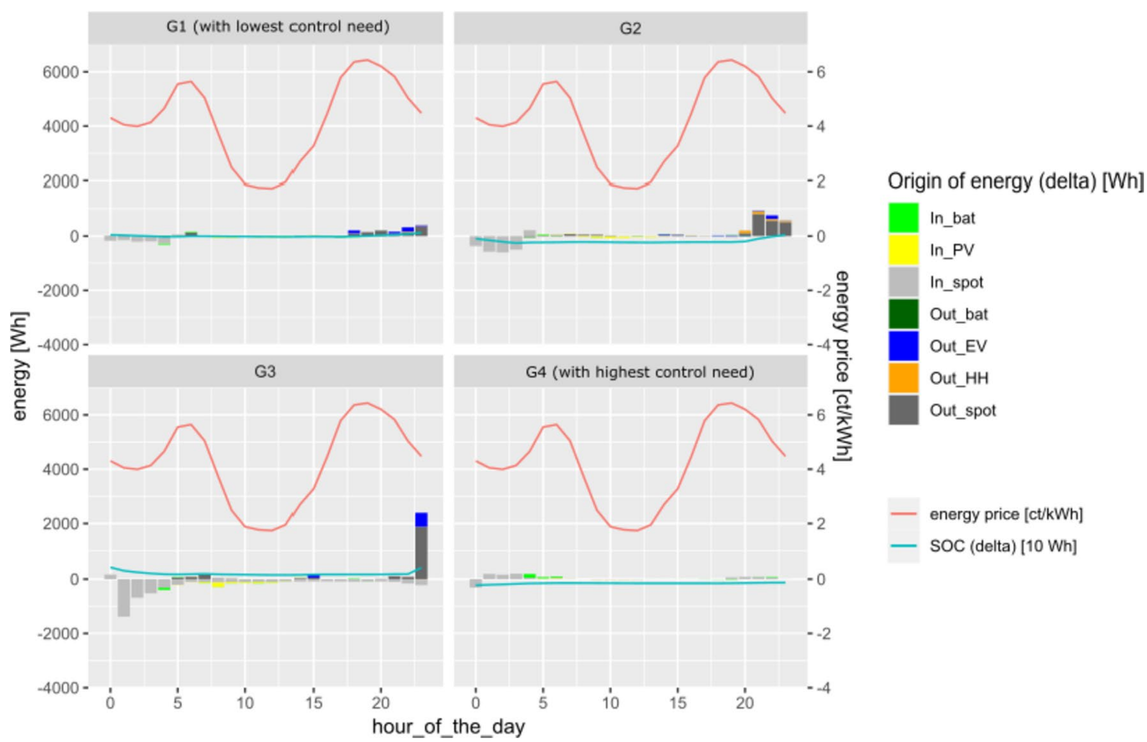

Fig. 5 Delta calculation between scenarios lowered target-SOC (moderate) and need for control for the in- and outflows of the flexible EV-battery from different sources. Negative values correspond to higher values in need for control than in the lowered target-SOC scenario, and vice versa. The SOC values in Wh are divided by 10 to fit the primary x-axis

Table 3 Comparison of the extreme values of each control parameter w.r.t. the mean monthly costs, the mean SOC, the weighted average purchasing and selling price

Mean monthly charging cost [EUR]		Target-SOC analysis			Mean SOC [kWh]		Target-SOC analysis		
		9.3 kWh	31 kWh	Diff			9.3 kWh	31 kWh	Diff
DLC-level analysis	0.211	0.45	17.26	16.80	DLC-level analysis	0.211	18.66	25.31	6.66
	0.844	16.65	16.03	-0.63		0.844	28.88	26.51	-2.37
	Diff	16.20	-1.23			Diff	10.22	1.19	
Selling price for EV [EUR/MWh]		**Target-SOC analysis**			**Purchas. price for EV [EUR/MWh]**		**Target-SOC analysis**		
		9.3 kWh	31 kWh	Diff			9.3 kWh	31 kWh	Diff
DLC-level analysis	0.211	53.43	47.11	-6.32	DLC-level analysis	0.211	37.18	40.42	3.24
	0.844	0.45	5.63	5.19		0.844	41.53	43.84	2.31
	Diff	-52.98	-41.48			Diff	4.35	3.43	

Reading guidance for the tables

Indicator [metric]		Target-SOC analysis		
		Relaxed (9.3 kWh)	Restrictive (31 kWh)	Diff
DLC-level analysis	Relaxed (0.211)	Control need G1	Rev. G4	Diff. for relaxed DLC
	Restrictive (0.844)	Rev. G1	Control need G4	Diff. for restrictive DLC
	Diff	Diff. for relaxed target-SOC	Diff. for restrictive target-SOC	

the charging cost. We examine the difference in the charging costs if one or both parameters are switched from a restrictive value (target-SOC of 31 kWh and DLC of 0.844) to a relaxed one (target-SOC of 9.3 kWh and/or DLC of 0.211) (Table 3).

