Applied Energy 330 (2023) 120347

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

e-Carsharing siting and sizing DLMP-based under demand uncertainty

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HIGHLIGHTS

- e-carsharing can ensure access to fair, reliable, sustainable, and modern mobility.
- Design a two-stage stochastic DLMP-based model under EV rental demand uncertainty.
- e-carsharing planning disregarding the DSO perspective is the most profitable.
- Operation may not be possible in real cases due to the high-power flows via V2G.
- The design of joint planning can be a win–win situation for e-carsharing and DSO.

ARTICLE INFO

Keywords:
Carsharing
Siting and sizing
Electric vehicles
Locational marginal price
Two-stage stochastic optimization

ABSTRACT

Electric vehicle (EV) sales and shared mobility are increasing worldwide. Despite its challenges, e-carsharing has an opportunity to still profit in periods of low rental demand compared to traditional carsharing. The purpose of this paper is to assess the profitability of an e–carsharing company based on distribution local marginal price (DLMP) and vehicle-to-grid (V2G) that cooperates with the distribution system operator (DSO) through a two-stage stochastic model. The AC optimal power flow (ACOPF) is modeled using second-order cone programming (SOCP) linearized by the global polyhedral approximation. The IEEE 33 bus test system and a real Kernel distribution for the EV rental demands are used in four planning cases in the GAMS environment. The results indicate that the proposed methodology does not affect EV user satisfaction. Moreover, the planning disregarding the power grid perspective is the most profitable, but the operation may not be possible in real applications due to the high-power flows via V2G. Finally, the e–carsharing planning considering the DSO perspective increased the charging cost by 1.66 % but also reduced the DLMP peak, losses, and peak demand by 2.5 %, 1.5 %, and 5.1 %, respectively. One important conclusion is that the technical benefits brought to the DSO by the e–carsharing company could be turned into services and advantages for both agents, increasing profit and mitigating negative impacts, such as higher operational costs.

1. Introduction

1.1. Motivation

The global electric vehicle (EV) fleet has increased considerably in recent years, and registrations increased by 41 % in 2020 compared to 2019 [1]. In parallel, the sharing economy is another growing business model, especially concerning shared mobility, known as carsharing [2]. This type of service is offered by some companies, such as Zipcar, Car2Go, and Didi [3–5]. There are three types of operating systems for e-carsharing companies: round-trip, one-way, and free-floating. The first requires users to return vehicles to the station of origin. The one-way system allows users to return vehicles to any company station. Finally, the last system allows users to return the vehicle anywhere [6–8].

Shared mobility can bring opportunities for agents who decide to operate in this new business model. EV manufacturers can improve people's perception of the company, as they offer the use of cutting-edge technology at an affordable price. In addition, the e-carsharing company (shared mobility companies that use EVs) can captivate potential

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https://doi.org/10.1016/j.apenergy.2022.120347
Received 26 May 2022; Received in revised form 11 November 2022; Accepted 13 November 2022
Available online 24 November 2022
0306-2619/

Nomenclature

Sets

$\omega \in \Omega_\omega$ Set of scenarios
$\in \in \Omega_\in$ Set of EVs
$\rho, i, j \in \Omega_\rho$ Set of nodes
$\delta \in \Omega_\delta$ Set of rental demands
$t \in \Omega_t$ Set of periods in short-term (hours)
$y \in \Omega_y$ Set of periods in long-term (years)
$S(j)$ Set of tail buses of lines whose head bus is j

Parameters

$p^i_{\rho,\in}$ Initial positions of vehicles
$SoC^i_\in$ Initial vehicle state-of-charge
$\zeta^e_{t,\rho}$ Energy tariff
ζ^r Vehicle rental tariff
ζ^{rl} Vehicle relocation tariff
ζ^g Energy cost at slack bus
E^b Vehicle battery energy
eff_{cha} Charger efficiency
P^c Maximum charging/discharging power
p_ω Scenario probability
p^{ev} Vehicle purchase price
p^{cs} Charging station installation price
p^{ch} Charger price
B_y Budget at year y
Ch^{min}_ρ Minimum number of chargers in position ρ
Ch^{max}_ρ Maximum number of chargers in position ρ
$D^O_{t,\delta,\rho,y,\omega}$ Rental demand origin in position ρ at time t
$D^D_{t,\delta,\rho,y,\omega}$ Rental demand destination to position ρ at time t
$D^d_{\delta,y,\omega}$ Rental demand trip duration
d_r Electric vehicle energy consumption
$P^d_{t,i,y,\omega}$ Active power demand at bus i in period t
$Q^d_{t,i,y,\omega}$ Reactive power demand at bus i in period t
$r_{i,j,y}$ Resistance of line (i,j)
$x_{i,j,y}$ Reactance of line (i,j)

First Stage Variables

$CS_{\rho,y}$ {0,1} Charging stations position at year y
$E_{\in,y}$ {0,1} Vehicles purchased at year y
$Ch_{\rho,y}$ $\mathbb{Z}$ Number of chargers in position ρ at year y

Second Stage Variables

$ev^r_{\delta,\in,y,\omega}$ {0,1} Accepted demand δ by vehicle $\in$
$ev^{cha}_{t,\rho,\in,y,\omega}$ [-1,1] Vehicle charging power when connected
$ev^d_{t,\rho,\in,y,\omega}$ {0,1} Vehicle that departure for relocation
$ev^a_{t,\rho,\in,y,\omega}$ {0,1} Vehicle that arrived from relocation
$ev^{con}_{t,\rho,\in,y,\omega}$ {0,1} Vehicle connection status on the power grid
$ev^{mov}_{t,\in,y,\omega}$ {0,1} Vehicle movement status
$SoC_{t,\in,y,\omega}$ $\mathbb{R}^+$ Vehicle state-of-charge
$rev_{y,\omega}$ $\mathbb{R}$ Revenue of year y
$P^{ev}_{t,\rho,y,\omega}$ $\mathbb{R}$ Total charging power at position ρ
$P_{i,j,t,y,\omega}$ $\mathbb{R}$ Active power injected at the head bus of line (i,j) in period t
$Q_{i,j,t,y,\omega}$ $\mathbb{R}$ Reactive power injected at the head bus of line (i,j) in period t
$v_{i,t,y,\omega}$ $\mathbb{R}^+$ Squared voltage magnitude at bus i in period t
$l_{i,j,t,y,\omega}$ $\mathbb{R}^+$ Squared current in line (i,j) in period t
$P^g_{t,i,y,\omega}$ $\mathbb{R}^+$ Active power generation at bus i in period t
$Q^g_{t,i,y,\omega}$ $\mathbb{R}^+$ Reactive power generation at bus i in period t

buyers. On the other hand, power utilities running this business can identify places where e-carsharing stations bring benefits to the power grid without jeopardizing the service to the customers. Moreover, distribution system operators (DSOs) can provide energy and ancillary services to the grid through e-carsharing charging optimization [9]. Hence, e-carsharing could ensure access to affordable, reliable, sustainable, and modern mobility [10].

However, the e–carsharing service depends on some factors to guarantee its profitability, such as the size of the city, the local population density, moving traffic, parking situation, population demographics, agreement with the administration, and demand uncertainty [11]. Thus, to increase the development of e–carsharing, it is important to evaluate other ways to guarantee the company's profitability.

Vehicle-to-Grid (V2G) defines a system capable of bidirectionally controlling the power flow between the power grid and EVs [12,13]. V2G can attenuate peaks and fill valleys of energy consumption and provide support to the power grid through ancillary services, such as voltage and frequency control [14–17]. It is noteworthy that constant battery charging and discharging in V2G can decrease the battery lifetime [18,19]. In this way, charging stations (CSs) can manage energy through a smart grid, charging EVs during low consumption times and supplying energy through EVs to the power grid during high consumption times [20–23]. For e-carsharing companies, V2G may represent an opportunity to increase profit.

The implementation of V2G requires price signals, such as time of use (TOU) or real-time pricing (RTP). Although these techniques reflect the power grid's state in time (load variation), they do not have information on nodal load. A technique that considers the load nodal and time variation widely applied in transmission systems is the local marginal price (LMP). In addition, LMP can be decomposed into three components: the marginal cost of energy, losses, and congestion [24,25].

