

ORIGINAL RESEARCH

End-user engagement in EV charging control at commercial locations through a user-friendly approach

 Toni Simolin  | Mehdi Attar | Sami Repo | Pertti Järventausta

 Unit of Electrical Engineering, Tampere University,
Tampere, Finland
Correspondence
 Toni Simolin, Unit of Electrical Engineering,
Tampere University, Tampere, Finland.
Email: toni.simolin@tuni.fi
Funding information
 LIFE Programme of the European Union,
Grant/Award Number: LIFE17 IPC/FI/000002
LIFE-IP CANEMURE-FINLAND
Abstract

Controlled electric vehicle (EV) charging at commercial locations has been seen as the key solution to mitigate the negative effects of uncontrolled charging on the power grid. In the scientific literature, EV users' willingness to participate in charging control has been analyzed, and various control algorithms have been studied. However, there is a gap regarding the best practices to encourage users to participate in charging control and the potential influences of the EV users' decisions on charging site operator's profits. In this article, the EV users' perspective on charging control is assessed to form a user-friendly charging control approach and compensation scheme for commercial charging locations. Then, simulations are carried out using real charging session data to analyze the potential influences of EV users' decisions on charging site operator's profits. According to the results, the profits of the charging site operator are more heavily dependent on the number of customers than the optimality of the charging control. Hence, charging site operators should carefully consider the attractiveness of the implemented control strategy to maximize profits.

1 | INTRODUCTION

Electric vehicle (EV) charging control at commercial locations has been seen as the key solution to mitigate issues caused by uncontrolled charging, for example, unwanted load peaks in distribution network or unnecessary high charging costs. In addition, the controllability of the charging loads could be used in today's power systems in order to accommodate the transition towards sustainable electricity generation and consumption. To provide value for different actors related to the power system, widely different charging control solutions have been proposed [1].

However, overcoming technical barriers from electrical engineering perspective alone does not enable the full potential of EV charging control [2]. The real benefits of the charging control are dependent on the EV users' acceptance. The higher the user acceptance to the charging control, the higher the controllability of the charging loads. Furthermore, EV users do not necessarily have the technical background to understand the benefits of smart EV charging for the power system or electricity markets. Therefore, there is also a cultural gap to be

bridged that, in case, can be replaced by an adequate compensation and user-friendly approach. To better understand EV users' responses to charging control and their influences, more work is required [3].

1.1 | Scope of the paper

The goal of the study is to discuss the factors that affect the EV user's acceptance and how the EV users' decisions affect the charging site operator (CSO) from the profits' perspective. The paper deals with level 2 (semi-fast, alternating current (AC)) charging of EVs at public charging locations mainly used for opportunity charging during shopping or leisure activities. Since public charging sites compete with other charging sites to attract customers, the need for user-friendliness is highly emphasized. The paper also focuses on operational aspects of the charging site, and thus, the assessment of optimal sizing or investment costs is excluded. Vehicle-to-grid operation is not considered as most EVs are not assumed to support it in level 2 charging within the near future.

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2024 The Author(s). *IET Generation, Transmission & Distribution* published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology.

1.2 | Contributions

The paper recognizes and fills a gap in the literature regarding the design and benefits of a user-friendly charging control approach and compensation scheme intended for public charging locations from CSO's profits perspective. The contributions are as follows:

1. Proposing a user-friendly compensation scheme that compensates EV users based on the inconvenience incurred (Section 3.2).
2. Analyzing the significance of the acceptance rate on the potential of reducing peak loads and increasing CSO's profits (Section 5.2).
3. Evaluating the proposed compensation scheme from EV users' and CSO's perspectives (Section 5.3).
4. Analyzing the impact of EV user's decision to relocate to another charging site on the charging site operator's profits (Section 5.4).

Through the aforementioned contributions, the paper will bring added value to the EV charging load management which plays an increasingly important role in the power system.

1.3 | Structure of the paper

The structure of the paper is as follows. Section 2 discusses the user acceptance-related literature. Section 3 presents and discusses the considered EV user-friendly charging control approach and the proposed compensation scheme. Section 4 describes simulation details. Section 5 presents and discusses the simulation results. The paper is finalized in Section 6 with conclusions and future work proposals.

2 | RELATED RESEARCH

This section discusses the results found in the related EV user surveys and the common assumptions in charging control-related studies. Finally, a summary of the related literature is given.

2.1 | User acceptance in EV charging control

Multiple surveys have been carried out to understand the users' acceptance and willingness to participate in charging control. In Table 1, the general details of five related surveys are presented. To analyze charging control from the EV users' perspective, the following subsections discuss the general attitude, motivation towards acceptance, concerns, and recommendations.

2.1.1 | General attitude

All surveys show positive attitudes towards user acceptance of charging control. In [4], 53% of users defined as potential EV buyers were willing to participate in charging control without

TABLE 1 EV charging control related surveys.

Study	Type	Participants	Key motivator	Key issue
[2]	Structural equation model	426	Social influence	Perceived risk*
[4]	Latent class choice model	1470	Cost incentives	Loss of control
[5]	Field test	10	Contribution to renewable usage	Burden
[6]	Structural equation model	237	Grid stability	Perceived risk*
[7]	Semi-structured interviews	60	Cost incentives	Perceived risk*

*Risk of EV not having enough energy for the next trip that may or may not have been planned.

incentives. In [2], 81.2% of EV users were willing to accept charging scheduling. In [5], respondents indicated through the Likert scale that they would be mostly willing to use the charging control after the piloting project in which they participated. In [6], 56% acceptance for smart charging was obtained.

2.1.2 | Motivations towards acceptance

In the surveys, the dominant motivation for EV users to participate in charging control varied a lot. In [4], cost incentives were seen as the most dominant factor, followed by ecological benefits. In [5], contribution towards renewable energy usage was the most important motivational factor and much more influential than cost reductions. In [6], the most influential factor was the security of electricity supply. In the survey, EV users requested discounts, but the security of electricity supply and renewable energy integration were seen as the key motivational factors instead of discounts for accepting smart charging [6]. In [2], social influence, which refers to the social pressure perceived by an individual to take a particular action, was the most influential factor. In the study, trust that charging is controlled while keeping the EV user's goal in mind was also seen as an important factor [2]. Due to the differences seen in the most influential motivational factors, study [2] points out that the incentivization principles should be designed separately for different regions where people have different attitudes or preferences towards flexibility acceptance.

2.1.3 | Concerns with charging control

In [4], 24% and 39% of respondents indicated privacy and loss of control concerns, respectively. Study [2] suggests that the unfamiliarity with the technology in terms of experience might reduce the perceived ease of use. The perceived risk may cause EV users to reject participation in the charging scheduling regardless of whether the charging schedule is seen as useful and easy to use [2]. In [7], charging control was seen as problematic in case of unexpected journeys as the driving range might not be enough. Even though

the frequency of unexpected journeys is low, a substantial weight has been put to the risk [7]. In [7], the daily effort (namely entering information such as required state-of-charge (SOC) into the charging app) was also seen as a negative factor in charging control. Study [7] points out that there exist trust issues in charging control related to SOC requirements not being met and unwanted sharing of personal data. In general, users had positive attitudes towards the smart charging [5], yet half of the users reported that the determination of EV use (departure time and energy requirement) was a burden, and some stated that it reduced comfort [5]. Even remembering to *opt-out* of smart charging was reported to be an issue [5]. Here, *opt-out* means choosing an uncontrolled charging option instead of controlled charging.

Experiment [5] shows that planning car usage is a big challenge. Furthermore, the questionnaire results show that the realized burden of planning car usage was slightly higher than the respondents initially thought [5]. In the study, the users were mostly satisfied with the benefits compared to the burden (max 0.8€ profit per charging session depending on the available charging duration and minimum charging requirement) [5]. At the beginning, the balance of costs and benefits was seen significantly more positively than at the end of the experiment [5]. Also, a minor decrease in the willingness to use smart charging was seen in the experiment [5]. This might indicate *response fatigue*, which has been shown to be an issue in demand response scenarios [8].

2.1.4 | Suggestions and recommendations

Study [2] recommends avoiding complex interactions from the user's perspective. Study [7] recommends a manual override option to opt-out from charging control. "Default settings" is recommended in [7] to minimize necessary user interactions. Study [7] also recommends offering a notable discount, tens of percent, to promote acceptance of charging control. Furthermore, study [7] suggests that there are two distinctive groups: those who prefer easy-to-use and those who prefer to retain control. In study [6], the EV users requested an option to opt-out of smart charging or to indicate the minimum range and departure time [6]. According to [4], a high level of trust should be maintained to promote user acceptance. Study [5] recommends advertising the ecological benefits of smart charging to promote acceptance. The study also suggests that feedback of the benefits of smart charging from grid perspective should be provided for the users to make the system more transparent [5]. Additionally, the reduction in acceptance could be prevented with higher benefits or by decreasing the effort required from EV users [5]. Study [2] also points out that end-user engagement and commercial mechanisms need more attention.

2.2 | EV users as a part of charging control

In the scientific literature, it has been common to assume that EV users are always willing to participate in the charging control

[4], e.g., in [9–12]. It is also often assumed that certain information about EVs is provided, for example, departure time and energy requirement, which is used as a basis for control optimization, for example, in [9–13], and for incentivization, for example, in [9, 12–15]. Yet, several studies have shown that the acquisition of such information is problematic from EV users' perspective due to response fatigue [8] and input inaccuracy [16, 17]. The information could also be measured for estimation purposes, but it could lead to privacy or trust issues, which are shown to be significant, as mentioned earlier. The accuracy of the information has also been seen as problematic, especially in commercial locations where users have less predictable charging behavior compared to work charging [16]. These kinds of inaccuracies could lead to insufficient battery levels at departure times [16], and thus, reduce EV users' willingness to participate in charging control.

In studies [14, 18–20], it is mentioned that the EV users' decisions to participate in charging control or to choose another charging site may be affected by the charging price. Study [18] assesses the charging pricing influences on the response willingness of EV users. However, no further assessment is carried out to analyze how the willingness affects the outcome of the charging control. In [21], flat discount is proposed to encourage EV users to participate in charging control. However, this kind of compensation is not seen as user-friendly as the users' inconvenience does not correlate with the compensation. Additionally, the CSO's profits decrease as the number of users willing to participate increases if there is no need for increased controllability [21].