The switch from a restrictive to a relaxed value results in similar charging cost savings for both control parameters. In fact, if one parameter is already defined in a relaxed manner, the switch of the other parameters creates higher savings (16.80 EUR for the target-SOC-switch or 16.20 EUR for the DLC-switch) than in the case of an already restrictively defined parameter (−0.63 EUR and 1.23 EUR).

How the two parameters affect the charging costs becomes apparent when looking at the weighted average prices and the average SOC. A relaxed DLC-level allows the service provider to select a more cost-optimal time to sell. In particular, the relaxed DLC-level of 0.211 leads to higher, more favorable selling prices (53.43 and 47.1 EUR/MWh) compared to the other combinations with a restrictive DLC-level of 0.822 (0.45 and 5.63 EUR/MWh). On the other side, a low target-SOC allows the EV-battery to be charged less fully, especially not during high-price periods, and results in lower purchasing prices (37.18 and 41.53 EUR/MWh) than the other two combinations with a high target-SOC (40.42 and 43.84 EUR/MWh, respectively).

Remarkably, combining both restrictive parameters leads to lower charging costs (16.03 EUR) than a combination with only one restrictive setting (16.80 EUR and 16.20 EUR). If only one control parameter is adapted, the other compensates for the EV-user's need for control, leading to higher charging costs. The implication is that service providers should aim for consistently chosen control parameters.

An easy-to-reach target-SOC combined with a restrictive DLC-level act as a strong incentive to charge beyond this level for EV-users, since the restrictive DLC-level does not permit the service provider to enforce compliance with the target-SOC. This additionally charged electricity is apparent in the high average SOC of 28.88 kWh.

Conversely, a more relaxed DLC-level (i.e., lower weight of 0.211) creates fewer incentives to charge the EV-battery. As a result, it takes longer to cover the SOC delta. This inertia has a particularly strong effect when combined with a restrictive, high target-SOC. EV-users lack the incentive to meet the target-SOC and miss opportunities to optimize their charging costs by selling electricity.

In a sensitivity analysis in Appendix E, we illustrate the effect of varying other parameters from Sect. 3.3.2. Lowering the risk attitude exponent alpha α has the strongest impact on charging costs. In this case, the marginal discomfort cost hardly decreases at the start of the optimization with an empty EV-battery and creates no incentive to charge electricity. We discuss the impact of the parameters affecting the diminishing marginal discomfort cost in Sect. 5.

Discussion

Our extension to the electricity cost optimization model of Kühnbach et al. (2022) allows us to systematically vary two parameters (target-SOC and DLC-level) that capture EV-users' need to retain control of charging and to explore the impact of these variations on the cost of charging in a future energy system with a higher share of renewables. If both parameters are set to provide greater degrees of freedom for the optimization, there is a disproportional increase in the additional cost savings. The prospect of additional savings incites EV-users to relinquish more control over their charging. However, if only one parameter is set to provide increased degrees of freedom, the other (constant) parameter offsets its positive impact on cost savings. Providers of smart charging services should try to incentivize that both parameters are set to maximize cost savings.

Our extended cost optimization analysis confirms expected findings but also reveals surprising particularities of EV-users' charging behavior. On the one hand, the model extension based on Prospect Theory achieves its aim of reproducing common charging practices documented in the literature. It confirms that a higher need to retain control results in higher charging costs. On the other hand, the model revealed an unexpected correlation between relinquished control and cost savings (in particular, if only one parameter is adapted). In the following, we discuss how the modeling results support the interpretation of these unexpected correlations by exposing the underlying mechanism of control needs and charging cost.

The comparison of the household groups with different needs to retain control demonstrates that changes in the control parameters result only in additional cost savings of the same magnitude if parameters are aligned. If EV-users decide to switch to more relaxed control parameters, the average cost savings are larger for those who already have relaxed parameters than for those with more restrictive ones. The group with the lowest needs for control realizes an almost cost-optimal level of charging costs. A scale-free variation of parameters over a larger range would help to explore the correlation between control needs and costs. Our finding of disproportionally large savings should be subjected to further research.

Changing only one parameter demonstrates behavioral peculiarities (rebound effects and inertia) that are known from other social science studies of residential energy. If the target-SOC is reduced, but service providers are not allowed to ensure compliance (= low DLC), then EV-users are inclined to charge beyond the target-SOC for the comfort of having a higher SOC. Since a lower target-SOC achieves cost savings by reducing the urge to purchase a large amount of electricity during high-price periods, the additional charging offsets any potential cost savings. Conversely, if service providers are allowed to control the charging (= high DLC) but are faced with a high target-SOC, their focus on optimizing charging costs leads to a high SOC delta for an extensive period. The discomfort cost of a high SOC delta distorts the optimization. This is counterproductive, as the higher DLC-level is supposed to create cost savings by selecting a more cost-optimal time to sell electricity. Both findings demonstrate that the properties of the sloped PT value function are a good fit for capturing different behavioral peculiarities. How different slopes and their diminishing marginal discomfort costs affect these peculiarities is a subject for further research.