Another recent trend is related to the concept of Energy as a Service (EAAS), which defines a business model where customers pay for an energy service without having to make any investment in infrastructure or generation (e.g., diesel or solar) [26]. Through V2G, the e–carsharing company can help the DSO reduce peak consumption and postpone investments in network reinforcement. However, in places where EVs are not yet widespread, the DSO needs to wait for EVs to reach higher penetrations to have a reliable service. Thus, the e-carsharing business model can play an important role in accelerating the sustainable energy transition. Moreover, the DSO can enjoy the benefits of V2G without necessarily expecting high EV penetration. Finally, the V2G provided by e–carsharing companies can be more reliable than those of individual users, as they can guarantee the energy supply through preestablished agreements.

1.2. Literature review

The e-carsharing operation is widely studied in the literature. Some authors assess different carsharing systems, such as one–way and round-trip. Leuven *et al.* [27] proposed a two-stage stochastic model to investigate the main drivers of vehicle replacement in a round-trip carsharing system and how it affects profit. Moreover, a sample average approximation is used to find solutions within an acceptable computation time. Yoon *et al.* [28] examine the factors that influence the use of carsharing systems in Beijing and the potential for carsharing systems that integrate EVs. Additionally, the authors explore how different factors impact how carsharing is utilized for one-way trips compared with round trips. The results indicate that the most statistically significant factor in attracting carsharing customers is the cost gap for both one-way and round trips. However, one-way systems are the most widely deployed, giving good convenience for both users and operators. Furthermore, other authors investigate the optimal tariff and price discount for e–carsharing profit maximization. Li *et al.* [29] presented a discrete-event simulation approach based on an framework for a one-way e–carsharing system. The proposed method considers the impact of road congestion on travel speed and designs a detailed charging process for EVs to approximate the real world. Their findings suggest that dynamic pricing can increase profit, and the optimal configuration avoids EV overstock. Zhang *et al.* [30] introduce a carsharing personalized price discounting scheme problem for one-way reservation-based services, considering user acceptance of the discounted price and various levels of service that the system provides to the users. Finally, some authors study different reallocation mechanisms, such as operator-based and user-based mechanisms. Huang *et al.* [31] compare the efficiency of operator-based and user-based relocation methods in a one-way station-based e–carsharing system. For this, the authors proposed an ε–optimal and iterated local search algorithm to handle the nonlinear demand. Moreover, Qin *et al.* [32] formulated a set-packing model for the one-way e-carsharing relocation problem and designed a branch-and-cut-and-price algorithm to solve it. The authors designed a bidirectional label-setting algorithm to deal with the pricing subproblem and implement two acceleration techniques. Operator-based relocation is easier to implement, but user-based relocation with dynamic tariffs can achieve higher profits and fewer relocation costs [33]. All these operation topics could lead to different decisions, which affect the e–carsharing profit. Therefore, it is important to consider e–carsharing operation decisions in long-term planning. However, unlike carsharing, long-term planning for e-carsharing involves additional complications, such as CS building and EV autonomy.

Thus, some authors investigated the CS's siting and sizing with EV fleet sizing planning for a one–way e-carsharing business model. Huang *et al.* [7] presented a mixed integer nonlinear program model solved by a golden section line search method that size the shared EV fleet and CS capacity as well as its operation. The model and solution method are tested in a large-scale case study in China. Hua *et al.* [8] proposed an innovative framework to deploy a one-way shared EV under demand uncertainty in a case study in New York. For this, the authors developed a multistage stochastic model and an accelerated solution algorithm to address the curse of dimensionality. To address a larger-scale problem, these authors simplify the EV energy aspect and do not consider the power grid. However, such analysis can lead to high investment costs in power grid reinforcement.

Predicting EV charging behavior can be used to allocate CSs as well as to estimate their charging impact on the power grid. Ullah *et al.* [34] employed four different ensemble machine-learning algorithms for predicting EV charging times. The prediction experiments were based on 2 years of real-world charging event data from 500 EVs in Japan's private and commercial vehicles. However, shared EVs have a different operating pattern than private EVs because of their high mobility. Therefore, the operator can take advantage of the controlled fleet to charge at the most convenient time. Shared EVs are important for estimating rental demand since they affect not only the company's profit but also the EV charging time. In this sense, Alencar *et al.* [35] characterized three distinct carsharing systems that operate in Vancouver (Canada) and nearby regions. The author's study uncovers patterns of users' habits and demands. Feng *et al.* [36] analyzed users' usage patterns based on GPS data provided by a carsharing company in Beijing. The results reveal that the carsharing program presents multiple usage patterns to meet the different travel needs of users.

Moreover, some authors focus on small regions to investigate the impacts of shared EV charging on the power grid in optimization models. Wang *et al.* [37] proposed an expansion planning model for distribution networks considering shared EV charging stations. A stochastic model is proposed to create the shared EV load demand. Fan *et al.* [38] proposed a joint distribution network expansion planning framework integrated with shared EVs, but the optimal CS allocation and EV relocation were neglected. In addition, those authors do not investigate the impacts of service provision by e-carsharing, such as V2G, and how its integration with the DSO affects the company's profit. Finally, Xie *et al.* [6] proposed a bilevel problem that optimizes the decisions of e–carsharing, taking into account the price elasticity of customers, EV mobility, and demand bidding in a distribution power market. However, the authors do not consider uncertainties in rental demand.

Finally, distribution locational marginal pricing (DLMP) has been used in the recent literature because it reflects the state of the power grid with more precision. Wei *et al.* [39] developed a DLMP-based industrial park demand management method. The numerical case studies indicate that their proposed methodology performs better than the traditional dispatch model. Moreover, in the EV context, Patnam and Pindoriya [40] developed an EV aggregator scheduling framework using DLMP, and bilevel optimization was formulated to minimize power grid congestion. Finally, Wang *et al.* [41] proposed a tri-level bidding and dispatching framework based on a competitive distribution operation with DLMP for the demand response of residential loads and EVs.

The recent literature shows that no authors investigate how the interaction between e-carsharing and the DSO affects the company's profit. Another point that also needs investigation is how other services, such as V2G, affect the company's profitability. Finally, most authors deal with the problem as deterministic. The demand uncertainty is of major importance in this context, impacting the long-term planning and daily operation of e-carsharing and consequently its profitability.

1.3. Main contributions

Most of the works found in the literature that approach shared EVs and DSO simplify the analysis of one of the agents. When the focus of the work is on e-carsharing, the power grid is generally modeled as a DCOPF (when not neglected). On the other hand, when the focus is on the operation of the power grid, e-carsharing is simplified, disregarding its operation and meeting the demands. To the authors' best knowledge, the present work is the first to carry out an analysis that contemplates important aspects of both agents (e–carsharing company and DSO), simultaneously.

Thus, this work intends to contribute to the assessment of the planning of an e-carsharing company regarding its profitability, considering its interaction with the DSO (we assume a regulated market, that is, customers cannot choose their energy supplier. Thus, the power utility is also the system operator. For this, an AC optimal power flow (ACOPF) is formulated by second-order cone programming (SOCP). However, solving both the e-carsharing problem and ACOPF with the SOCP formulation is difficult not only because of the nonconvexity but also because of their intrinsic numeric instability due to the constraint [6]. This problem can be avoided with linearization techniques, which are well-known in the literature, such as Big-M, piecewise linearization, and the polyhedral global approximation [42,43]. Thus, we have used the global polyhedral approximation to linearize the ACOPF with the SOCP formulation, allowing us to model the whole problem as a MILP problem.

The scenarios of uncertainty in the EV rental demand are based on kernel distribution from real data. Therefore, the problem is formulated with two-stage stochastic programming. The first-stage variables are the position of CSs, the number of chargers per CS, and the size of the EV fleet. The second-stage variables refer to both the operation of the company's EVs (charging and rental) and the power grid. The TOU and RTP tariffs are widely used as energy tariffs in the literature. To date, these types of tariffs have a good application for private EVs, which tend to have stricter origins and destinations. Although these tariffs reflect the state of the network, they are the same for an entire concession area (assuming a regulated market). The authors consider that DLMP has a good application in the context of shared mobility. Thus, EVs on constant trips can take advantage of cheaper prices in different parts of the city to reduce charging costs and provide services for the DSO. Finally, four different planning cases are proposed to assess the decisions of the e-carsharing and the DSO w/o V2G and w/o power grid constraints.

Specifically, this work contributes to the literature in the following ways:

- Raise a discussion on the feasibility of cooperation between an e-carsharing company and the DSO. The design of this joint planning business model can be a win–win situation for both agents. The company can increase profitability, while the DSO can mitigate the impact on the power grid with V2G;
- We design a two-stage stochastic DLMP-based model that considers both DSO and e–carsharing operating constraints under EV rental demand uncertainty. Solve the ACOPF with a SOCP formulation linearized by the global polyhedral approximation in the shared mobility context.