In the mentioned studies, charging price is assumed to be the only factor affecting the users' decisions. While economic incentivization is one of the major motivators towards acceptance, it is not the only one. Thus, both the charging control approach and compensation scheme should be user-friendly to promote acceptance. According to the authors' knowledge, such solutions for commercial charging locations have not been designed and analyzed from the CSO's perspective before.

2.3 | Summary of the related research and literature gap

The surveys demonstrate that EV users are generally willing to accept charging control. As the most impactful motivational factor varies from study to study, it is advisable to combine them all: cost incentives and advertising the benefits from an environmental and grid perspective. It is worth noting that the target groups in the surveys are early adopters who might be more interested in new technology and more worried about environmental challenges. Consequently, they may be more familiar with charging control concepts and more willing to accept it. Nevertheless, the surveys show that issues related to the burden, privacy, and trust exists. The issues are presumed to be even more influential in the future when the share of early adopters is no longer dominant. Furthermore, response fatigue has been shown to be a significant barrier to demand response in cases where user effort is required.

To overcome the issues, it is recommended that charging control schemes include the following features:

- ease of use (i.e. minimize the required user actions)
- with opt-out option (i.e. an option for uncontrolled charging)
- with a relatively notable discount of tens of percents
- trustworthiness (i.e. minimize the risk of excess charging power curtailment)
- information security (i.e. minimize privacy concerns)
- transparency (i.e. the basic operational and pricing/compensation principle should be understandable to the users)

As mentioned in Section 2.2, EV users are often assumed to participate in charging control, and the influence of users' decisions on CSO's profits has not been studied before. These findings act as motivators for this study.

3 | END-USER ENGAGEMENT

This section describes the considered charging control approach and proposed compensation scheme to meet the required properties related to user-friendliness.

3.1 | Considered charging control approach

In this article, an “opt-in or opt-out”-approach is considered where EV users must only indicate whether they want to participate in charging control (“opt-in”) or not (“opt-out”). This selection is made to minimize the EV users' burden. However, the EV users still have to make a decision whether to use the charging site and whether to opt-in or opt-out from the charging control.

The “opt-out”-option eases the potential range anxiety of EV users and encourages users with urgent charging demand to choose the charging site. The “opt-in”-option is subject to charging control and charging price compensation. It is suitable for users with less urgent charging demands. The compensation scheme and the details of the charging control algorithm are described in the next subsections.

The approach does not require information about departure time and charging demand; thus, the privacy concerns are minimized. Additionally, this kind of approach makes the operation more transparent and robust as there are no risks that the critical information (energy demand and departure time) is incorrectly estimated/inpugged or forwarded to a third party.

In the case of “opt-in”, a minimum charging current limit of 8 A is used. This selection ensures that the charging sessions can always be active, thus removing the risk that an EV will not get any charging capacity.

3.2 | Proposed compensation scheme

This paper proposes a charging control compensation scheme where the *discount percentage* equals the *control percentage*. The term

control percentage refers to the percentual amount that the charging power is curtailed from the maximum power supported by the EV and charging infrastructure.

So, if the charging power is curtailed notably, the user gets a notable discount, and if the power is curtailed slightly, the user gets a small discount. This has three advantages: (1) there is a discount only when the charging control is utilized, (2) charging efficiency often reduces as power reduces [22], so users get the energy cheaper when power is reduced more, and (3) simplicity of the scheme makes it easy to understand as inconvenience correlates with discount.

It is worth emphasizing that the discount here should be based on the maximum charging power of the EV and the realized power to ensure that the benefits correlate with the inconvenience. Equations (1) and (2) describe the calculations of the energy price $c_{c,t,opt-in}$, and the amount of compensation $C_{t,comp}$ in case of “opt-in”-charging. In the equations, c_c is the normal price of charging energy (€/kWh), $P_{t,max}$ is the maximum power of the EV (assumed to be known by the charging control system), P_t is the realized power of EV, and E_t is the charged energy. The maximum power of the EV ($P_{t,max}$) takes the limitations of on-board charger (OBC), battery management system (BMS), and charging station into account. If the charging control does not limit the charging power (i.e. $P_t = P_{t,max}$), no compensation will be given.

$$c_{c,t,opt-in} = c_c * \frac{P_t}{P_{t,max}}, \quad (1)$$

$$C_{t,comp} = (c_c - c_{c,t,opt-in}) * E_t. \quad (2)$$

3.3 | Charging control

The key objective of the charging control is to limit peak loading to a predefined value while charging as much energy as possible into the EVs. Different peak load limits are considered, and their correlation with the required acceptance rate (i.e. the share of EV users choosing “opt-in”) and the profits of the CSO are analyzed.

The algorithm starts by forming separate lists of EVs whose users have chosen “opt-out” and “opt-in”. Then, charging current measurements are read to allow Charging Characteristics Expectation (CCE) feature to track the charging characteristics of the EVs. CCE feature is described in more detail in Section 3.5. Charging capacity distribution starts by allocating full capacity (3×32 A) for the “opt-out” EVs and the minimum capacity (3×8 A) for the “opt-in” EVs. Then, the remaining capacity is distributed for the “opt-in” EVs using a proportionally fair sharing method. It is worth emphasizing that all EVs may not be able to utilize the allocated capacity due to the limits of the OBC and BMS, and thus, realized charging power may be lower. The capacity distribution method is explained in the following subsection. A block diagram of the charging control is shown in Figure 1. The control algorithm is executed every time step (1 min).

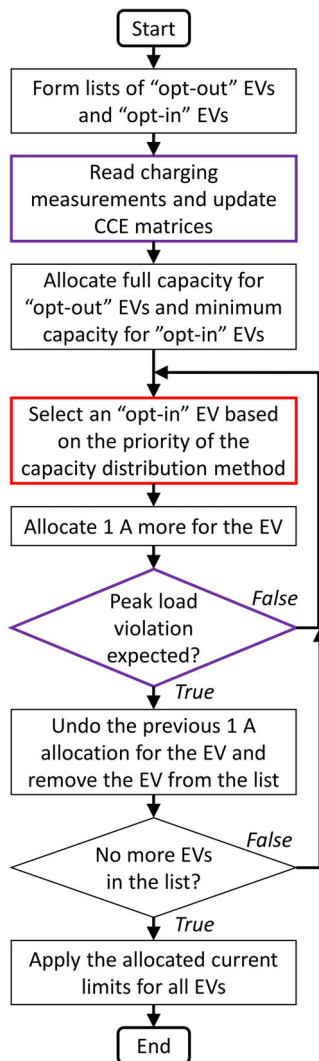


FIGURE 1 A block diagram of the charging control operation.

3.4 | Capacity distribution

In the proportional fair sharing method, the charging powers of the EVs are reduced in equal proportions in case a charging load curtailment is needed. To allocate capacity, an iterative approach, similar to the water filling method described in [23], is used. In this approach, the charging current limits of EVs are increased until there are no more EVs remaining whose charging current limit can be increased without violating the peak load limit. Since power limit allocation is not directly possible in level 2 charging, current limit allocation is used along with a weighting factor that considers the number of used phases. This is done to consider that the charging powers of 3-phase EVs increase 3 times as fast as the powers of single-phase EVs when the current limit increases. 1 A current limit increments are considered in this article as smaller increments might not be supported by commercial charging stations [24]. Load balancing is not focused on this paper as the peak load limit is not affected by the potential unbalances.

In the iterative allocation method, 1 A current limit increment is given to the EV that has the highest prioritization (the block with the red outline in Figure 1). The priority for an EV is calculated according to Equation (3), where I_{temp} is the current limit under consideration and n_p is the number of phases used for charging. The final current limits will be applied only after the iterative allocation procedure.

$$Priority = \frac{P_{r,max}}{I_{temp} \times n_p}. \quad (3)$$

3.5 | CCE feature

As said, this paper considers level 2 charging in a realistic manner where the charging current limit set by the charging point and the real charging current are not always equal. The real charging current may be limited by, for example, the maximum charging power supported by the OBC of EV or the BMS if the battery is fully charged or close to its temperature limits. In these cases, the charging control system does not get any direct information why an EV does not utilize the whole capacity allocated for it.

To overcome these issues caused by the non-ideal response of EVs in the charging control, Charging Characteristics Expectation (CCE) feature is used [25]. In the feature, charging current measurements are used to separately track the responses of the individual EVs using lookup tables (the first block with the purple outline in Figure 1). The lookup tables define what currents are expected with each current limit integer. Therefore, they can be used to estimate what charging currents a certain current limit would lead to or whether some EVs are already fully charged (the second block with purple outline in Figure 1). When a charging session starts, CCE feature essentially assumes ideal charging behavior for it, that is, real charging currents equal to current limits. However, CCE feature then updates the expected response of the EV as charging current measurement values are read. Further explanation of CCE feature can be found in [25]. In [26], a mean absolute error of ~ 0.4 A was achieved using CCE feature. The study used commercial EVs in hardware-in-the-loop simulations, demonstrating that CCE feature works relatively accurately in real-life implementations.

4 | SIMULATIONS

In this section, the details of the simulations are described. The following subsections present the used data, the investigated scenarios, the charging profile modeling, the EV users' choices modeling, and the used simulation model.

4.1 | Data

Simulations utilize real charging session data from two commercial charging sites to model realistic charging point usage. The

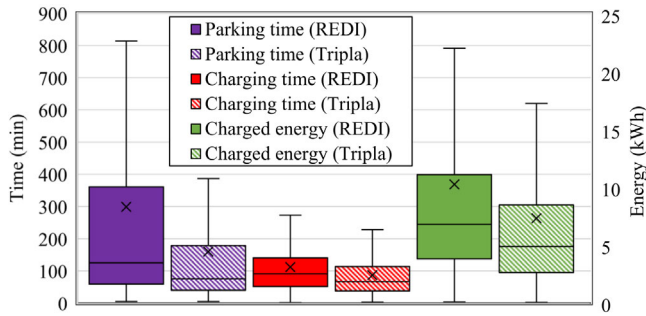


FIGURE 2 Charging station usage behavior at REDI and Tripla shopping malls located in Helsinki, Finland.