The empirically substantiated implementation of diminishing discomfort costs that drive EV-users' charging decisions captures common charging practices. It allows us to explore the interaction between EV-users and the electricity market systematically, based on the empirical evidence. Nevertheless, we recommend caution with interpreting these findings for a future electricity market for two reasons. First, current EV-users' need to retain control might change in the context of our reference electricity system in 2030. Second, the composition of the EV-user group is likely to change with a more widespread adoption of EVs. Future EV-users are less likely to own private charging infrastructure and to relinquish more control of charging (Pelka et al. 2024b). These changes need to be examined in the future using updated empirical data or in countries where smart charging services are already more widely established.

Updating and extending the existing empirical data basis would increase the robustness of the results. Future research should seek to substantiate the monetary value of being able to drive by collecting subject- and time-dependent values. For instance, if they are ill, EV-users in remote areas may be willing to pay more for a sufficient SOC to drive to the hospital than healthy urban EV-users.

Apart from improving the empirical data basis of the model input, we propose two model adaptations to capture charging behavior more realistically. On the one hand, EV-users are expected to adapt the control parameters depending on their mobility experiences. If EV-users are unable to make planned trips, high discomfort costs occur, and they will select their control parameters more restrictively as a result. We recommend implementing a learning algorithm based on these experiences and a more targeted occurrence of unexpected trips (so far, only randomly implemented for different distances and points in time). On the other hand, EV-users are expected to optimize their charging over a longer time period. Participants of the field experiment described in Sect. 3.3.3 reported charging their EV every 3 days on average (Gabriel et al. 2022). Longer periods to optimize the charging process are likely to augment the differences between EV-users with varying control needs. As a future model adaptation, such longer charging periods could be implemented as longer, rolling optimization horizons.

For policymakers and service providers, our extended cost optimization reveals which changes in the control parameters have the biggest impact on saving charging costs and providing flexibility. Our recommendation to encourage equal relaxation of both control parameters might be in conflict with EV users' charging practices. In the field experiment described in Sect. 3.3.3, participants changed their target-SOC more frequently than their DLC-level. A possible explanation for this discrepancy is that the DLC-level is associated with greater uncertainties and other biases (e.g., concern about having to make unexpected trips), while the electricity needed to cover planned trips is easier to predict on a daily basis. Empirical research needs to identify EV users' preferences and conditions for accepting the transfer of control over both charging aspects.

Conclusion

We investigated how EV-users' need to retain control of charging affects them becoming flexibility providers for the electricity system. Our results suggest providers of smart charging services should encourage EV-users to transfer a greater degree of control of charging. Ideally, any relaxation of control should equally apply to both assessed control parameters, the target-SOC and the DLC-level, as they are mutually dependent. We arrived at these results by modeling EV-users' trade-off between minimizing the discomfort of relinquishing control and minimizing the charging costs by implementing two cost elements in one cost-minimization function. This novel approach extends the current state-of-the-art in modeling smart charging. It allows us to consider the EV-users' need for more nuanced estimations of the flexibility potential and to make recommendations for the design of smart charging services.

Our results show that the charging cost savings for EV-users increase disproportionally if they lower their need to retain control of the charging. The prospect of additional savings incites EV-users to relinquish further control. We find that both control parameters, the level of DLC and the target-SOC of the EV-battery, are equally important for realizing electricity cost savings. While lowering the target-SOC reduces the purchasing price and the amount of charged electricity, higher degrees of freedom when choosing the (dis-)charging timing (i.e., higher DLC) have a significant impact on the selling price.

We, therefore, encourage service providers to convince EV-users to transfer a greater degree of control for both parameters equally. If only one parameter is changed, the other (constant) parameter offsets the positive impact on cost savings. For instance, if the target-SOC is reduced, but the service provider is not allowed to ensure its compliance via a high level of DLC, EV-users are inclined to charge beyond the target-SOC for the comfort of having a higher SOC. In real life, this inconsistent setting of control parameters is likely to lead to erratic, additional charging activities.

How households charge their EVs is strongly but not exclusively driven by electricity costs. Limited time, lack of perfect information (e.g., unscheduled trips), and competing needs (e.g., comfort of not planning ahead) strongly influence their decision-making. We successfully combine these cost- and comfort-driven aspects in our model extension and recommend further exploiting the synergies between empirical and model-based research. As a next step, empirical research is required to determine whether EV-users would be willing to transfer control over both control parameters equally in light of the potential charging cost savings.

Appendix 1: Variables and parameters used for the prosumer modeling

See Table 4.