1.4. Paper structure

The paper is organized as follows: In addition to this introductory section, Section II presents the stochastic problem formulation, divided into objective function and first-stage and second-stage constraints. Section III presents the case study, with information about the e-carsharing company and the distribution network. In section IV, the results are discussed, and the main conclusions are developed in section V.

2. Stochastic e-carsharing problem formulation

The objective of this work is to maximize the e-carsharing company's profit through the optimization of the position and capacity of the CS, as well as the fleet of EVs and their operation. An ACOPF with V2G is also considered. The planning proposal is modeled as a two-stage stochastic programming model taking into account two scenarios (low and high probability). Finally, the energy tariff is based on the energy marginal cost of the power grid – DLMP – without EVs. The siting, sizing, and e-carsharing operation problem is formulated as mixed-integer linear programming (MILP). The ACOPF is formulated using the SOCP relaxation and further linearized using the global polyhedral formulation. Hence, the final problem is cast as an MILP formulation. Fig. 1 summarizes the proposed methodology in a flowchart, presenting the model and the inputs as the output variables.

The problem considers e-carsharing operating in a one-way system. More precisely, customers can rent a vehicle for a tariff ζ^r at its origin and drop it off at its destination. The transportation network is not considered in this work. In addition, the actual demand data do not have the drivers' path, as it violates the privacy agreement. The company has $CS_{\rho,y}$ charging stations, $Ch_{\rho,y}$ chargers per station, and $E_{\in,y}$ of an EV fleet. The model considers a set of Ω_y years and Ω_t time intervals in the planning. It is noteworthy that the decisions of the first stage refer to one year, while the decisions of the second stage refer to one operating day. Finally, the model has a set of scenarios Ω_ω with p_ω probabilities.

2.1. Objective function

The objective of this work is to evaluate the interaction of the e-carsharing operation with the DSO. For this, two main objective functions are modeled, as shown in (1a) and (1b). In this first objective function, only the interests of the e-carsharing operator are considered. Hence, the first main objective is to maximize profit from vehicle rental (obf_{rental}) and minimize charging costs (obf_{cha}) and relocation costs (obf_{relo}), respectively. The second main objective also considers the perspective of the DSO, which aims to maximize the e–carsharing profit

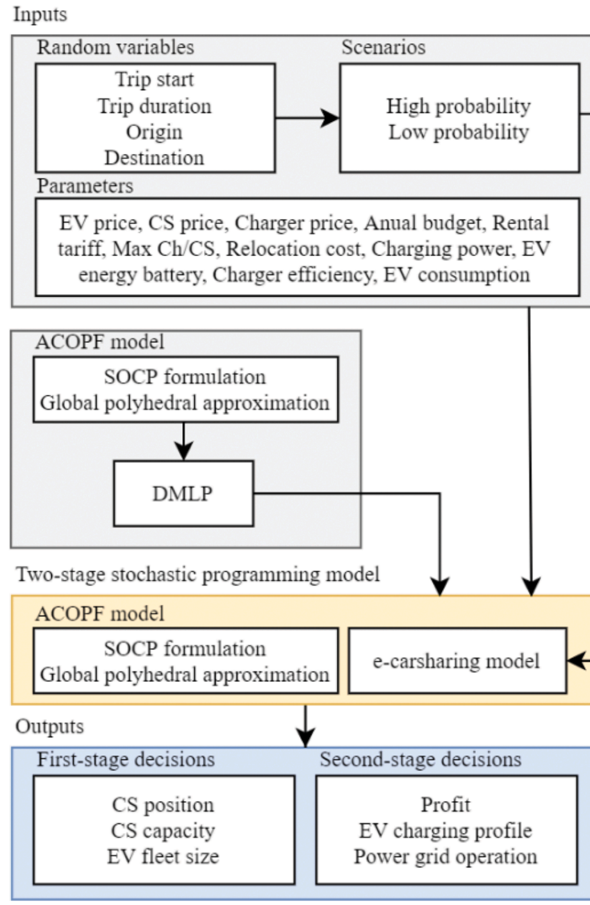

Fig. 1. Proposed methodology flowchart.

while minimizing the cost of energy generation (obf_{ecost}). It is worth noting that in (1b), there is joint decision–making between the two agents, the e-carsharing operator, and the DSO. Moreover, the first-stage variables are not represented in the objective function. To maximize profit, the model needs to invest in CSs, chargers, and EVs. Hence, only constraints for the first-stage variables are needed. In the following, the objective functions that define the main objective functions are presented.

$$OF_1 = obf_{rental} - obf_{cha} - obf_{relo} \tag{1a}$$

$$OF_2 = obf_{rental} - obf_{cha} - obf_{relo} - obf_{ecost} \tag{1b}$$

Eq. (2a) gives the rental profit due to a given trip acceptance ($ev^r_{\delta,\in,y,\omega}$) and its duration ($D^d_{\delta,t,y,\omega}$). The EV charging cost is given by (2b), in which the energy tariff ($\zeta^e_{t,\rho}$) is the DLMP regarding the time and position. Eq. (2c) shows the operator-based relocation cost of the vehicles. It is worth mentioning that without relocation, more vehicles are needed to meet the demand. Thus, if the relocation tariff is a reasonable price (less than the rental tariff), the company can increase profit and meet demand. Finally, (2d) gives the dispatch cost from the primary energy source at the slack bus.

$$obf_{rental} = 365\sum_{\Omega_\omega} p_\omega \sum_{\Omega_y}\sum_{\Omega_\delta}\sum_{\Omega_\in} ev^r_{\delta,\in,y,\omega} D^d_{\delta,y,\omega}\zeta^r \tag{2a}$$

$$obf_{cha} = 365\sum_{\Omega_\omega} p_\omega \sum_{\Omega_y}\sum_{\Omega_t}\sum_{\Omega_\rho}\sum_{\Omega_\in} ev^{cha}_{t,\rho,\in,y,\omega} P^c \zeta^e_{t,\rho} \tag{2b}$$

$$obf_{relo} = 365\sum_{\Omega_\omega} p_\omega \sum_{\Omega_y}\sum_{\Omega_t}\sum_{\Omega_\rho}\sum_{\Omega_\in} ev^d_{t,\rho,\in,y,\omega} \zeta^{rl} \tag{2c}$$

$$obf_{ecost} = 365\sum_{\Omega_\omega} p_\omega \sum_{\Omega_y}\sum_{\Omega_t}\sum_{\Omega_\rho} P^g_{t,\rho,y,\omega}\zeta^g \quad (2d)$$

2.2. First stage constraints: siting and sizing

The first-stage constraints of this work refer to the investment cost in CSs, chargers, and the EV fleet. The CS installation cost considers all the costs involved in CS construction (land purchase, earthworks, electrical installation, infrastructure construction, etc.), except for the cost of the chargers. The cost of the charger could be included in the CS installation cost. However, this modeling allows limiting the number of chargers given that each CS may have different physical space limitations [34]. Eq. (3a) is the generalized form of the e-carsharing financial balance. The general idea of the equation is that the expenses of year y (left side) must be less than the budget available at year y plus the remaining amount invested from previous years (right side). For example, once an EV is purchased, it does not need to be purchased again the following year. Finally, note that for $y = 1$, (3a) shows that the total expenses must be less than the initial budget only. The origin and destination of demands are randomly generated. Thus, the first-stage optimal variables may differ for each year due to the e-carsharing operation. Hence, (3b), (3c), and (3d) are nonanticaptivity constraints, which prevent the model from removing the CSs, chargers, and EVs once installed/bought, respectively. Note that if $y = 1$, (3b), (3c), and (3d) indicate that $CS_{\rho,y}$, $Ch_{\rho,y}$, and $E_{\epsilon,y}$, respectively, must only be an integer. The space availability in urban areas can be a limiting factor in planning. In this sense, (3e) limits the chargers to be installed only where CS was installed. In addition, the number of chargers is also limited to a minimum (Ch^{min}_ρ) and maximum (Ch^{max}_ρ) amount, which depends on the position ρ.