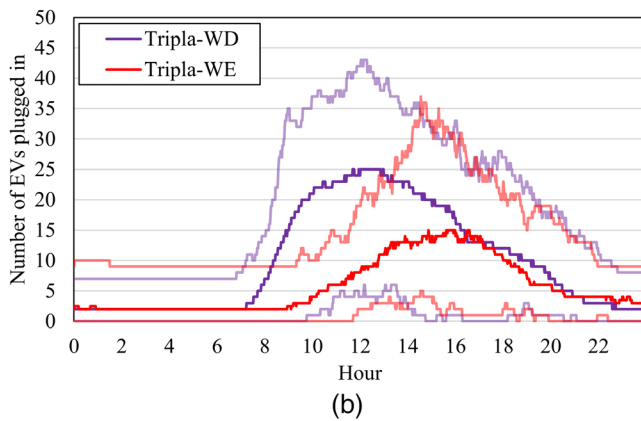
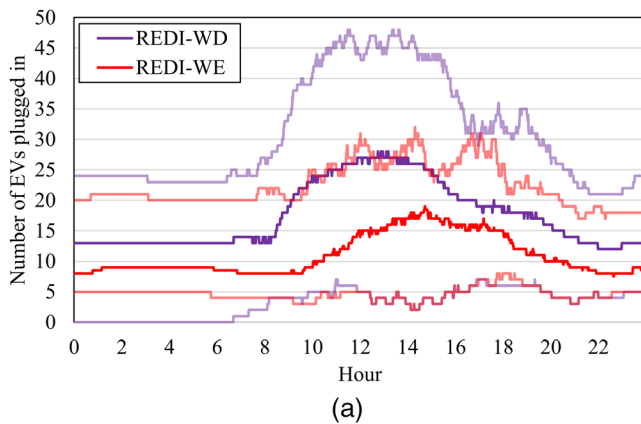


FIGURE 3 The number of EVs plugged in at (a) REDI and (b) Tripla in case of weekday (WD) or weekend (WE). Darker colors represent median values and lighter colors min and max values.

charging sites are located at REDI and Tripla shopping malls' premises in Helsinki, Finland. The data is measured between 09/2021–02/2022 and includes plug-in time, plug-out time, active charging time, charging peak power of each session. The data include 16,705 and 14,856 sessions for REDI and Tripla, respectively. To illustrate the charging behavior in the charging sites, parking times, charging times, and charge energies are presented for both locations in Figure 2. Additionally, the number of EVs plugged in is illustrated in Figures 3 and 4. The maximum number of EVs simultaneously plugged in at REDI, and Tripla is 48 and 43, respectively. To

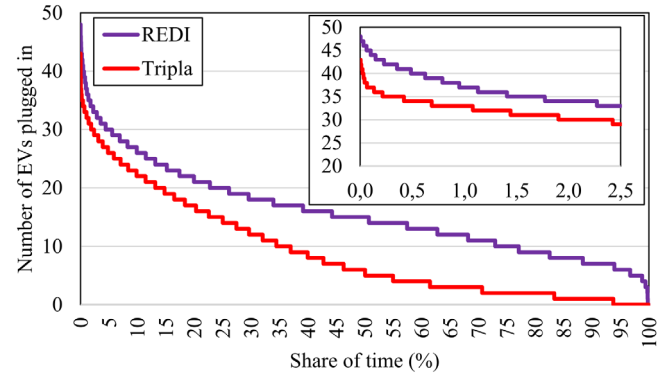


FIGURE 4 Persistence curve for the number of EVs plugged in at REDI and Tripla.

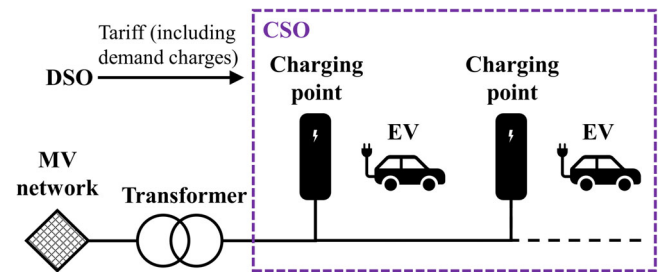


FIGURE 5 Investigated scenario of a charging site within a shopping mall premises where DSO incentivizes CSO to limit peak loading.

calculate parking times, it is assumed that plug-in and plug-out times correspond to arrival and departure times, respectively. Likely, other EVs were also parked, but not plugged in, at the locations during that time. However, no information is available about these EVs; thus, their existence in the simulations is disregarded.

4.2 | Investigated scenarios

This paper investigates two public charging sites within shopping mall premises. The charging sites are connected to medium voltage network through a transformer. Distribution tariffs are assumed to include demand charges (€/kW) that incentivize the CSO to limit peak loading. By using charging control, the peak demand and the related costs of the charging site can be limited. The feeder of the charging site could be used to supply other loads as well (e.g. fast charging station or non-EV loads), but for simplicity's sake, only level 2 charging loads are considered here. An illustration of the scenarios is presented in Figure 5.

The nominal capacities of the charging points are assumed to be 22 kW, which is the case in REDI and Tripla [27, 28]. However, the real charging powers depend on the limitations of OBCs and BMSs of the EVs. A previous analysis of the data has shown that maximum charging powers of the EVs are often around 4 kW [29].

Different total charging capacity limits and user decisions are considered to analyze the potential influences of the end-user

engagement. The user decisions are explained in Subsection 4.4. The investigations consider the same 181-day period (09/2021–02/2022) from which the used data was gathered. The investigation period's length allows the simulations to take daily variations of the charging behavior into account. But since the period represents wintertime mostly, seasonal differences are not taken into account.

4.3 | Charging profile modeling

The simulation model used in this article considers EVs' realistic charging control behavior. In level 2 charging, the charging point can only set a current limit for an EV, and the EV chooses the actual charging current based on the current limit and the limitations of the EV's OBC and BMS. BMSs of EVs may limit the charging powers when SOC gets close to 100% and prevent overcharging when SOC reaches 100%. For example, in case of uncontrolled charging, if an EV charges from 50% SOC to 60% SOC, it is likely that the charging power is relatively constant and only limited according to the maximum power of the OBC (= linear charging profile). Conversely, if an EV charges from 90% SOC to 100% SOC, the charging power likely decreases towards the end (= non-linear charging profile). However, from the charging session data, it is not possible to determine the SOC of the EVs or how the charging power behaved over the charging duration. Yet, it is shown that assuming only linear charging profiles may lead to inaccurate results, especially in cases with charging control [30].

To model the charging profiles of the EVs (i.e. how the charging power behaves over the charging duration), an assumption is made to categorize the charging profiles of different charging sessions into linear or non-linear based on the initial laxity of the charging sessions. Laxity refers to the available time when the charging should be started in order to meet the charging demand [31]. The initial laxity (l_0) for an EV seen in the data is calculated as follows:

$$l_0 = \Delta T - \frac{\Delta E_{req}}{P_{0,max}}, \quad (4)$$

where ΔT is the remaining plug-in time, ΔE_{req} is the remaining charging demand, and $P_{0,max}$ is the initial maximum charging power of the EV. The initial laxity is then used to determine the charging profile modeling method for an EV as follows:

$$\begin{cases} \text{linear profile} & \text{if } l_0 \leq \theta \\ \text{nonlinear profile} & \text{if } l_0 > \theta \end{cases}, \quad (5)$$

where θ is a threshold. Ideally, the initial laxity should be zero for charging sessions with constant power. In reality, laxity is practically never zero, as the charging power may have minor fluctuations. Hence, a threshold (θ) of 5 min is selected. In the charging session data of REDI and Tripla, 71.2% and 41.0% of the sessions have a laxity of >5 min and, thus, are modeled with non-linear charging profiles. For simplicity's

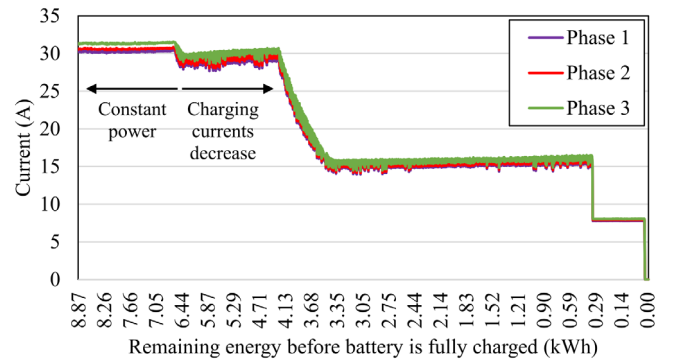


FIGURE 6 Illustration of the realized charging currents and the remaining energy demand for Smart EQ ForFour in case of 32 A current limit set by the charging point.

TABLE 2 The key parameters of the simulated EV models.

Model name and year	Max charging current	Max charging power	Charging power group
Nissan Leaf 2012	1 × 17 A	3.9 kW	0–5 kW
Nissan Leaf 2019	1 × 30 A	6.9 kW	5–10 kW
BMW i3 2016	3 × 16 A	11.0 kW	10–15 kW
Smart EQ ForFour 2020	3 × 31 A	21.3 kW	15–25 kW
Renault Zoe 2020	3 × 31 A	21.5 kW	15–25 kW

sake, it is assumed that the charged energy seen in the data is also the total energy demand of the EV before being fully charged.