Table 4 Variables and parameters used for the prosumer modeling

Variables and parameters used for the prosumer modeling in the original minimization of energy costs from Kühnbach et al. (2022)	
t∈T	Hours per optimization interval
k	Prosumer k
p_t^{selling}	Price for selling electricity to the market in hour t
p_t^{buying}	Price for buying electricity from the market in hour t
$P^k_{\text{EV}_{\text{total}},t}$	Total EV charging load in hour t
$P^{k,\text{evMax}}$	Minimum and maximum charging power of the EV
$\vartheta_{\text{EVflex,in}}$	Efficiency of EV-battery when charging/discharging
$\text{SFL}_{min}^{k,\text{EVflex}}, SFL_{max}^{k,EVflex}$	Minimum and maximum storage fill level of the EV storage (i.e., the share of the EV-battery available for demand response) Parameters declaring if an EV is connected at home or mobile in t
$P^{k,evMin}, P^{k,evMax}$	Minimum and maximum charging power of the EV PV generation in hour t
$P_t^{k,grid\rightarrow hh}$	Electricity flow from the market to the prosumer
$P_t^{k,grid\rightarrow bat}$	Electricity flow from the market to the home storage system
$P_t^{k,bat\rightarrow grid}$	Electricity flow from the home storage system to the market
$P_t^{k,pv\rightarrow grid}$	Electricity from the PV unit sold to the market
$P_t^{k,pv\rightarrow EV}$	Electricity generated by the prosumer's own PV unit to charge the EV-battery
$P_t^{k,bat\rightarrow EV}$	Electricity flow from the home storage system to the EV-battery energy content of the home storage system in kWh Power flow from spot market to the DR-ready fraction of the EV-battery
$P_t^{k,grid\rightarrow EV}$	Power flow from spot market to the mobility fraction of the EV-battery
$P_t^{k,EVflex\rightarrow EV}$	Power flow from the DR-ready fraction of the EV-battery to the mobility fraction of the EV-battery energy content of the (virtual) DR-fraction of the EV-battery in kWh Power flow from PV to the demand response fraction of the EV-battery
$P_t^{k,bat\rightarrow EVflex}$	Power flow from home storage system to the demand response fraction of the EV-battery
$P_0^{k,unexpected}$	Power of unexpected trips deducted from SOC_t^k in the first hour of the day
$vsh_{conn_t^k},$	Binary parameter indicating whether the EV is connected [1] or disconnected from the grid [0]
Variables and parameters used for the prosumer modeling in the extended minimization of discomfort costs	
θ^k	Weighting parameter, which indicates how much importance prosumer k assigns to the discomfort cost in relation to energy cost
SOC_{Ref}^k	Target-SOC that is indicated by prosumer k as needed state of charge to cover her mobility needs
mV_t^k	Monetary value, which is assigned to the delta between SOC_t^k and SOC_{Ref}^k
λ	Coefficient expressing the loss aversion
α	Exponent expressing the risk attitude

Appendix 2: Implementation of MINLP based on BigM method

This MINLP is implemented with the BigM method (Cococcioni and Fiaschi 2021):

$$minC_{tot}^k = \sum_{t=h_{min}}^{t=h_{max}} [\left(P_t^{k,grid\rightarrow EV} + P_t^{k,grid\rightarrow EVflex} + P_t^{k,grid\rightarrow hh} + P_t^{k,grid\rightarrow bat}\right) \cdot p_t^{buying} - \left(P_t^{k,EVflex\rightarrow grid} + P_t^{k,pv\rightarrow grid} + P_t^{k,bat\rightarrow grid}\right) \cdot p_t^{selling}] \cdot (1-\theta_t^k) - \theta_t^k \cdot mV_t^k \cdot -\lambda \cdot utility_t^k \cdot vsh_{conn_t^k} \tag{B.1}$$

$$SOC_t^k \geq SOC_{Ref}^k - bigM \bullet \left(1-\delta_t\right) \tag{B.2}$$

$$SOC_t^k \leq SOC_{Ref}^k + bigM \bullet \delta_t \tag{B.3}$$

$$utility_t^k \geq (SOC_t^k - SOC_{Ref}^k)^\alpha - bigM \bullet (1-\delta_t) \tag{B.4}$$

$$utility_t^k \leq (SOC_t^k - SOC_{Ref}^k)^\alpha + bigM \bullet (1-\delta_t) \tag{B.5}$$

$$utility_t^k \geq (SOC_{Ref}^k - SOC_t^k)^\beta - bigM \bullet \delta_t \tag{B.6}$$

$$utility_t^k \leq (SOC_{Ref}^k - SOC_t^k)^\beta + bigM \bullet \delta_t \tag{B.7}$$

In order to assess the risk of finding local optima rather than global ones, we implement a linear transformation of our MINLP with an exemplary set of parameters. After comparing both approaches, we recognize no significant differences and assess the risk of distortions due to local optima as small.