$$\sum_{\Omega_\rho}\left(CS_{\rho,y}p^{cs} + Ch_{\rho,y}p^{ch}\right) + \sum_{\Omega_\epsilon} E_{\epsilon,y}p^{ev} \le \sum_{\varphi=1}^{y} B_\varphi \quad (3a)$$

$$CS_{\rho,y} \ge CS_{\rho,y-1} \quad (3b)$$

$$Ch_{\rho,y} \ge Ch_{\rho,y-1} \quad (3c)$$

$$E_{\epsilon,y} \ge E_{\epsilon,y-1} \quad (3d)$$

$$Ch^{min}_\rho CS_{\rho,y} \le Ch_{\rho,y} \le Ch^{max}_\rho CS_{\rho,y} \quad (3e)$$

2.3. Second stage constraints: e-carsharing operation

This section presents the operating constraints of e–carsharing, which are cast as follows. The set of Equations (4) referring to the daily operation of e-carsharing (second stage) also presents the year index. Thus, in addition to the first-stage variable linkage, the model can also execute the operation according to parameters that can change annually, such as rental demand or energy consumption. Eq. (4a) refers to the balance of EVs connected to the CS. The term $\sum_{\Omega_\delta} ev^r_{\delta,\epsilon,y,\omega}D^D_{t,\delta,\rho,y,\omega}$ are all the accepted demands that arrive at destination ρ at time t, while the term $\sum_{\Omega_\delta} ev^r_{\delta,\epsilon,y,\omega}D^O_{t,\delta,\rho,y,\omega}$ is all the accepted demands that depart from destination ρ at time t. Moreover, the vehicles arriving and departing from relocation are added and subtracted in (4a), respectively. Eq. (4b) defines the initial position of EVs ($p^i_{\rho,\epsilon}$) only if the CS has been installed in the first stage. Moreover, Eq. (4c) indicates that EVs must finish the day in the same initial position to complete an operation cycle. It is worth noting that the EV's initial position could be a first-stage optimization variable. Thus, the e-carsharing operator could identify the best initial position to maximize profit in all scenarios. To simplify, we assigned random initial positions to the EVs. Eq. (4d) shows that a rental demand from or to position ρ can only be accepted if the CS at position ρ has been built in the first stage. Eq. (4e) defines that the number of EVs connected must be less than or equal to the number of chargers in the station. It is worth mentioning that all spots have a charger, which can connect only one EV each time. Therefore, the CS capacity is equal to the number of chargers. Eq. (4f) defines that each demand must only be accepted once and by one EV. Eq. (4g) defines that if purchased in the first stage, a vehicle must be either moving, connected, or relocating. The reallocation duration time is simplified as a 1-time interval for any position, as indicated in (4h).

$$ev^{con}_{t,\rho,\epsilon,y,\omega} = ev^{con}_{t-1,\rho,\epsilon,y,\omega} + \sum_{\Omega_\delta} ev^r_{\delta,\epsilon,y,\omega}D^D_{t,\delta,\rho,y,\omega} - \sum_{\Omega_\delta} ev^r_{\delta,\epsilon,y,\omega}D^O_{t,\delta,\rho,y,\omega} + ev^a_{t,\rho,\epsilon,y,\omega} - ev^d_{t,\rho,\epsilon,y,\omega} \quad (4a)$$

$$ev^{con}_{t_{in},\rho,\epsilon,y,\omega} = p^i_{\rho,\epsilon}CS_{\rho,y} \quad (4b)$$

$$ev^{con}_{t_{end},\rho,\epsilon,y,\omega} = p^i_{\rho,\epsilon}CS_{\rho,y} \quad (4c)$$

$$ev^r_{\delta,\epsilon,y,\omega} \le CS_{\rho,y} \quad (4d)$$

$$\sum_{\Omega_\epsilon} ev^{con}_{t,\rho,\epsilon,y,\omega} \le Ch_{\rho,y} \quad (4e)$$

$$\sum_{\Omega_\epsilon} ev^r_{\delta,\epsilon,y,\omega} \le 1 \quad (4f)$$

$$ev^{mov}_{t,\epsilon,y,\omega} + \sum_{\Omega_\rho}\left(ev^{con}_{t,\rho,\epsilon,y,\omega} + ev^d_{t,\rho,\epsilon,y,\omega} + ev^a_{t,\rho,\epsilon,y,\omega}\right) = E_{\epsilon,y} \quad (4g)$$

$$\sum_{\Omega_\rho} ev^d_{t,\rho,\epsilon,y,\omega} = \sum_{\Omega_\rho} ev^a_{t+1,\rho,\epsilon,y,\omega} \quad (4h)$$

Eq. (4i) defines the state of charge (SoC) of an EV battery. The battery energy consumption (d_r) is constant for both rental and relocation. Note that the charging power ($ev^{cha}_{t,\rho,\epsilon,y,\omega}$) varies from -1 to 1 when V2G is considered and from 0 to 1 when V2G is not considered. Using a single variable for vehicle charging makes it easier in terms of implementation and computational effort, as an equation to avoid simultaneous charging and discharging is not needed. On the other hand, it has drawbacks due to simplification, such as the use of charger efficiency for both charging and discharging. Eqs. (4j) and (4k) impose equal operating states in the SoC at the beginning and the end of each day to complete a daily cycle. Eq. (4k) is relaxed with $\ge$, but it holds at SoC^i_ϵ to reduce the charging cost. The total charging power of each CS at position ρ is presented in (4l). Finally, (4m) defines that an EV can only charge if it is connected. Note that to disable V2G, the lower limit must be set to zero instead of $-ev^{con}_{t,\rho,\epsilon,y,\omega}$.

$$SoC_{t,\epsilon,y,\omega} = SoC_{t-1,\epsilon,y,\omega} - \left(ev^{mov}_{t,\epsilon,y,\omega} + \sum_{\Omega_\rho} ev^d_{t,\rho,\epsilon,y,\omega}\right)\frac{d_r}{E^b} + \sum_{\Omega_\rho}\frac{ev^{cha}_{t,\rho,\epsilon,y,\omega}P^c eff_{cha}}{E^b} \quad (4i)$$

$$SoC_{t_{in},\epsilon,y,\omega} = SoC^i_\epsilon \quad (4j)$$

$$SoC_{t_{end},\epsilon,y,\omega} \ge SoC^i_\epsilon \quad (4k)$$

$$P^{ev}_{t,\rho,y,\omega} = \sum_{\Omega_\epsilon} ev^{cha}_{t,\rho,\epsilon,y,\omega}P^c eff_{cha} \quad (4l)$$

$$-ev^{con}_{t,\rho,\epsilon,y,\omega} \le ev^{cha}_{t,\rho,\epsilon,y,\omega} \le ev^{con}_{t,\rho,\epsilon,y,\omega} \quad (4m)$$

2.4. Second stage constraints: AC OPF

This section presents the set of constraints related to the operation of the power grid. The constraints of an ACOPF are complex, nonlinear, and nonconvex. The branch flow model (BFM) with the SOCP formulation is used to relax the original problem. Finally, the global polyhedral approximation is used to linearize the problem. Thus, the problem reads as follows.

Eqs. (5a) and (5b) present the balance of active and reactive power, while (5c) and (5d) present the respective power flow limits. The DMLP is given by the dual variable associated with the active power balance (Eq. (5a)). The voltage calculation at each node is given by (5e), and its limits are presented in (5f). Finally, (5g) is a nonconvex equality that defines the branch flow at the head node of each line. Although the BFM guarantees the same voltages and power flows as the traditional AC power flow, the problem is more computationally tractable when (5g) is linearized [44]. Thus, replacing $=$ for $\leq$, the second-order cone equation becomes convex, given by the canonical form of (5h). It was proven in [45] that in distribution systems, (5h) holds in the optimal solution under some mild conditions. The polyhedral global approximation is developed for second-order cone equations in the form of $\sqrt{x_1^2+x_2^2}\leq x_3$ [46]. Thus, (5h) is decomposed into Eqs. (5i) and (5j). Applying the technique of [46] in Eqs. (5i) and (5j), one can obtain the set of linear constraints of (5k) and (5l), where $\xi^1_{i,j,\varkappa,t,y,\omega}$, $\eta^1_{i,j,\varkappa,t,y,\omega}$, $\xi^2_{i,j,\varkappa,t,y,\omega}$, $\eta^2_{i,j,\varkappa,t,y,\omega}$, and φ are auxiliary variables and $\varkappa$ is a positive integer, which is used to adjust the approximation accuracy. According to [46], if (5h) is satisfied, then (5k) and (5l) must hold. Thus, (5h) can be replaced by (5k) and (5l).