The simulation model uses a three-dimensional lookup table formed in [30] to model non-linear charging profiles. The lookup table defines the simulated charging current based on the EV's model, the remaining energy demand before the battery is fully charged, and the current limit set by the charging point. The lookup table has been formed based on extensive laboratory measurements. The measurements were repeated for each current limit integer and each EV model. These measurements were then used to map the realistic current behavior regarding the EV model, remaining energy demand before the battery is fully charged, and current limit. The lookup table is formed only for the part where charging currents decrease. The charging power is assumed to be constant otherwise (i.e. with higher remaining energy demands). An illustration of the formulation of the lookup table is given in Figure 6, where the EV model is Smart EQ ForFour, and the current limit is 32 A. The charging energy is measured from the grid perspective, similar to the energy seen in the charging session data. Investigation of the energy flow inside the EV, including charging losses etc., is excluded from the study. Further explanation of the lookup table formulation can be found in [30].

Five different EV models are considered in the simulations. The key parameters of these EVs are shown in Table 2. According to [32], the exact charging profiles of all different EV models are not needed to ensure accurate modeling of charging

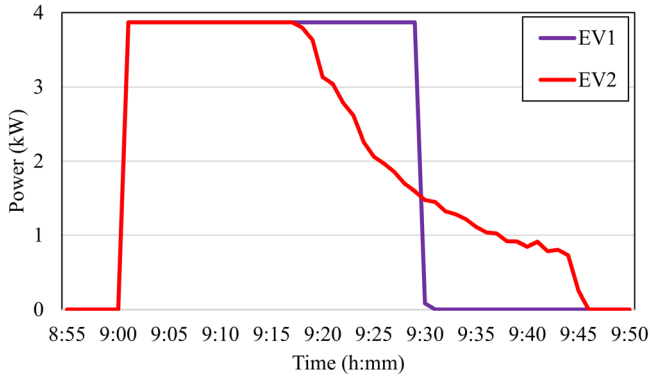


FIGURE 7 Illustration of linear and non-linear charging profiles. EV1 stays 9:00–9:30 and has laxity of 1 min, and thus, is modeled with linear profile. EV2 stays 9:00–10:00 and has laxity of 31 min, and thus, is modeled with non-linear profile.

loads. Instead, modeling should consider the charging profiles of different EVs with different maximum charging powers [32]. The considered EVs represent well the most distinctive charging power groups seen in [29], thus giving reliable basis for the simulations. The *charging power group* is used to couple EV models (i.e. charging profile modeling method) with charging sessions (i.e. arrival time, energy demand etc., provided in the data). For example, if the maximum charging power in the charging session data is 20 kW, the model is assumed to be either Smart or Renault. Between the two models, a random decision is made. The BMW i3 2016 has three different operation modes (slow, reduced, and maximum), which cannot be changed by the charging control system [33]. Each mode has a different charging profile, but the key parameters remain the same. In case the maximum charging power of the charging session is between 5 and 10 kW, BMW i3 with randomly generated operation mode (slow, reduced, maximum) is assigned.

To demonstrate the difference between linear and non-linear charging profiles, Figure 7 presents two example profiles. In the figure, the simulated EVs have the same model (Nissan Leaf 2012), charging demand (1.9 kWh), max charging power (3.9 kW) and arrival time (9:00). But, since they have different departure times (9:30 and 10:00), they have different initial laxities (1 and 31 min, respectively, according to Equation 4). Consequently, they will be modeled with linear and non-linear charging profiles based on Equation (5), respectively.

It is worth noting that the laxity is used for modeling purposes only. Consequently, the information regarding the laxity is not required in real-life applications of the considered charging control or proposed compensation scheme.

4.4 | Modeling user decisions

This paper studies the impacts of different choices made by the users. Here, the EV users decide to accept charging control (i.e. opt-in), reject charging control (i.e. opt-out), or go to another charging site (i.e. relocate).

The used charging session data do not include any direct information regarding the urgency of the charging demand or users' charging preferences. Hence, assumptions are needed to determine their decisions. Here, the opt-in/opt-out decision for EV_{*i*} is denoted by $\omega_{opt,i}$. Specifically, $\omega_{opt,i} = 1$ (respectively, 0) means that the user of EV_{*i*} decides to opt-in for the charging control (respectively, opt-out from charging control). Similarly, the decision to choose another charging site is denoted by $\omega_{rel,i}$. Specifically, $\omega_{rel,i} = 1$ (respectively, 0) means that the user of EV_{*i*} decides to relocate to another charging site (respectively, stay at the charging site). Parameters *acceptance rate* (\mathcal{O}_{opt}) and *relocation rate* (\mathcal{O}_{rel}) are used to indicate the share of EV users who opt-in for charging control and who choose to relocate to another charging site. In this article, it is assumed that the initial laxity (l_0) of the charging sessions (see Equation 4) determines their tendencies for the decision: the higher the laxity, the more likely the EV user accepts charging control, and the lower the laxity, the more likely the user goes to another charging site if uncontrolled charging is not available. The decisions are determined according to Equations (6) and (7). Since there is no information about the user decisions, different acceptance (\mathcal{O}_{opt}) and relocation rates (\mathcal{O}_{rel}) are considered in the simulations. As an example of Equation (6) in case of $\mathcal{O}_{opt} = 5\%$, EV_{*i*} is assumed to accept charging control if its initial laxity ($l_{i,0}$) is in the top 5% highest initial laxities of all considered EVs (L_0).

$$\begin{cases} \omega_{opt,i} = 1 & \text{if } l_{i,0} > \text{percentile}(L_0, \mathcal{O}_{opt}) \forall l_{i,0} \in L_0 \\ \omega_{opt,i} = 0 & \text{otherwise} \end{cases}, \quad (6)$$

$$\begin{cases} \omega_{rel,i} = 1 & \text{if } l_{i,0} < \text{percentile}(L_0, \mathcal{O}_{rel}) \forall l_{i,0} \in L_0 \\ \omega_{rel,i} = 0 & \text{otherwise} \end{cases}. \quad (7)$$

4.5 | Simulation model

The simulations start by reading the input data and parameters. The real charging session data include plug-in time, plug-out time, active charging time, charged energy, and charging peak power for each modelled EV. Charging profile lookup tables include the information how the charging powers of the non-linear charging profiles change over the charging session. After reading the input data, the initial laxities of the charging sessions are calculated to determine their modeling method (linear or non-linear, see Equation 5) and the related user decisions (opt-in, opt-out or relocate, see Equations 6 and 7) based on the charging session input data. The simulation model loops through every time step and calculates the energies charged into the EVs, energy-related costs, and the highest peak load of the charging site. In the simulations, a 1-minute temporal resolution is used. This selection is made based on the findings of the study [34], where this resolution was shown to be reasonably accurate in cases with charging control. After all scenarios with different user decisions and peak load limits have been simulated, the results can be analyzed. A block diagram for the simulation model is presented in Figure 8.

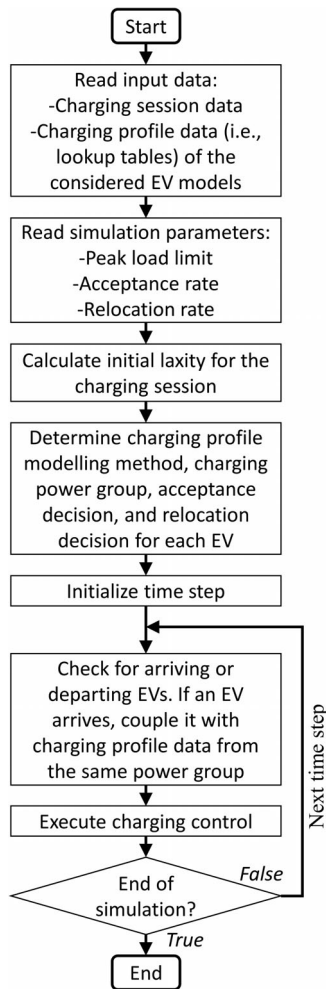


FIGURE 8 A block diagram for the simulation model.

5 | RESULTS

The results are analyzed from different perspectives in separate subsections. The analysis focuses on uncontrolled charging, peak load curtailment potential, evaluation of the proposed compensation scheme, and the impacts of the users' relocation decisions on CSO's profits. Finally, the results are discussed.

As said, the paper focuses on the operational aspects of the charging site and how the users' decisions affect it. Hence, analysis of the investment costs and optimal sizing of the charging site are excluded from the paper. Instead, the number of charging points is assumed to be 48 so that all EVs can always find an unoccupied charging point.

5.1 | Uncontrolled charging

In Figure 9, the persistence curves are shown for the relative charging powers of both locations in case of uncontrolled charging. The peak demands, that is, the powers corresponding to the 100% relative values, are 218.4 kW and 171.8 kW for REDI and Tripla, respectively. The persistence curves indicate very high

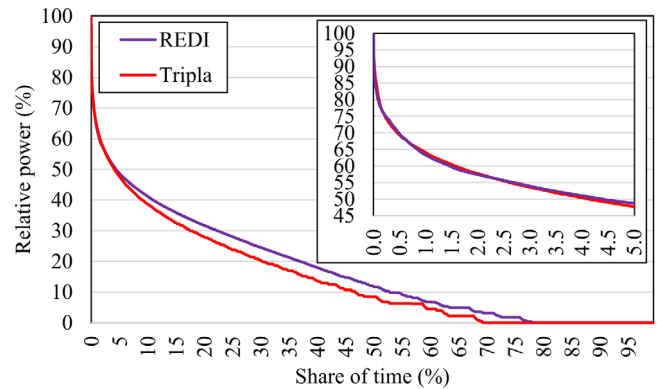


FIGURE 9 Persistence curve for the relative charging powers of both locations in case of uncontrolled charging assuming that there are enough charging points for all EVs.

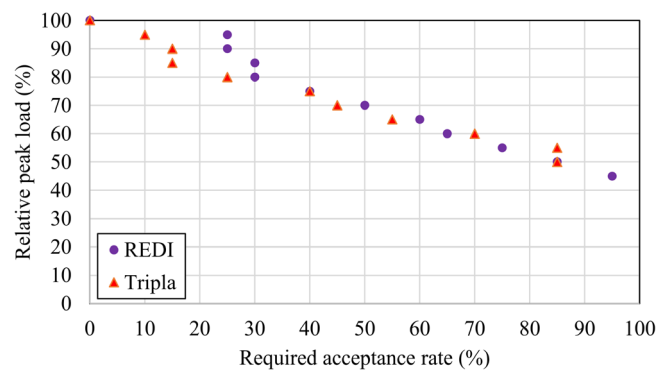


FIGURE 10 The correlation between required acceptance rate and achieved peak load reduction.

peak-to-average ratios (6.0 and 6.9). This indicates that charging control is needed for a relatively short time to achieve a relatively high peak demand reduction. For example, the power is above the 50% relative value less than 5% of the time for both locations. During this time, 15.6% and 17.0% of the total energy delivery takes place at REDI and Tripla, respectively.