Due to risk of local optima, the results of the MINLP were compared with those of the linear approximation approach. As an example, Fig. 6 depicts the results of both

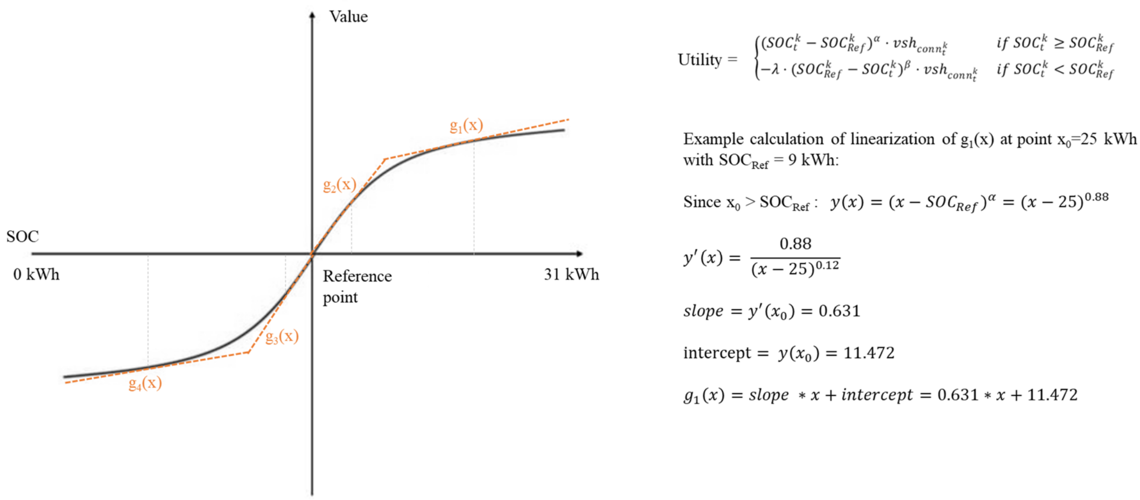

Fig. 6 Linear approximation of MINLP

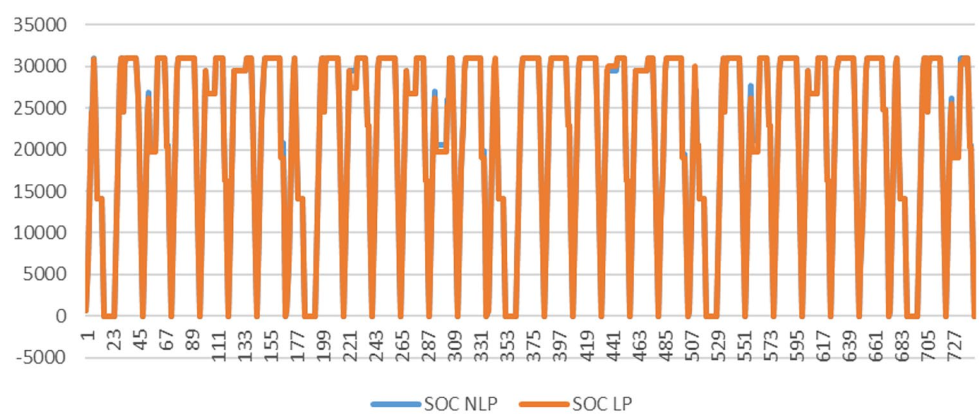

Fig. 7 Comparison of MINLP and linearized approach for the SOC of the EV-battery

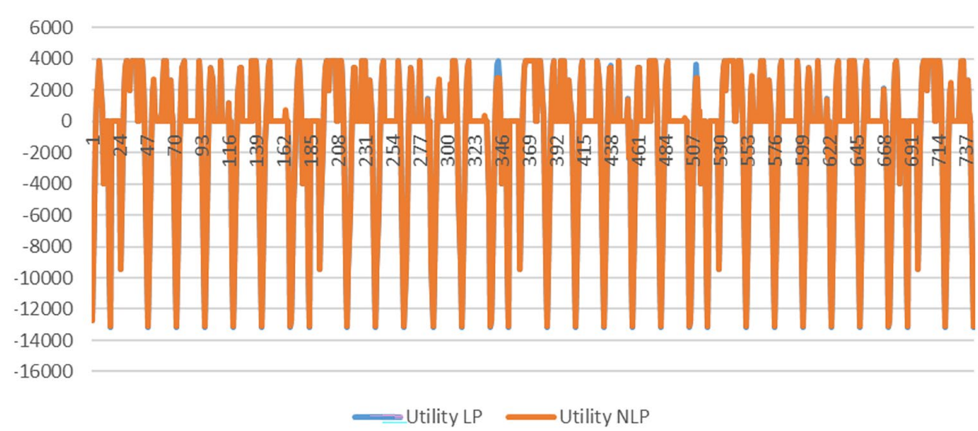

Fig. 8 Comparison of MINLP and linearized approach for the utility

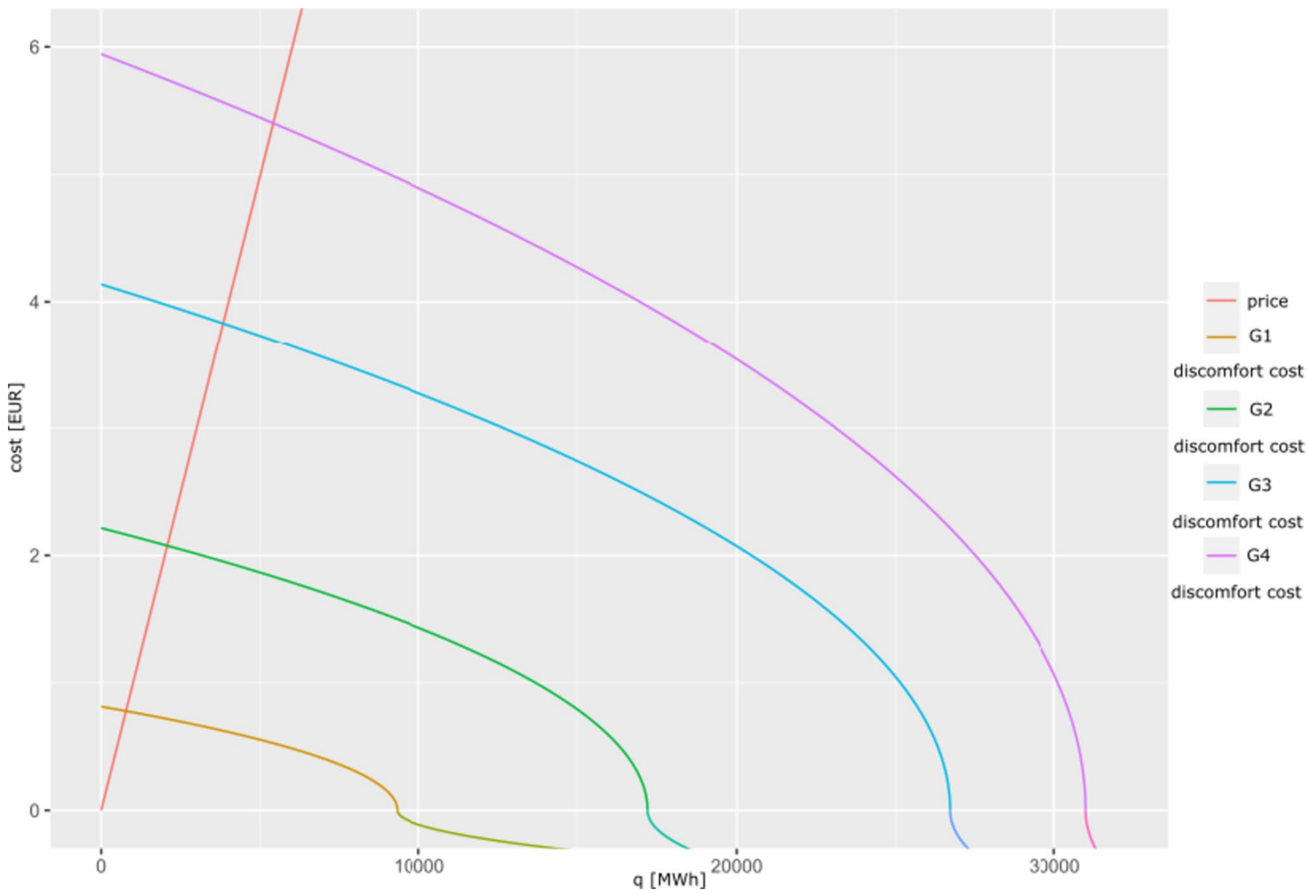

Fig. 9 Simplified illustration of the cost mechanism, which determines the amount of charged electricity based on the electricity price and the discomfort cost, when the EV-battery is empty

approaches for the EV-battery SOC and for the prosumer utility. The results are based on one data from a test run: both approaches were run for one prosumer for 1 month, and the resulting SOCs and utility values were used. As Figs. 7 and 8 show, both approaches produce the same results except for minimal deviations.

Appendix 3: Stylized examples for the relation between both cost elements in the combined cost-minimization function

We illustrate how the relation between the charging and discomfort cost determines the charging and discharging of the EV-battery by two stylized examples of SOCs for the four groups. In Figs. 9 and 10, the four curves represent the value function of each prosumer group as subject to the quantity of charged electricity. The red line represents the electricity costs. The EV-users are willing to pay for the charged electricity, as long as the electricity costs are below the discomfort costs of having a low SOC. The willingness to pay for the charged electricity decreases with a higher SOC. We illustrate this based on empty EV-batteries (Fig. 9) and EV-batteries that reached half of the target-SOC of the four groups (Fig. 10).

Appendix 4: Transforming the lowered target-SOC in the field experiment into model parameters for the EV-battery

The minimum of target-SOC of eight responsive participants ranged between 25 and 80% of their EV-battery volume. The average standard deviation accounted for 17%. We use the standard deviation as a moderate scenario with a medium target-SOC and the quartiles of the minimum target-SOC as an extreme scenario for the adjusted mobility needs due to smart charging services. The target-SOC in % is applied to the standard battery volume of the model (62 kWh). In addition, 50% of the EV-battery volume, which is withheld for its inflexible fraction, are deducted. For the scenario with a minimum target-SOC, this implies that no fraction of the flexible battery is withheld as safety buffer for group 1 and