$$P_{i,j,t,y,\omega}-r_{i,j,y}l_{i,j,t,y,\omega}+P^{g}_{t,i,y,\omega}-P^{d}_{t,i,y,\omega}-P^{ev}_{t,\rho,y,\omega}=\sum_{k\in S(j)}P_{j,k,t,y,\omega}:\zeta^{e}_{t,\rho} \tag{5a}$$

$$Q_{i,j,t,y,\omega}-x_{i,j,y}l_{i,j,t,y,\omega}+Q^{g}_{t,i,y,\omega}-Q^{d}_{t,i,y,\omega}=\sum_{k\in S(j)}Q_{j,k,t,y,\omega} \tag{5b}$$

$$P^{min}_{i,j,t,y,\omega}\leq P_{i,j,t,y,\omega}\leq P^{max}_{i,j,t,y,\omega} \tag{5c}$$

$$Q^{min}_{i,j,t,y,\omega}\leq Q_{i,j,t,y,\omega}\leq Q^{max}_{i,j,t,y,\omega} \tag{5d}$$

$$v_{j,t,y,\omega}=v_{i,t,y,\omega}-2\left(r_{i,j,y}P_{i,j,t,y,\omega}+x_{i,j,y}Q_{i,j,t,y,\omega}\right)+\left(r^2_{i,j,y}+x^2_{i,j,y}\right)l_{i,j,t,y,\omega} \tag{5e}$$

$$v^{min}_{j,t,y,\omega}\leq v_{j,t,y,\omega}\leq v^{max}_{j,t,y,\omega} \tag{5f}$$

$$l_{i,j,t,y,\omega}v_{i,t,y,\omega}=P^2_{i,j,t,y,\omega}+Q^2_{i,j,t,y,\omega} \tag{5g}$$

$$\left\|\begin{matrix}2P_{i,j,t,y,\omega}\\ 2Q_{i,j,t,y,\omega}\\ l_{i,j,t,y,\omega}-v_{i,t,y,\omega}\end{matrix}\right\|\leq l_{i,j,t,y,\omega}+v_{i,t,y,\omega} \tag{5h}$$

$$\sqrt{\left(2P_{i,j,t,y,\omega}\right)^2+\left(2Q_{i,j,t,y,\omega}\right)^2}\leq W_{i,j,t,y,\omega} \tag{5i}$$

$$\sqrt{\left(W_{i,j,t,y,\omega}\right)^2+\left(l_{i,j,t,y,\omega}-v_{i,t,y,\omega}\right)^2}\leq l_{i,j,t,y,\omega}+v_{i,t,y,\omega} \tag{5j}$$

$$\begin{cases}\xi^1_{i,j,0,t,y,\omega}\geq 2P_{i,j,t,y,\omega},\ \xi^1_{i,j,0,t,y,\omega}\geq -2P_{i,j,t,y,\omega}\\ \eta^1_{i,j,0,t,y,\omega}\geq 2Q_{i,j,t,y,\omega},\ \eta^1_{i,j,0,t,y,\omega}\geq -2Q_{i,j,t,y,\omega}\end{cases}$$

$$\begin{cases}\xi^1_{i,j,\varphi,t,y,\omega}=\cos\left(\dfrac{\pi}{2^{\varphi+1}}\right)\xi^1_{i,j,\varphi-1,t,y,\omega}+\sin\left(\dfrac{\pi}{2^{\varphi+1}}\right)\eta^1_{i,j,\varphi-1,t,y,\omega}\\ \eta^1_{i,j,\varphi t,y,\omega}\geq -\sin\left(\dfrac{\pi}{2^{\varphi+1}}\right)\xi^1_{i,j,\varphi-1t,y,\omega}+\cos\left(\dfrac{\pi}{2^{\varphi+1}}\right)\eta^1_{i,j,\varphi-1,t,y,\omega}\\ \eta^1_{i,j,\varphi,t,y,\omega}\geq +\sin\left(\dfrac{\pi}{2^{\varphi+1}}\right)\xi^1_{i,j,\varphi-1,t,y,\omega}-\cos\left(\dfrac{\pi}{2^{\varphi+1}}\right)\eta^1_{i,j,\varphi-1,t,y,\omega}\end{cases}$$

$\varphi=1,\cdots,\varkappa$

$$\begin{cases}\xi^1_{i,j,\varkappa,t,y,\omega}\leq W_{i,j,t,y,\omega}\\ \eta^1_{i,j,\varkappa,t,y,\omega}\leq\tan\left(\dfrac{\pi}{2^{\varkappa+1}}\right)\xi^1_{i,j,\varkappa,t,y,\omega}\end{cases} \tag{5k}$$

$$\begin{cases}\xi^2_{i,j,0,t,y,\omega}\geq W_{i,j,t,y,\omega},\ \xi^2_{i,j,0,t,y,\omega}\geq -W_{i,j,t,y,\omega}\\ \eta^2_{i,j,0,t,y,\omega}\geq l_{i,j,t,y,\omega}-v_{i,t,y,\omega},\ \eta^2_{i,j,0,t,y,\omega}\geq -\left(l_{i,j,t,y,\omega}-v_{i,t,y,\omega}\right)\end{cases}$$

$$\begin{cases}\xi^2_{i,j,\varphi,t,y,\omega}=\cos\left(\dfrac{\pi}{2^{\varphi+1}}\right)\xi^2_{i,j,\varphi-1,t,y,\omega}+\sin\left(\dfrac{\pi}{2^{\varphi+1}}\right)\eta^2_{i,j,\varphi-1,t,y,\omega}\\ \eta^2_{i,j,\varphi t,y,\omega}\geq -\sin\left(\dfrac{\pi}{2^{\varphi+1}}\right)\xi^2_{i,j,\varphi-1t,y,\omega}+\cos\left(\dfrac{\pi}{2^{\varphi+1}}\right)\eta^2_{i,j,\varphi-1,t,y,\omega}\\ \eta^2_{i,j,\varphi,t,y,\omega}\geq +\sin\left(\dfrac{\pi}{2^{\varphi+1}}\right)\xi^2_{i,j,\varphi-1,t,y,\omega}-\cos\left(\dfrac{\pi}{2^{\varphi+1}}\right)\eta^2_{i,j,\varphi-1,t,y,\omega}\end{cases}$$

$\varphi=1,\cdots,\varkappa$

$$\begin{cases}\xi^2_{i,j,\varkappa,t,y,\omega}\leq l_{i,j,t,y,\omega}+v_{i,t,y,\omega}\\ \eta^2_{i,j,\varkappa,t,y,\omega}\leq\tan\left(\dfrac{\pi}{2^{\varkappa+1}}\right)\xi^2_{i,j,\varkappa,t,y,\omega}\end{cases} \tag{5l}$$

3. Case study

Four scenarios are proposed for the case study, denoted Cases 1A, 1B, 2A, and 2B. Case 1 is the benchmark case. In Case 1A, e-carsharing planning is carried out only with EV charging optimization, without considering the V2G and power grid constraints. Case 1B is similar to 1A but with V2G. Cases 1A and 1B problem formulations are given by (6a), with the optimality gap set as 0.1 %. Case 2A contains the power grid constraints, but without V2G. Finally, Case 2B considers V2G and the power grid constraints. Cases 2A and 2B problem formulations are given by (6b), with the optimality gap also set as 0.1 %. Table 1 presents a summary of the main aspects of each case.

$\max(OF_1)$
s.t. (3), and (4)
$\max(OF_2)$
s.t. (3), (4), (5a) – (5f), (5k), and (5l)

It is assumed that all EVs are the same, as are the chargers. The rental tariff and relocation cost are constant, while the energy tariff is based on the DLMP from the grid without any EV. Table 2 summarizes the parameters for the e–carsharing model [47,48]. The authors in [35] provide a real database with 644,511 vehicle rental trips over five months. The data contain the trip start time ($trip_{start}$), trip duration ($trip_d$), trip end time ($trip_{end}$), trip start and end locations, distance traveled per trip, SoC at the end of a trip and date of the trip. An algorithm was developed to treat this database, as shown in Table 3. The algorithm extracts the trip start time probability density function (PDF) based on the kernel distribution to generate scenarios, as shown in Fig. 2. As the analysis of the operation in this study is for one day (24 h), we use the average PDF of the week to avoid biased daily data. In addition, it is observed that most trips last less than 1 h. As the time interval of our model is 1 h, it was considered that trips can take between one and two hours, with the same probability. The travel route is not given, as it is confidential customer data. Hence, the origin and destination are randomly generated through a uniform integer distribution contained in the set of positions Ω_ρ. It is noteworthy that for real cases, an in-depth study is needed to create the region's start trip PDF.