5.2 | Peak load curtailment potential

To determine the required acceptance rate for a certain maximum peak load curtailment, simulations are repeated while increasing the acceptance rate in 5%-unit steps until the targeted maximum peak load is not exceeded. In case of 0% acceptance rate, the charging is essentially uncontrolled. This leads to the highest hourly loads of 199.7 kW and 158.6 kW for REDI and Tripla, respectively. These values represent the 100% relative powers used to determine the percentual peak load reduction potential. The highest hourly loads are considered here, as the demand charges are often based on these values.

The correlation between the required acceptance rate and achieved percentual peak load is illustrated in Figure 10. The reallocation rate is assumed to be zero in the figure. The results show that the correlation is relatively linear. It is also seen that

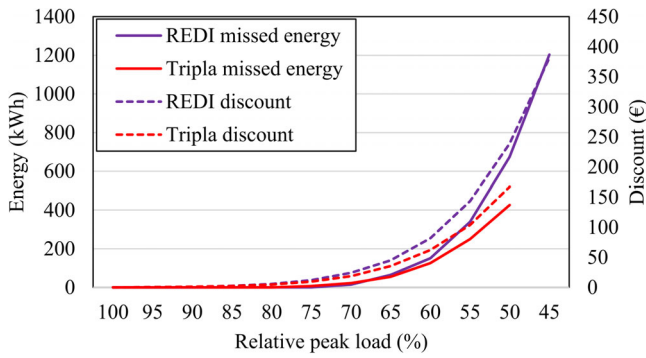


FIGURE 11 The average monthly compensation given to the EV users and the energy that is not charged due to the peak load curtailment.

the peak loads can be reduced up to 45% and 50%, for REDI and Tripla, in case of 100% acceptance rate using the considered approach. More numerical results can be found in Tables A.1 and A.2 in the appendix.

5.3 | Evaluation of the compensation scheme

5.3.1 | EV user perspective

In Figure 11, the average monthly compensation (calculated based on (2)) and the energy that is not charged into the opt-in EVs are presented. Based on the figure, the compensation given to the EV users in the proposed charging pricing correlates well with the charging energy-related inconvenience experienced by the users: the greater the charging power curtailment, the greater the discount given to the EV users. Thus, the proposed compensation scheme is seen as user-friendly, and incentivizes EV users with less urgent charging demand to opt-in.

5.3.2 | CSO perspective

The average monthly profits (ψ) of the CSO are calculated according to

$$\psi = R - C_{op}, \quad (8)$$

where R is the average monthly revenue and C_{op} are the average monthly incurred operational costs. The average monthly revenues are calculated according to

$$R = (E_{total,opt-out} \times c_c + \sum_i \sum_t E_{i,t,opt-in} \times c_{c,i,t,opt-in}) / n_m, \quad (9)$$

where $E_{total,opt-out}$ is the total energy charged into the opt-out EVs, c_c is the baseline charging price for the EV users, i is the index for an EV, t is time step, $E_{i,t,opt-in}$ is the energy charged into an opt-in EV, and n_m is the number of months. The operational costs are calculated according to

$$C_{op} = P_{peak} \times c_{peak} + E_{total} \times (c_{de} + c_{ee}) / n_m + c_b, \quad (10)$$

TABLE 3 The parameters for the economic evaluation.

Parameter	Description	Value
c_c	Charging cost for the EV users	22.5 c/kWh ^a
c_{ee}	Energy purchase price for the CSO	15.42 c/kWh [35]
c_{de}	Energy distribution price for CSO	1.66 c/kWh [36]
c_{peak}	Demand charge for CSO	4.5€/kW, month [36]
c_b	Basic charge for CSO	26.0€/month [36]

^a Average value of the price used in the two locations [27, 28].

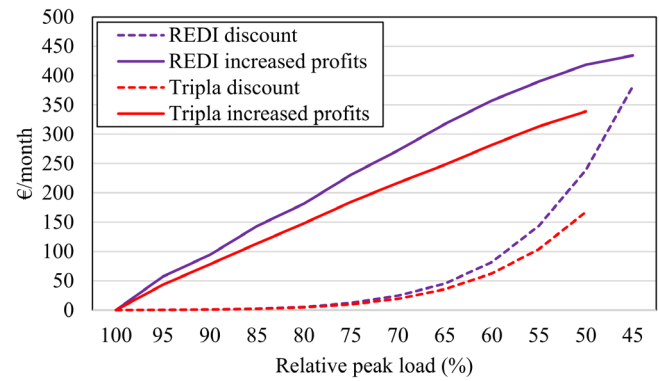


FIGURE 12 The average monthly discount given to the EV users and the CSO's increased profit obtained using peak load curtailment.

where P_{peak} is the highest hourly peak load, c_{peak} is the demand charge, c_{de} is the distribution price of the electrical energy, c_{ee} is the electrical energy purchase price, and c_b is the basic monthly distribution charge (€/month). The parameters for the economic calculations are shown in Table 3.

Figure 12 presents the average monthly discount given to the EV users and the CSO's increased profits using the peak load curtailment. The case with uncontrolled charging (100% relative peak load) is used as a reference point to determine the CSO's profit increment. Here, the profit increment does not include the discount that is given to the EV users. Based on the figure, it can be seen that the discount given to the EV users does not correlate with the profit increment of the CSO. Thus, it is an objective for the CSO to determine the optimal peak load to maximize the total benefits. Without the compensation scheme, it would be more profitable for the CSO to limit the peak loads even further below the 50% relative value if it didn't influence on the number of customers. Conversely, by using the proposed EV user-friendly compensation scheme, reducing the peak load to 60% leads to the highest profits for both charging sites. Based on Figure 10, this would require 65% and 70% acceptance rate to be possible, respectively, for REDI and Tripla. The correlation between profits and the relative peak load is illustrated in Figure 13.

The compensation scheme's profitability depends on the users' acceptance rate to participate in charging control. This correlation is illustrated in Figure 14. In both locations, the

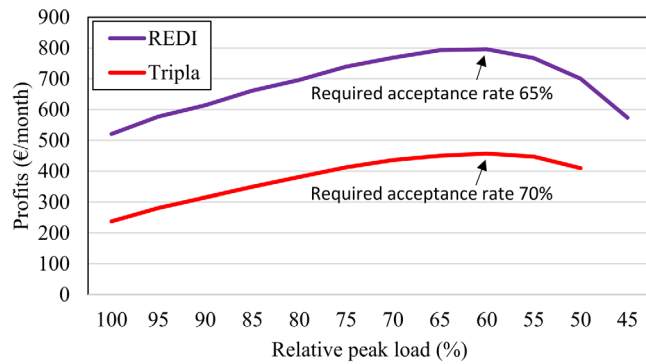


FIGURE 13 The correlation between the profits and the peak load reduction.

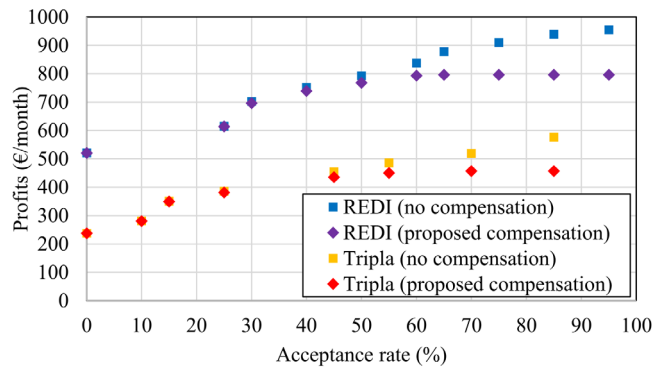


FIGURE 14 The average monthly profits of the CSO with and without the proposed compensation scheme.

compensation scheme does not bring any value if the acceptance rate is $\geq 50\%$ without any compensations. Instead, the profits of the CSO may only be reduced by giving compensation to the EV users. However, if the original acceptance rate is below 50% and the proposed compensation scheme would increase it so that a lower peak load can be achieved, the profits of the CSO would increase up to 275€/month or 219€/month for REDI and Tripla, respectively. The lower the original acceptance rate is, the higher the benefits of the acceptance rate increment. These additional benefits should motivate the CSO to promote charging control acceptance and to utilize the available flexibility.

5.4 | Influence of EV users' decisions to relocate

By making uncontrolled charging not an option, the charging site could always limit the peak loads according to the most profitable level seen in Figure 13. However, in this case, the users who have concerns about the charging control or have more urgent charging demand might choose to relocate to another charging site. Therefore, the question is whether it is more profitable for the CSO to have an optimal charging control or to maximize the number of customers.

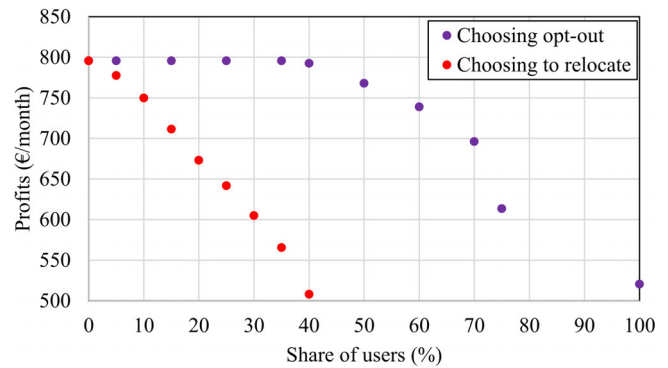


FIGURE 15 The correlation between profits and user decisions for REDI. Here, user decisions are to opt-out from charging control or to relocate to another charging site.