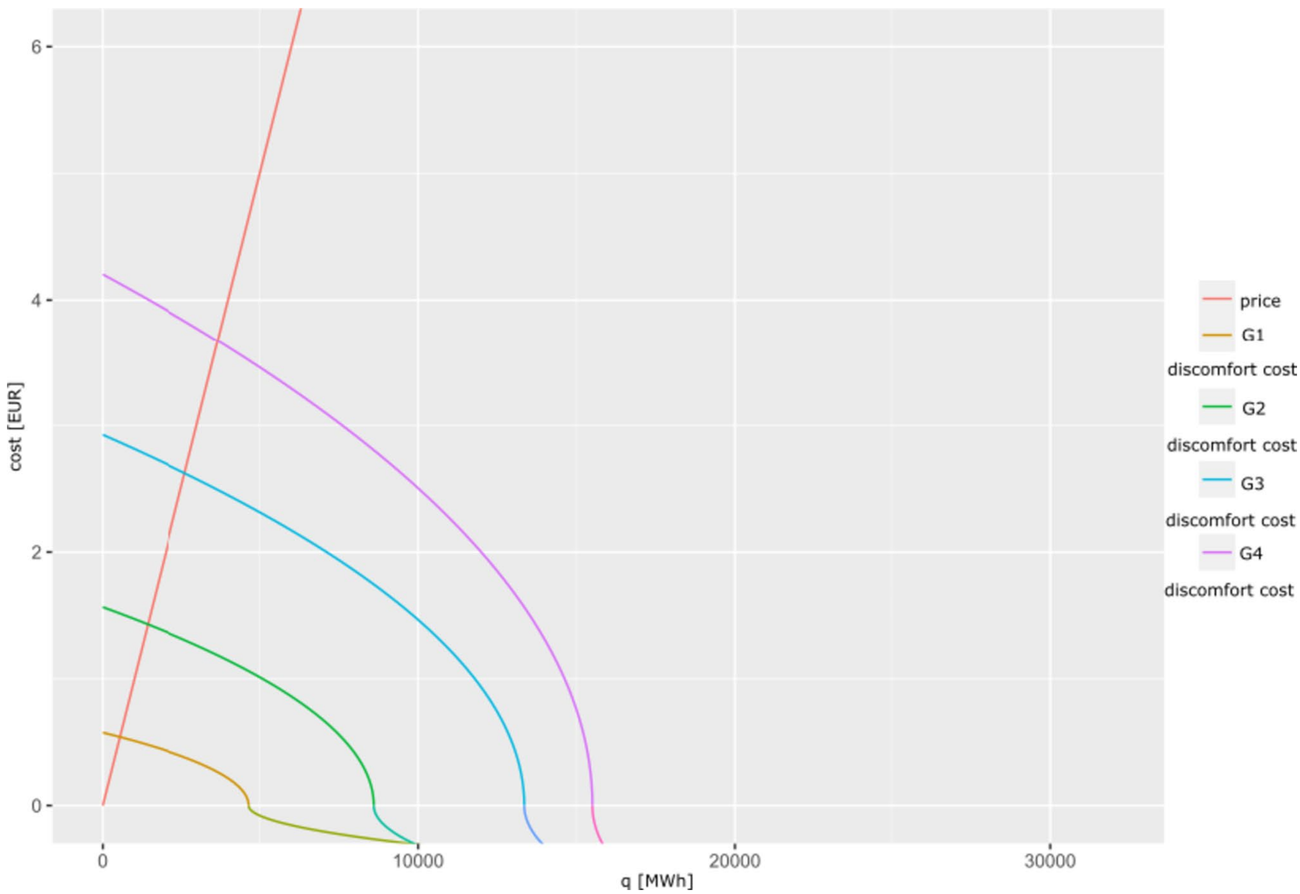

Fig. 10 Simplified illustration of the cost mechanism, which determines the amount of charged electricity based on the electricity price and the discomfort cost, when the EV-battery reached half of the target-SOC

2, since the first (35%) and second quartile (45%) is below this threshold.

Appendix 5: Sensitivity analysis of other behavioral parameters

We presented in Sect. 4 how changes in the target-SOC and the DLC-level parameter influence the electricity cost savings. In the following, we test how a change of the other behavioral parameters, particularly the alpha, lambda, and monetary value, influence the results. Since the values for lambda and alpha are already at the higher end of their range, we reduce them (alpha from 0.88 to 0.5, lambda from 2.25 to 1.125). Furthermore, we test a higher spread of the monetary values (2 × its standard deviation), as well as its overall reduction (0.5 × its mean). We use the control need scenario as the basis for the sensitivity analysis.

As illustrated in Fig. 11, the greatest changes are recognized for the lowered alpha. It entails that the slope of the discomfort cost curve increases around the target-SOC and shows saturation at the outer side of the curve. The initially empty EV-battery combined with this lower alpha leads to almost constant discomfort costs, independently of the change in SOC. These minor incentives to increase the SOC are overruled by the price signals. Consequently, they charge their EV more cost optimally (see Fig. 12).

The given implementation of PT successfully captures the tradeoff on the amount of charged electricity when a high alpha is applied. For the application of smaller alphas, another formulation of the SOC delta or a higher initial SOC needs to be defined.