The 33-bus IEEE system is used as the power grid, whose topology is shown in Fig. 3. The line data are obtained from [49]. All cable limits are

Table 1
Case studies summary.

	Optimization without V2G	Optimization with V2G	Power Grid
Case 1A	✓	×	×
Case 1B	×	✓	×
Case 2A	✓	×	✓
Case 2B	×	✓	✓

Table 2
E-carsharing parameters summary.

Parameter	Value
Electric vehicle price (p^{ev}) [$]	30,000
Charging station price (p^{cs}) [$]	100,000
Charger price (p^{ch}) [$]	1,000
Initial budget ($B_{y=1}$) [$]	3,000,000
Maximum/minimum number of chargers per station ($Ch_\rho^{max}/Ch_\rho^{min}$)	10/1
Rental tariff (ζ^r) [$/h]	4
Relocation cost (ζ^{rl}) [$/h]	2
Charger power (P^c) [kW]	7.2
EV energy battery (E^b) [kWh]	40
EV energy consumption (d_r) [kWh/h]	4.4
Charger efficiency (eff_{cha}) [%]	95

Table 3
Algorithm for scenario generation.

	Scenario generation Algorithm
1	Input data
2	Collects the parameter $trip_{start}$
3	Selects the base time: week or day
4	Treat the parameters according to the selected base time
5	Estimate the Kernel distribution based on $trip_{start}$
6	$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right)$
7	Defines the number of demands δ
8	**for** each year y
9	**for** each scenario ω
10	**for** each demand δ
11	Defines the origin/destination based on uniform integer distribution within the set Ω_ρ
12	Defines the $trip_{start}$ based on the Kernel distribution $\hat{f}_h(x)$
13	Defines the $trip_d$ based on uniform integer distribution within [1,2]
14	$trip_{end} = trip_{start} + trip_d$
15	**end for**
16	**end for**
17	**end for**

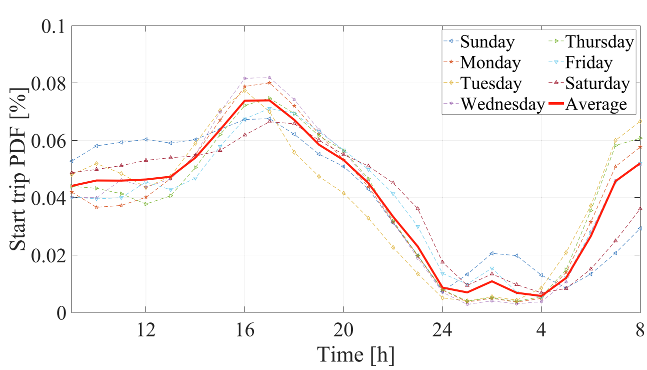

Fig. 2. Carsharing start trip probability density function.

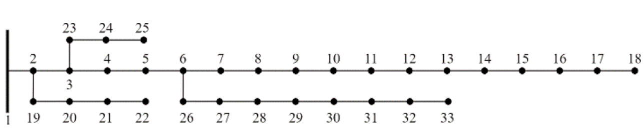

Fig. 3. IEEE 33 bus system.

set to 5 MVA to avoid overload. The energy cost of the slack bus (bus 1) ζ^g is set to $20/MWh. The voltage lower and upper bounds are set to 0.95 and 1.05 pu, respectively. Different load shapes for each bus could highlight the DLMP. However, in this case study, the different buses and line capacities are sufficient conditions to change the DLMP. Thus, we use the same load shape for all the buses, as shown in Fig. 4.

4. Results

The model is developed in GAMS using the CPLEX solver [50]. Due to high computational time, it is considered to be only one year for the planning horizon ($\Omega_y = 1$). A set of five scenarios has been simulated, although, for the sake of simplicity, only two scenarios are presented. The scenarios are defined as low and high rental demand, with a total of 20 and 50 daily trips and 20 % and 80 % probability, respectively. The main objective of the scenarios is to observe the uncertainty in total daily demand. Thus, one can evaluate e-carsharing decisions in both cases. Table 4 presents the main decision variables' results. The rental profit is the same in all cases.

The case with V2G and no power grid constraints (Case 1B) is the one with the highest profit, given that there is no limit to the company's interaction with the power grid. Moreover, when power grid constraints are considered (Case 2B), the company's profit decreases compared with Case 1B. Cases 1A and 2A present the same behavior. It is worth mentioning that the decision in the first stage (number of chargers) changed according to the operation mode (with or without V2G) and the power grid constraints. This only happened to reduce charging costs because the meeting demand remained the same. This indicates that the company's mode of operation could affect the siting and sizing of CSs according to the agent planning perspective. Moreover, the relocation mechanism was used as a way to maximize profit, meeting rental demand instead of moving the EVs to charge in positions where the energy tariff was cheaper. However, if there is a trade-off between relocation and charging costs, EVs could take advantage of low rental demand to move and charge at locations with low tariffs and discharge at locations with high tariffs.

Regarding the scenarios, the demand was not met in either scenario or case due to the budget limit of the first stage. However, one can notice that the meeting demand was the same in all scenarios and cases, which shows that the proposed methodology does not affect the user's experience. Therefore, the rental and energy tariffs ratio must be carefully assessed, otherwise, there will be no business model shift. It is also noted that the total daily losses in the case with V2G are slightly lower than in the case without V2G, which highlights its benefits for the DSO.

Finally, the profits in decreasing order are Case 1B > Case 2B > Case 1A > Case 2A. Case 1B was expected to present the highest profit, given that there are no constraints for power injection into the grid. On the other hand, Case 2A was also expected to present the lowest profit, since there is no flexibility of V2G and there are power grid constraints. However, Cases 1A and 2B have a less straightforward interpretation. If the electrical grid is operating close to its limit, the power flows will be more limited, preventing EVs from injecting more energy into the grid and leading to a higher charging cost. Although Case 1A does not have V2G, its profit may be higher due to fewer constraints.

Fig. 5 presents the power on the slack bus in Cases 2A and 2B with scenarios 1 and 2 (S1 and S2). Most of the EV charge is concentrated at night in Case 2A when rental demand and charging cost are low. In this case, the EV charging optimization benefits are smaller for the DSO. As

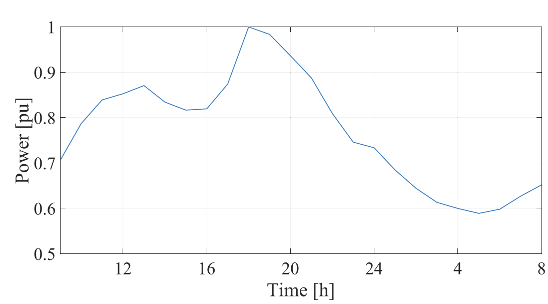

Fig. 4. Demand load shape.

Table 4
Decisions summary.

	Case 1A		Case 1B		Case 2A		Case 2B	
Total profit [$]	55,570		55,662		55,569		55,635	
Total rental profit [$]	69,788		69,788		69,788		69,788	
Total charging cost [$]	1,662		1,570		1,663		1,597	
Total relocation cost [$]	12,556		12,556		12,556		12,556	
First stage decisions								
Number of charging stations	23		23		23		23	
Number of chargers	37		36		36		35	
Number of electric vehicles	20		20		20		20	
Total acquisition cost [$]	2,937,000		2,936,000		2,936,000		2,935,000	
Second stage decisions								
	Scenarios							
	1	2	1	2	1	2	1	2
Meeting demand [%]	40	70	40	70	40	70	40	70
Total daily losses [MW]	–	–	–	–	2.81	4.11	2.76	4.06
Simulation time [s]	58		217		2,945		23,838	

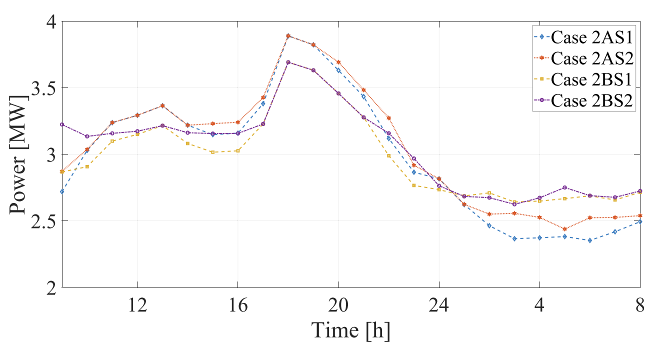

Fig. 5. Power on the slack bus.

in this case study, few trips are being considered, and the intensity of vehicle use is small compared to the battery capacity, so the total discharge throughout the day is low. Thus, the charging demand is also low. Despite the rental demand during the day (8 h ~ 24 h), some parked EVs take advantage of the high DLMP to discharge into the grid, reducing the substation demand (slack bus) in Case 2B. On the other hand, this discharge during the day is compensated at night, when the EVs charge (with more intensity than Case 2A).