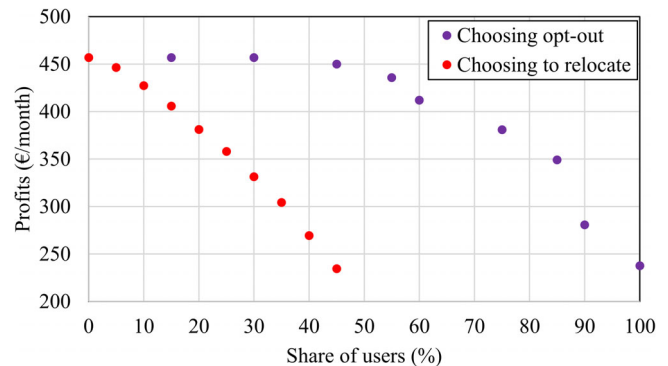


FIGURE 16 The correlation between profits and user decisions for Tripla. Here, user decisions are to opt-out from charging control or to relocate to another charging site.

To analyze the potential impacts of this, the profits of the charging sites are calculated with different shares of users who choose opt-out or relocation. The correlations are shown in Figures 15 and 16 for REDI and Tripla, respectively. According to the figures, it is always more profitable for the CSO if the users choose to opt-out instead of relocating. Even if 55% of the users who would prefer opt-out choose to opt-in and the remaining choose to relocate, having the opt-out option would lead to higher profits for the CSO. This indicates that encouraging EV users to choose the charging site is far more important than the optimality of the peak load curtailment. More numerical results can be found in Tables A.3 and A.4 in the appendix.

5.5 | Discussions

This paper assumes that the maximum charging power of the EVs are known by the charging control system. In reality, this information is not available in level 2 charging. However, in level 3 fast charging of EVs, the EV already communicates information regarding the charging powers to the control system. If the same protocol is applied to the level 2 charging, charging system could easily execute the proposed compensation scheme.

It is clear that the charging control implementation cannot be optimized from every stakeholder's perspective at the same time. Maximizing user acceptance may not be optimal from the grid perspective, and optimizing the charging loads from the grid perspective may not be optimal from the user acceptance perspective. Consequently, a CSO should find a solution between these extremes to maximize profitability and competitiveness.

This paper considers only a distribution tariff with a demand charge component as an incentive for the CSO to control charging loads. The flexibility of the charging loads could be used to gain further benefits from, for example, flexibility markets, which would increase the value of the "opt-in" EVs and profits of the CSO. Nevertheless, the same logic is assumed to apply: the number of users highly affects the profits, and having an "opt-out" EV is more beneficial than a relocated EV. Consequently, EV users' acceptance is assumed to play an important role in all kinds of charging control scenarios and, thus, should be taken into account.

It is also worth remembering that EV charging can be seen in a larger picture where it provides a service, perhaps for a bigger aim of attracting more customers to nearby businesses. In this case, the charging control's algorithm is not only influenced by electrical engineering constraints coming from the distribution grid or CSO's profit but also user friendliness and minimization of reallocation rate because the financial significance of having more customers for businesses can overshadow other involved considerations.

The considered control approach and proposed pricing scheme utilize only the information of "opt-in" or "opt-out" decisions of EV users and maximum charging power of the EVs. Consequently, computational burden and data privacy risks are relatively low compared with the examples mentioned in Section 2.2 where departure time and energy demand are required. The computational requirement of the considered CCE feature is also shown to be suitable for real-life operation [25]. Further assessment of cyber security and computational complexity are excluded from the paper.

6 | CONCLUSIONS

While EV charging has been studied extensively and multiple surveys have been conducted to analyze EV users' perspective in charging control, a gap exists regarding the potential influences of the EV users' response to charging control on the charging site operator's profits. This acted as the motivator for the study.

The goal of the paper was to assess the potential means and benefits of end-user engagement in public charging sites with level 2 charging. In order to do so, firstly, EV users' perspective was analyzed based on the literature. Secondly, the paper developed an EV user-friendly charging control approach and proposed a compensation scheme that provides compensation for EV users based on the incurred inconvenience. Finally, simulations were conducted for two locations under

demand charges (€/kW) to analyze the potential effects of users' decisions from the charging site operator's perspective.

The analysis of the persistence of uncontrolled charging loads showed that the highest peak loads occur very rarely. Consequently, a relatively high peak load curtailment can be achieved with relatively low impacts on the EV charging loads. For example, the power is above the 50% relative value less than 5% of the time in both locations.

By using the considered charging control approach, the highest peak load can be cut to half, which would require 100% acceptance rate. However, the optimal charging site operator's profits are achieved when the peak load is limited to 60% of the original value. This would require 65–70% acceptance rate, and thus, 100% acceptance rate is not required to optimize the charging site operator's profits.

The evaluation of the proposed compensation scheme showed that the compensation correlates well with the charging energy-related inconvenience experienced by EV users. Since the compensation scheme also has an EV user-friendly design, it can be a very attractive choice from the users' perspective. Conversely, the compensation does not correlate with the peak load curtailment-related benefits obtained by the charging site operator. Therefore, the charging site operator retains the task of optimizing charging control and carries the risks of suboptimal peak load curtailment.

When assessing the influences of EV users' decisions to relocate to another charging site, the results showed that offering an option to "opt-out" from charging control can be highly beneficial. Even if only 45% of the users who prefer "opt-out" option relocate while the rest accept the charging control, the charging site operator's profits would be higher by having the option to "opt-out". So, even though uncontrolled EVs reduce the optimality of the charging control, a very high emphasis should be put on attracting as many users as possible to maximize the profits of the charging site operator.

This paper underlines that EV users' acceptance plays an important role in charging control, and thus, it is not feasible to focus solely on optimizing the charging from grid perspective. Instead, the user acceptance should be ensured by taking the users' concerns into account via user-friendly approach where users' compensation is only one factor among the rest.

To further understand the potential influences of the EV users' response, future work should investigate more complex scenarios where the flexibility of the EVs is used in different ways. This could increase the value of the "opt-in" users, and thus, higher compensations could be given to them to increase the acceptance rate. This would likely increase the complexity of the charging control, and thus, the EV users' perspective should be carefully addressed. Additionally, the effect of sizing and congestion of a charging site on EV users' response should be studied. Furthermore, the current surveys focus on early adopters who may have more positive attitude towards charging control acceptance. To more accurately analyze future scenarios with large-scale EV charging, more knowledge of the behavior and tendencies of the future majority of EV users is needed.

NOMENCLATURE

Indices

- i Index for EV
 t Index for time step

Parameters and variables

- c_c Baseline price of charging energy (€/kWh)
 $c_{c,t,opt-in}$ Charging price for EV users who accept charging control (€/kWh)
 c_{de} Distribution price of the electrical energy (€/kWh)
 c_{ee} Electrical energy purchase price (€/kWh)
 c_{peak} Demand charge (€/kW/month)
 C_{op} Operational costs (€)
 $C_{t,comp}$ Charging price compensation (€)
 ΔE_{req} Remaining charging demand (kWh)
 E_t Charged energy (kWh)
 E_{total} Total energy charged into all EVs (kWh)
 $E_{t,opt-in}$ Energy charged into an opt-in EV (kWh)
 $E_{total,opt-out}$ Total energy charged into the opt-out EVs (kWh)
 I_{temp} Temporal variable for a charging current limit (A)
 l_0 Initial laxity (min)
 L_0 List of initial laxities of all EVs in the data (min)
 n_m Number of months
 n_p Number of phases used for charging
 $P_{0,max}$ Initial maximum charging power (kW)
 P_{peak} Highest peak load (kW)
 P_t Realized charging power (kW)
 $P_{t,max}$ Maximum charging power at time t (kW)
 R Average monthly revenue (€)
 ΔT Remaining available time for charging (min)
 θ Laxity threshold to determine charging profile modeling (min)
 $\omega_{opt,i}$ Decision to opt-in for charging control for the user of EV $_i$ (0 or 1 to opt-out or opt-in, respectively)
 $\omega_{rel,i}$ Decision to choose another charging site for the user of EV $_i$ (0 or 1 to stay or relocate, respectively)
 \mathcal{O}_{opt} Acceptance rate (%)
 \mathcal{O}_{rel} Relocation rate (%)
 ψ Average monthly profits (€)

Abbreviations

- AC Alternating current
 BMS Battery management system
 CCE Charging characteristics expectation (a charging control feature to track the non-ideal responses of EVs)
 CSO Charging site operator
 DSO Distribution system operator

- EV Electric vehicle
 OBC On-board charger
 SOC State of charge

AUTHOR CONTRIBUTIONS

Toni Simolin: Conceptualization; methodology; software; validation; formal analysis; investigation; data curation; writing—original draft; writing—review & editing; visualization. **Mehdi Attar:** Conceptualization; methodology; writing—original draft; writing—review & editing. **Sami Repo:** Writing—review & editing. **Pertti Järventausta:** Resources; writing—review & editing; funding acquisition.