The decrease of the discomfort costs in all other parameter variations leads to a more cost-optimal charging behavior of G1. For the other groups with a higher DLC-level and target-SOC, the decrease does not substantially change the tradeoff between minimizing charging

Fig. 11 Changes in electricity costs and underlying factors for the sensitivity analysis compared to the scenario control need. Since the costs are close to 0 (0.36 EUR) for G1 in the control need scenario, relative changes result in extreme values on the secondary y-axis (e.g., see for 0.5 * mean of monValue). For G1 in alpha = 0.5, the change in cost is not even displayed (from 0.36 EUR to −8.64 EUR). The same applies for the 9 times higher selling price (from 5.63 EUR/MWh to 54.81 EUR/MWh)

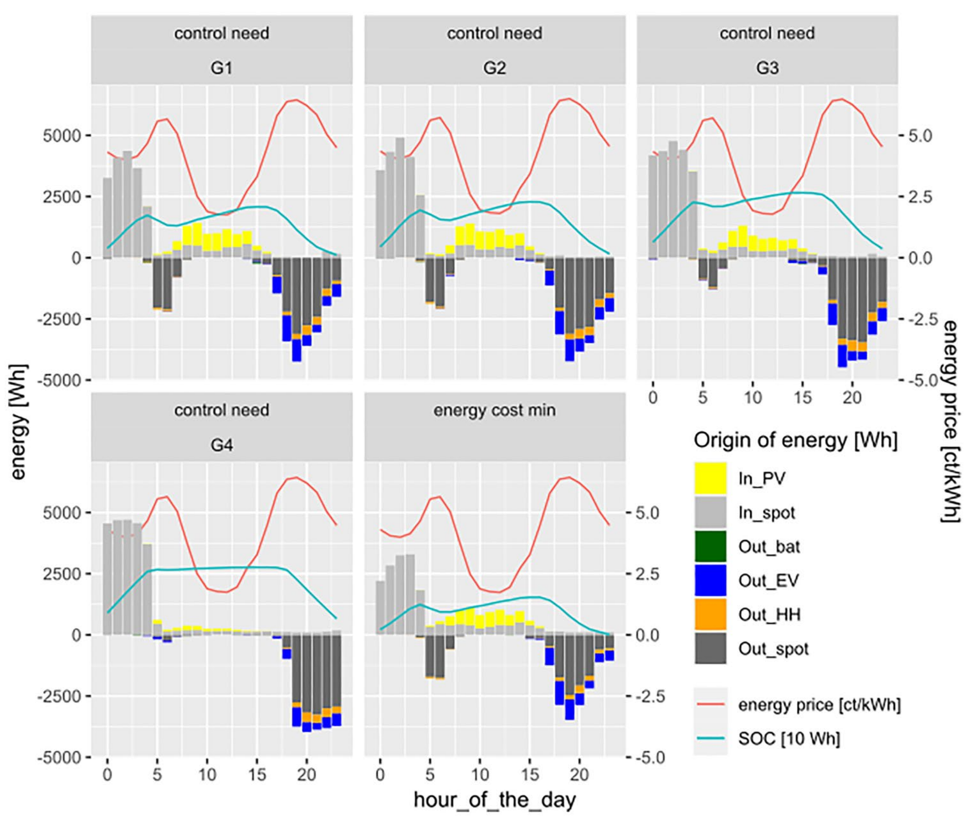

Fig. 12 Average in- and outflows of the EV-battery within 24 h for a lowered alpha of 0.5, distinguished by sources (In_[…] = charged electricity from […], Out_[…] = discharged electricity provided to […], spot = electricity spot market, bat = stationary battery, EV = inflexible charging demand, HH = inflexible household demand)

and discomfort costs. We expect this result since G1's low target-SOC results in high marginal discomfort costs. Its relative decrease has a stronger effect on G1 than the other groups.

Acknowledgements The authors gratefully acknowledge the contributions of Werner Neumeier and Dorina Rauth from the energy solution supplier beegy, and Johanna Isenhuth from the utility MVV Energie AG for carrying out the field experiment, as well as the anonymous participants. Furthermore, we are grateful to Michael Haendel and Marian Klobasa for their guidance, as well as Vasilios Anatolitis for being a tireless, creative and smart sparring partner.

Author contributions SP: conceptualization, methodology, formal analysis, investigation, software, data curation, writing—original draft preparation, writing—review and editing. AB: methodology, investigation, software, data curation, writing—review and editing. EC: conceptualization, writing—review and editing, supervision. FL: software, writing—review and editing. MK: software, writing—review and editing. LdV: writing—review and editing, supervision.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability The data presented in this study are available on request from the corresponding author. The data are not publicly available to safeguard the anonymity and privacy of the local stakeholders.

Declarations

Conflict of interest The data collection for this work was supported by the European Union's Horizon 2020 research and innovation program project NUDGE under grant agreement no. 927012, as well as the project "Digitale Geschäftsmodelle mit selbstbestimmten Anwendern für smarte Verteilnetze (DiMA-Grids)", funded by the German Federal Ministry for Economic Affairs and Climate Action under grant number no. 03EI6038A. The authors have no competing interests to declare that are relevant to the content of this article.

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