Fig. 6 presents a comparison of the total EV charging load between Cases 1A and 1B and Cases 2A and 2B. The charging power peaks are more accentuated (both positive and negative) in cases where there are no power grid constraints. On the other hand, with the power grid constraints, the total load curve is smoother. In this way, if the e-carsharing operator is coordinated with the DSO, a coordinated charge (with or without V2G) can be used to postpone investments in network reinforcement and still keep meeting the rental demand.

Fig. 7 shows the DLMP at bus 18 (farthest from the substation). Note that the DLMP change is very small in Case 2A, while there is a greater variation in Case 2B for both scenarios. This behavior is repeated in all the system buses, as shown in the summary in Table 5. Despite the average DLMP remaining constant, the maximum and minimum DLMPs decreased in Case 2B compared to Case 2A. This reinforces the idea of the benefits of coordinated planning of both agents.

On the other hand, if the e-carsharing company operates using a flat tariff, its charging cost would remain the same regardless of the time of day. This could lead to a further increase in the DLMP at peak consumption times, as there would be no incentive to charge during off-peak times. Furthermore, a relatively large EV fleet (not only e-carsharing but also EV taxis) charging at the same time at a single CS can significantly influence the DLMP. Thus, energy costs would be passed on to all consumers in that region, even those who do not use e-carsharing.

Therefore, V2G increased the company's profit (not as much as in case 1B), reduced the total system losses, reduced the DLMP, and flattened the substation demand. Although the difference between the profits of Cases 1A and 2A and Cases 1B and 2B are relatively low, this may indicate that cooperation between agents is beneficial. However, assuming the company took a selfish stance and proceeded with Case 1B planning to maximize profit. The DSO may not be able to operate as planned. Thus, there may be a blackout due to the unexpected increase

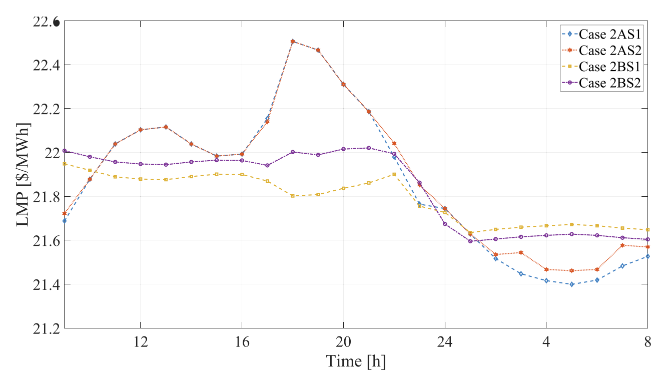

Fig. 7. Distribution local marginal price at bus 18.

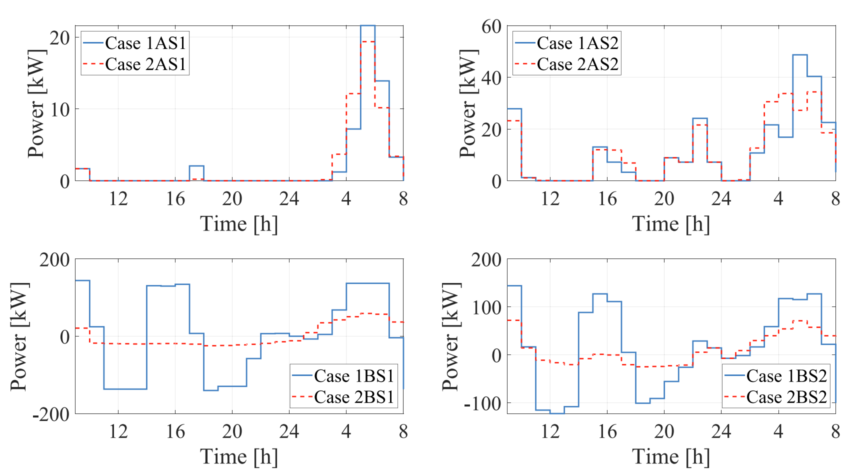

Fig. 6. EV charging and discharging power.

Table 5
DLMP summary.

		Min			Average	Max		
		Bus	Time [h]	DLMP [$/MWh]	DLMP [$/MWh]	Bus	Time [h]	DLMP [$/MWh]
Case 2A	S1	1	[1,24]	20.00	21.06	18	18	22.51
	S2	1	[1,24]	20.00	21.07	18	18	22.51
Case 2B	S1	1	18	19.81	21.00	18	9	21.95
	S2	1	18	19.87	21.05	18	21	22.02

in load or even load shedding if considering a smart grid with proper control. Both situations are disadvantageous for the e-carsharing company and the DSO, which highlights the importance of cooperation between them.

5. Conclusions

The recent literature shows that previous works do not consider both the operational characteristics of an e-carsharing company and the DSO in carsharing planning. Other aspects that could help sustain the profitability of e-carsharing planning are also neglected, such as V2G and DLMP. Thus, this work proposes a model for siting and sizing CSs and the EV fleet of an e-carsharing company under demand uncertainty. The ACOPF was modeled using SOCP relaxation and linearized by the polyhedral global approximation. For this, two-stage stochastic programming was used to model the problem. To the authors' best knowledge, our work is the first to carry out an analysis that contemplates a detailed operation of the e-carsharing and DSO simultaneously. Finally, four cases were proposed to assess the company's profitability in different EV charging situations and agents' planning perspectives in the GAMS environment.

The results indicate that planning considering V2G and ignoring the power grid constraints is the most profitable. The charging cost, in this case, is approximately 1.66 % less than the case with power grid constraints. However, in a real application, there is a probability of this case not occurring, since the power grid may not be able to cope with high power flows due to V2G. Thus, e-carsharing designers should consider an analysis of the power grid for proper design to limit potential problems. On the other hand, coordinated planning with the DSO showed reductions of approximately 2.5 %, 1.5 %, and 5.1 % in the DLMP peak, losses, and peak demand, respectively. Although they were not included in this work, the benefits that e–carsharing brought to the DSO (at the expense of profit) could be converted into financial compensation. Thus, the provision of services to the DSO could work as a buffer for the company in periods of low rental demand, making its profit more sustainable. Furthermore, the realization of this scenario is more plausible in real applications, as the operation is within the limits of the power grid.

Despite dealing with demand uncertainty, this article considered only two scenarios and a small number of daily trips due to the high computational effort. Another simplification considered is the travel time and the route of the users. As the model is for car rental, it is important to maintain users' privacy. However, applications in which routes are also controlled (such as taxis and buses), considering the transport network, can influence the optimization results. Moreover, customer satisfaction was not modeled. Instead, the meeting rental demand was evaluated in terms of total demand, which was not affected by the proposed methodology. Finally, for this work, we choose a small test system to show that by using the proposed methodology, the e–carsharing company can provide valuable services to the DSO (i.e., peak shaving and voltage regulation) in exchange for a low increase in EV charging cost.

Therefore, future improvements to reduce computational time involve improving the model through decomposition techniques, such as Bender's decomposition or dynamic programming. In addition, the model can also be adapted for applications with controlled routes, considering the transport network, traffic, and Dijkstra's algorithm. Finally, we are considering in our future works using the IEEE-123 test system, to make different analyses, such as load imbalance due to EV charging.

CRediT authorship contribution statement

Leonardo Bitencourt: Conceptualization, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing, Data curation, Visualization, Formal analysis. **Bruno Dias:** Conceptualization, Supervision, Writing – review & editing, Validation, Funding acquisition. **Tiago Soares:** Conceptualization, Supervision, Writing – review & editing, Validation. **Bruno Borba:** Supervision, Writing – review & editing, Validation, Funding acquisition. **Jairo Quirós-Tortós:** Supervision, Writing – review & editing, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This research was supported in part by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) under Grant 001, Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) under grants 404068/2020-0, Fundação de Amparo à Pesquisa do Estado de Minas Gerais (FAPEMIG) under grant APQ-03609-17, and Instituto Nacional de Energia Elétrica (INERGE). This work was also partially supported by the Norte Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, through the European Regional Development Fund (ERDF), within the DECARBONIZE project (NORTE-01-0145-FEDER-000065) and by the Scientific Employment Stimulus Programme from the Fundação para a Ciência e a Tecnologia (FCT) under the agreement 2021.01353.CEECIND.