ACKNOWLEDGEMENTS

This work was supported by the LIFE Programme of the European Union (LIFE17 IPC/FI/000002 LIFE-IP CANEMURE-FINLAND) and Walter Ahlström, Fortum and Neste Foundations. The authors would like to thank IGL Technologies for providing the charging session data. The authors would also like to thank Prof. Mario Paolone from EPFL-DESL, Switzerland, for the support and guidance during the work.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data available on request from the authors

ORCID

Toni Simolin  <https://orcid.org/0000-0002-0254-1113>

REFERENCES

- Alaee, P., Bems, J., Anvari-Moghaddam, A.: A review of the latest trends in technical and economic aspects of EV charging management. *Energies* 16, 3669 (2023). <https://doi.org/10.3390/en16093669>
- Wang, N., Tian, H., Zhu, S., Li, Y.: Analysis of public acceptance of electric vehicle charging scheduling based on the technology acceptance model. *Energy* 258, 124804 (2022). <https://doi.org/10.1016/j.energy.2022.124804>
- Li, X., Wang, Z., Zhang, L., Sun, F., Cui, D., Hecht, C., Figgenger, J., Sauer, D.U.: Electric vehicle behavior modeling and applications in vehicle-grid integration: An overview. *Energy* 268, 126647 (2023). <https://doi.org/10.1016/j.energy.2023.126647>
- Bailey, J., Axsen, J.: Anticipating PEV buyers' acceptance of utility controlled charging. *Transp. Res. Part A* 82, 29–46 (2015). <http://doi.org/10.1016/j.tra.2015.09.004>
- Schmalfuß, F., Mair, C., Döbelt, S., Kämpfe, B., Wüstemann, R., Krems, J.F., Keinath, A.: User responses to a smart charging system in Germany: Battery electric vehicle driver motivation, attitudes and acceptance. *Energy Res. Social Sci.* 9, 60–71 (2015). <http://doi.org/10.1016/j.erss.2015.08.019>
- Will, C., Schuller, A.: Understanding user acceptance factors of electric vehicle smart charging. *Transp. Res. Part C* 71, 198–214 (2016). <http://doi.org/10.1016/j.trc.2016.07.006>
- Delmonte, E., Kinnear, N., Jenkins, B., Skippon, S.: What do consumers think of smart charging? Perceptions among actual and potential plug-in electric vehicle adopters in the United Kingdom. *Energy Res. Social Sci.* 60, 101318 (2020). <https://doi.org/10.1016/j.erss.2019.101318>
- Kim, J.-H., Shcherbakova, A.: Common failures of demand response. *Energy* 36, 873–880 (2011). <https://doi.org/10.1016/j.energy.2010.12.027>

9. Yang, L., Geng, X., Guan, X., Tong, L.: EV charging scheduling under demand charge: A block model predictive control approach. *IEEE Trans. Autom. Sci. Eng.* 21, 2125–2138 (2023). <https://doi.org/10.1109/TASE.2023.3260804>
10. Botkin-Levy, M., Engelmann, A., Mühlfordt, T., Faulwasser, T., Almassalki, M.R.: Distributed control of charging for electric vehicle fleets under dynamic transformer ratings. *IEEE Trans. Control Syst. Technol.* 30, 1578–1594 (2022). <https://doi.org/10.1109/TCST.2021.3120494>
11. Zahedmanesh, A., Muttaqi, K.M., Sutanto, D.: A cooperative energy management in a virtual energy hub of an electric transportation system powered by PV generation and energy storage. *IEEE Trans. Transp. Electrification* 7, 1123–1133 (2021). <https://doi.org/10.1109/TTE.2021.3055218>
12. Zahedmanesh, A., Muttaqi, K.M., Sutanto, D.: Coordinated charging control of electric vehicles while improving power quality in power grids using a hierarchical decision-making approach. *IEEE Trans. Veh. Technol.* 69, 12585–12596 (2020). <https://doi.org/10.1109/TVT.2020.3025809>
13. Wang, M., Li, X., Dong, C., Mu, Y., Jia, H., Li, F.: Day-ahead optimal bidding for a retailer with flexible participation of electric vehicles. *IEEE Trans. Smart Grid* 14, 1482–1494 (2023). <https://doi.org/10.1109/TSG.2022.3208093>
14. Wang, S., Bi, S., Zhang, Y.A.: Reinforcement learning for real-time pricing and scheduling control in EV charging stations. *IEEE Trans. Ind. Inf.* 17, 849–859 (2021). <https://doi.org/10.1109/TII.2019.2950809>
15. Giraldo, J.S., Arias, N.B., Duque, E.M.S., Hoogsteen, G., Hurink, J.L.: A compensation mechanism for EV flexibility services using discrete utility functions. In: *IEEE PES Innovative Smart Grid Technologies Conference*. IEEE, Piscataway (2022). <https://doi.org/10.1109/ISGT-Europe54678.2022.9960542>
16. Hahnel, U.J.J., Gözl, S., Spada, H.: How accurate are drivers' predictions of their own mobility? Accounting for psychological factors in the development of intelligent charging technology for electric vehicles. *Transp. Res. Part A: Policy Pract.* 48, 123–131 (2013). <https://doi.org/10.1016/j.tra.2012.10.011>
17. Lee, Z.J., Li, T., Low, S.H.: Adaptive charging networks: A framework for smart electric vehicle charging. In: *e-Energy '19: Proceedings of the Tenth ACM International Conference on Future Energy Systems*, pp. 139–149. ACM, New York (2019). <https://doi.org/10.1145/3307772.3328313>
18. Xu, X., Li, K., Wang, F., Mi, Z., Jia, Y., Wei, W., Jing, Y.: Evaluating multi-timescale response capability of EV aggregator considering users' willingness. *IEEE Trans. Ind. Appl.* 57, 3366–3376 (2021). <https://doi.org/10.1109/TIA.2021.3081402>
19. Sun, X., Qiu, J.: Hierarchical voltage control strategy in distribution networks considering customized charging navigation of electric vehicles. *IEEE Trans. Smart Grid* 12, 4752–4764 (2021). <https://doi.org/10.1109/TSG.2021.3094891>
20. Singhal, A., Hanif, S., Bhattarai, B., dos Reis, F.B., Reeve, H., Pratt, R.: Designing a transactive electric vehicle agent with customer's participation preference. *Int. J. Electr. Power Energy Syst.* 151, 109147 (2023). <https://doi.org/10.1016/j.ijepes.2023.109147>
21. Hou, H., Wang, Y., Xie, C., Xiong, B., Zhang, Q., Huang, L.: A dispatching strategy for electric vehicle aggregator combined price and incentive demand response. *IET Energy Syst. Integr.* 3, 508–519 (2021). <https://doi.org/10.1049/esi2.12042>
22. Apostolaki-Iosifidou, E., Codani, P., Kempton, W.: Measurement of power loss during electric vehicle charging and discharging. *Energy* 127, 730–742 (2017). <https://doi.org/10.1016/j.energy.2017.03.015>
23. Rudnik, R., Wang, C., Reyes-Chamorro, L., Achara, J., Le Boudec, J.-Y., Paolone, M.: Real-time control of an electric vehicle charging station while tracking an aggregated power setpoint. *IEEE Trans. Ind. Appl.* 56, 5750–5761 (2020). <https://doi.org/10.1109/TIA.2020.2984409>
24. Rauma, K., Simolin, T., Rautiainen, A., Järventausta, P., Rehtanz, C.: Overcoming non-idealities in electric vehicle charging management. *IET Electr. Syst. Transp.* 11, 310–321 (2021). <https://doi.org/10.1049/els2.12025>
25. Simolin, T., Rauma, K., Rautiainen, A., Järventausta, P., Rehtanz, C.: Foundation for adaptive charging solutions: Optimised use of electric vehicle charging capacity. *IET Smart Grid* 4, 599–611 (2021). <https://doi.org/10.1049/stg2.12043>
26. Rauma, K., Simolin, T., Järventausta, P., Rautiainen, A., Rehtanz, C.: Network-adaptive and capacity-efficient electric vehicle charging site. *IET Gener. Transm. Distrib.* 16, 548–560 (2021). <https://doi.org/10.1049/gtd2.12301>
27. REDI: Parking. <https://www.redi.fi/en/parking/>. Accessed 12 Sept 2023
28. Tripla: Arrival and parking. <https://malloftripla.fi/arrival-and-parking-1/>. Accessed 12 Sept 2023
29. Simolin, T., Rauma, K., Viri, R., Mäkinen, J., Rautiainen, A., Järventausta, P.: Charging powers of the electric vehicle fleet: Evolution and implications at commercial charging sites. *Appl. Energy* 303, 117651 (2021). <https://doi.org/10.1016/j.apenergy.2021.117651>
30. Simolin, T., Rautiainen, A., Järventausta, P., Rauma, K., Rehtanz, C.: Assessing the influence of electric vehicle charging profile modelling methods. *IET Gener. Transm. Distrib.* 16, 3027–3035 (2022). <https://doi.org/10.1049/gtd2.12494>
31. Chen, N., Kurniawan, C., Nakahira, Y., Chen, L., Low, S.H.: Smoothed least-laxity-first algorithm for electric vehicle charging: Online decision and performance analysis with resource augmentation. *IEEE Trans. Smart Grid* 13, 2209–2217 (2022). <https://doi.org/10.1109/TSG.2021.3138615>
32. Frendo, O., Graf, J., Gaertner, N., Stuckenschmidt, H.: Data-driven smart charging for heterogeneous electric vehicle fleets. *Energy AI* 1, 100007 (2020). <https://doi.org/10.1016/j.egyai.2020.100007>
33. Bayerische Motoren Werke AG: The BMW i3. Owner's Manual, p. 183. München (2016)
34. Simolin, T., Rauma, K., Rautiainen, A., Järventausta, P., Rehtanz, C.: Assessing the influence of the temporal resolution on the electric vehicle charging load modeling accuracy. *Electr. Power Syst. Res.* 208, 107913 (2022). <https://doi.org/10.1016/j.epsr.2022.107913>
35. Helen Ltd: Electricity products. <https://www.helen.fi/en/companies/electricity-for-companies/electricity-products-for-smes-and-associations>. Accessed 12 Sept 2023
36. Helen Electricity Network: Distribution tariffs. https://www.helensahkoverkko.fi/globalassets/hinnastot-ja-sopimusedot/hsv-enku/electricity-distribution-tariffs_en2.pdf. Accessed 10 June 2024

How to cite this article: Simolin, T., Attar, M., Repo, S., Järventausta, P.: End-user engagement in EV charging control at commercial locations through a user-friendly approach. *IET Gener. Transm. Distrib.* 1–17 (2024). <https://doi.org/10.1049/gtd2.13234>

APPENDIX

See Tables A.1–A.4.

TABLE A.1 Numerical results in terms of monthly average values for peak load curtailment potential for RED1.

Relative peak load	Peak power (P_{peak})	Required acceptance rate (θ_{opt})	Number of opt-in EVs	Demand charge	Charged energy			Charging energy price opt-out ^a	Charged energy ($E_{total,opt-in}$)	Charging energy price opt-in ^a	Average opt-in charging price ($c_{e,opt-in,avg}$)	Charging energy costs ^b	Discount (C_{emp})	Profit (ψ)
					opt-out ($E_{total,opt-out}$)	opt-out	opt-in							
100%	199.7 kW	0%	0	898.8€	26668.3 kWh	6000.4€	0€	0 kWh	0€	22.50 snt/kWh	4554.9€	0.0€	520.6€	
95%	187.0 kW	25%	696	841.6€	18167.5 kWh	4087.7€	1912.3€	8500.8 kWh	1912.3€	22.50 snt/kWh	4554.9€	0.4€	577.4€	
90%	178.8 kW	25%	696	804.7€	18167.5 kWh	4087.7€	1911.7€	8500.8 kWh	1911.7€	22.49 snt/kWh	4554.9€	0.9€	620.5€	
85%	167.9 kW	30%	835	755.5€	16410.2 kWh	3692.3€	2305.7€	10258.1 kWh	2305.7€	22.48 snt/kWh	4554.9€	2.4€	661.5€	
80%	159.4 kW	30%	835	717.4€	16410.2 kWh	3692.3€	2302.5€	10258.1 kWh	2302.5€	22.45 snt/kWh	4554.9€	5.6€	696.4€	
75%	148.4 kW	40%	1113	668.0€	13539.7 kWh	3046.4€	2941.6€	13127.8 kWh	2941.6€	22.41 snt/kWh	4554.8€	12.1€	739.2€	
70%	139.1 kW	50%	1392	626.0€	10633.8 kWh	2392.6€	3580.0€	16019.8 kWh	3580.0€	22.35 snt/kWh	4552.4€	24.4€	768.2€	
65%	128.5 kW	60%	1670	578.2€	7539.0 kWh	1696.3€	4244.7€	19064.9 kWh	4244.7€	22.26 snt/kWh	4544.0€	44.9€	792.8€	
60%	118.5 kW	65%	1809	533.4€	6229.0 kWh	1401.5€	4482.9€	20288.2 kWh	4482.9€	22.10 snt/kWh	4529.1€	81.9€	795.9€	
55%	109.0 kW	75%	2088	490.6€	4198.9 kWh	944.8€	4835.8€	22130.5 kWh	4835.8€	21.85 snt/kWh	4497.1€	143.6€	766.8€	
50%	98.7 kW	85%	2366	444.1€	2212.7 kWh	497.9€	5112.1€	23781.5 kWh	5112.1€	21.50 snt/kWh	4439.8€	238.7€	700.1€	
45%	88.8 kW	95%	2644	399.4€	475.4 kWh	107.0€	5241.3€	24989.8 kWh	5241.3€	20.97 snt/kWh	4349.4€	381.4€	573.4€	

^a Describes the charging energy costs for the EV users.

^b Describes the charging energy costs for the CSO.

TABLE A.2 Numerical results in terms of monthly average values for peak load curtailment potential for Tripla.

Relative peak load	Peak power (P_{peak})	Required acceptance rate (θ_{opt})	Number of opt-in EVs	Charged energy				Charging energy price opt-out ^a	Charged energy opt-in ($E_{total,opt-in}$)	Charging energy price opt-in ^a	Average opt-in charging price ($c_{opt-in,avg}$)	Charging energy costs ^b	Discount (C_{comp})	Profit (ψ)
				Demand charge	energy opt-out ($E_{total,opt-out}$)	energy price opt-out ^a	energy opt-in							
100%	158.6 kW	0%	0	713.6€	18029.9 kWh	4056.7€	0.0 kWh	0.0€	22.50 snt/kWh	3079.5€	0.0€	237.6€		
95%	148.9 kW	10%	247	670.2€	15106.3 kWh	3398.9€	2923.6 kWh	657.4€	22.49 snt/kWh	3079.5€	0.4€	280.6€		
90%	141.2 kW	15%	371	635.4€	13687.5 kWh	3079.7€	4342.4 kWh	976.0€	22.48 snt/kWh	3079.5€	1.0€	314.8€		
85%	133.3 kW	15%	371	600.1€	13687.5 kWh	3079.7€	4342.4 kWh	975.0€	22.45 snt/kWh	3079.5€	2.0€	349.1€		
80%	125.7 kW	25%	619	565.6€	10876.1 kWh	2447.1€	7153.8 kWh	1605.0€	22.43 snt/kWh	3079.5€	4.7€	381.0€		
75%	117.6 kW	40%	990	529.1€	7959.1 kWh	1790.8€	10064.2 kWh	2254.7€	22.40 snt/kWh	3078.4€	9.7€	412.0€		
70%	110.1 kW	45%	1114	495.5€	7079.8 kWh	1592.9€	10928.4 kWh	2440.1€	22.33 snt/kWh	3075.8€	18.8€	435.7€		
65%	102.8 kW	55%	1361	462.6€	5277.2 kWh	1187.4€	12697.4 kWh	2821.3€	22.22 snt/kWh	3070.1€	35.6€	450.0€		
60%	94.5 kW	70%	1733	425.2€	3015.8 kWh	678.6€	14888.8 kWh	3287.7€	22.08 snt/kWh	3058.1€	62.3€	456.9€		
55%	85.9 kW	85%	2104	386.8€	1246.8 kWh	280.5€	16532.8 kWh	3616.2€	21.87 snt/kWh	3036.8€	103.7€	447.2€		
50%	78.2 kW	85%	2104	351.8€	1246.8 kWh	280.5€	16356.8 kWh	3513.2€	21.48 snt/kWh	3006.7€	167.1€	409.2€		

^a Describes the charging energy costs for the EV users.

^b Describes the charging energy costs for the CSO.

TABLE A.3 Numerical results in terms of monthly average values for the influence of relocation for RED1.

Relocation rate (θ_{rel})	Acceptance rate (θ_{opt})	Number of opt-in EVs	Relative peak load	Peak power (P_{peak})	Demand charge	Charged energy opt-in ($E_{total,opt-in}$)	Charging energy price opt-in ^a	Average opt-in charging price ($c_{opt-in,avg}$)	Charging energy costs ^b	Discount (C_{comp})	Profit (ψ)
0%	100%	2784	60%	118.6 kW	533.6€	26450.1 kWh	5872.0€	22.20 snt/kWh	4517.7€	79.3€	794.8€
5%	100%	2644	60%	118.6 kW	533.5€	26000.7 kWh	5777.2€	22.22 snt/kWh	4440.9€	72.9€	776.8€
10%	100%	2505	60%	118.6 kW	533.6€	25307.4 kWh	5631.1€	22.25 snt/kWh	4322.5€	63.1€	748.9€
15%	100%	2366	60%	118.6 kW	533.6€	24344.4 kWh	5429.3€	22.30 snt/kWh	4158.0€	48.1€	711.7€
20%	100%	2227	45%	108.6 kW	488.7€	23185.0 kWh	5148.2€	22.20 snt/kWh	3960.0€	68.5€	673.5€
25%	100%	2088	55%	108.6 kW	488.7€	22364.1 kWh	4976.5€	22.25 snt/kWh	3819.8€	55.4€	642.0€
30%	100%	1948	50%	98.7 kW	444.1€	21392.0 kWh	4729.0€	22.11 snt/kWh	3653.8€	84.2€	605.1€
35%	100%	1809	50%	98.7 kW	444.1€	20334.4 kWh	4509.1€	22.17 snt/kWh	3473.1€	66.2€	565.8€
40%	100%	1670	50%	98.7 kW	444.0€	19054.7 kWh	4232.8€	22.21 snt/kWh	3254.5€	54.5€	508.2€
45%	100%	1531	45%	88.7 kW	399.3€	17509.0 kWh	3869.6€	22.10 snt/kWh	2990.5€	69.9€	453.7€

^a Describes the charging energy costs for the EV users.

^b Describes the charging energy costs for the CSO.

TABLE A.4 Numerical results in terms of monthly average values for the influence of relocation for Tripla.

Relocation rate (θ_{rel})	Acceptance rate (θ_{opt})	Number of opt-in EVs	Relative peak load	Peak power (P_{peak})	Demand charge	Charged energy opt-in ($E_{total,opt-in}$)	Charging energy price opt-in ^a	Average opt-in charging price ($c_{opt-in,avg}$)	Charging energy costs ^b	Discount (C_{comp})	Profit (ψ)
0%	100%	2476	60%	93.9 kW	422.7€	17884.5 kWh	3962.3€	22.15 snt/kWh	3054.7€	61.7€	458.9€
5%	100%	2352	60%	93.9 kW	422.7€	17574.7 kWh	3896.5€	22.17 snt/kWh	3001.8€	57.8€	446.0€
10%	100%	2228	60%	93.9 kW	422.7€	17153.4 kWh	3805.5€	22.19 snt/kWh	2929.8€	54.0€	427.0€
15%	100%	2104	60%	93.9 kW	422.7€	16679.3 kWh	3703.3€	22.20 snt/kWh	2848.8€	49.6€	405.7€
20%	100%	1980	60%	93.9 kW	422.7€	16150.6 kWh	3588.5€	22.22 snt/kWh	2758.5€	45.4€	381.3€
25%	100%	1857	55%	86.0 kW	387.0€	15525.6 kWh	3422.8€	22.05 snt/kWh	2651.8€	70.5€	358.0€
30%	100%	1733	55%	86.0 kW	387.0€	14907.7 kWh	3290.6€	22.07 snt/kWh	2546.2€	63.6€	331.4€
35%	100%	1609	55%	86.0 kW	387.0€	14277.2 kWh	3155.8€	22.10 snt/kWh	2438.5€	56.6€	304.2€
40%	100%	1485	55%	86.0 kW	387.0€	13536.2 kWh	2994.4€	22.12 snt/kWh	2312.0€	51.3€	269.3€
45%	100%	1361	50%	78.2 kW	351.8€	12664.5 kWh	2775.3€	21.91 snt/kWh	2163.1€	74.2€	234.4€
50%	100%	1238	50%	78.2 kW	351.8€	11803.8 kWh	2588.0€	21.93 snt/kWh	2016.1€	67.8€	194.1€

^a Describes the charging energy costs for the EV users.

^b Describes the charging energy costs for the CSO.