References

[1] IEA. Global EV Outlook 2021 2021.
[2] Luna TF, Uriona-Maldonado M, Silva ME, Vaz CR. The influence of e-carsharing schemes on electric vehicle adoption and carbon emissions: An emerging economy study. Transp Res Part D: Transp Environ 2020;79:102226. https://doi.org/10.1016/j.trd.2020.102226.
[3] Zipcar. Zipcar webpage 2022. https://www.zipcar.com/ (accessed September 22, 2020).
[4] Car2Go. Car2Go webpage 2022. https://www.share-now.com/ (accessed September 22, 2020).
[5] Didi. Didi webpage 2022. https://www.didiglobal.com/ (accessed September 22, 2020).
[6] Xie R, Wei W, Wu Q, Ding T, Mei S. Optimal service pricing and charging scheduling of an electric vehicle sharing system. IEEE Trans Veh Technol 2020;69:78–89. https://doi.org/10.1109/TVT.2019.2950402.
[7] Huang K, An K, Correia GH de A. Planning station capacity and fleet size of one-way electric carsharing systems with continuous state of charge functions. Eur J Oper Res 2020;287:1075–91. https://doi.org/10.1016/j.ejor.2020.05.001.
[8] Hua Y, Zhao D, Wang X, Li X. Joint infrastructure planning and fleet management for one-way electric car sharing under time-varying uncertain demand. Transp Res B Methodol 2019;128:185–206. https://doi.org/10.1016/j.trb.2019.07.005.
[9] Pastor AV, Nieto-Martin J, Bunn DW, Varga L. Design of local services markets for pricing DSO-TSO procurement coordination. 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR: IEEE; 2018, p. 1–5. https://doi.org/10.1109/PESGM.2018.8586517.
[10] Negru M. SDG 7: Affordable and clean energy. 2030Builders 2018. https://2030.builders/articles/affordable-clean-energy/ (accessed May 19, 2022).

[11] Stolle WO, Steinmann W, Rodewyk V, Gil AR, Peine A. The demystification of car sharing 2020.
[12] Adrene Briones, James Francfort, Paul Heitmann, Michael Schey, Steven Schey, John Smart. Vehicle to Grid Power Flow Regulations and Building Codes. EnergyGov 2012. http://energy.gov/eere/vehicles/downloads/avta-vehicle-grid-power-flow-regulations-and-building-codes-review (accessed October 7, 2015).
[13] Lin X, Sun J, Ai S, Xiong X, Wan Y, Yang D. Distribution network planning integrating charging stations of electric vehicle with V2G. Int J Electr Power Energy Syst 2014;63:507–12. https://doi.org/10.1016/j.ijepes.2014.06.043.
[14] Bai X, Qiao W, Wei H, Huang F, Chen Y. Bidirectional coordinating dispatch of large-scale V2G in a future smart grid using complementarity optimization. Int J Electr Power Energy Syst 2015;68:269–77. https://doi.org/10.1016/j.ijepes.2014.12.072.
[15] Drude L, Pereira Junior LC, Rüther R. Photovoltaics (PV) and electric vehicle-to-grid (V2G) strategies for peak demand reduction in urban regions in Brazil in a smart grid environment. Renew Energy 2014;68:443–51. https://doi.org/10.1016/j.renene.2014.01.049.
[16] Tan KM, Ramachandaramurthy VK, Yong JY. Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. Renew Sustain Energy Rev 2016;53:720–32. https://doi.org/10.1016/j.rser.2015.09.012.
[17] Liu L, Kong F, Liu X, Peng Y, Wang Q. A review on electric vehicles interacting with renewable energy in smart grid. Renew Sustain Energy Rev 2015;51:648–61. https://doi.org/10.1016/j.rser.2015.06.036.
[18] Habib S, Kamran M, Rashid U. Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks – A review. J Power Sources 2015;277:205–14. https://doi.org/10.1016/j.jpowsour.2014.12.020.
[19] Kempton W, Tomić J. Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. J Power Sources 2005;144:268–79. https://doi.org/10.1016/j.jpowsour.2004.12.025.
[20] Lamedica R, Teodori S, Carbone G, Santini E. An energy management software for smart buildings with V2G and BESS. Sustain Cities Soc 2015;19:173–83. https://doi.org/10.1016/j.scs.2015.08.003.
[21] A. Rahman H, Majid MdS, Rezaee Jordehi A, Chin Kim G, Hassan MY, O. Fadhl S. Operation and control strategies of integrated distributed energy resources: A review. Renewable and Sustainable Energy Reviews 2015;51:1412–20. https://doi.org/10.1016/j.rser.2015.07.055.
[22] Haddadian G, Khalili N, Khodayar M, Shahiedehpour M. Security-constrained power generation scheduling with thermal generating units, variable energy resources, and electric vehicle storage for V2G deployment. Int J Electr Power Energy Syst 2015;73:498–507. https://doi.org/10.1016/j.ijepes.2015.05.020.
[23] Noel L, McCormack R. A cost benefit analysis of a V2G-capable electric school bus compared to a traditional diesel school bus. Appl Energy 2014;126:246–55. https://doi.org/10.1016/j.apenergy.2014.04.009.
[24] Li R, Wu Q, Oren SS. Distribution locational marginal pricing for optimal electric vehicle charging management. IEEE Trans Power Syst 2014;29:203–11. https://doi.org/10.1109/TPWRS.2013.2278952.
[25] Yuan Z, Hesamzadeh MR, Biggar DR. Distribution locational marginal pricing by convexified ACOPF and hierarchical dispatch. IEEE Trans Smart Grid 2018;9:3133–42. https://doi.org/10.1109/TSG.2016.2627139.
[26] Ingalalli A, Kamalasadan S. Participation of networked microgrids in energy-as-a-service model for enhancing grid resiliency. 2021 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA: IEEE; 2021, p. 1–5. https://doi.org/10.1109/ISGT49243.2021.9372223.
[27] Smet P. Vehicle substitution in heterogeneous round-trip carsharing systems. Comput Ind Eng 2021;162:107703. https://doi.org/10.1016/j.cie.2021.107703.
[28] Yoon T, Cherry CR, Jones LR. One-way and round-trip carsharing: A stated preference experiment in Beijing. Transp Res Part D: Transp Environ 2017;53:102–14. https://doi.org/10.1016/j.trd.2017.04.009.
[29] Li Y, Chen S, Hu L, Liang Z, Jiang Y, Tang Y. Simulation-optimization for station capacities, fleet size, and trip pricing of one-way electric carsharing systems. J Clean Prod 2021;321:129035. https://doi.org/10.1016/j.jclepro.2021.129035.
[30] Zhang S, Sun H, Wang X, Lv Y, Wu J. Optimization of personalized price discounting scheme for one-way station-based carsharing systems. Eur J Oper Res 2022:S037722172200131X. https://doi.org/10.1016/j.ejor.2022.02.026.
[31] Huang K, An K, Rich J, Ma W. Vehicle relocation in one-way station-based electric carsharing systems: A comparative study of operator-based and user-based methods. Transp Res Part E: Logistics Transp Rev 2020;142:102081. https://doi.org/10.1016/j.tre.2020.102081.
[32] Qin H, Su E, Wang Y, Li J. Branch-and-price-and-cut for the electric vehicle relocation problem in one-way carsharing systems. Omega 2022;109:102609. https://doi.org/10.1016/j.omega.2022.102609.
[33] Xu M, Meng Q, Liu Z. Electric vehicle fleet size and trip pricing for one-way carsharing services considering vehicle relocation and personnel assignment. Transp Res B Methodol 2018;111:60–82. https://doi.org/10.1016/j.trb.2018.03.001.
[34] Ullah I, Liu K, Yamamoto T, Zahid M, Jamal A. Prediction of electric vehicle charging duration time using ensemble machine learning algorithm and Shapley additive explanations. Intl J of Energy Research 2022;46:15211–30. https://doi.org/10.1002/er.8219.
[35] Alencar VA, Rooke F, Cocca M, Vassio L, Almeida J, Vieira AB. Characterizing client usage patterns and service demand for car-sharing systems. Inf Syst 2021;98:101448. https://doi.org/10.1016/j.is.2019.101448.
[36] Feng X, Sun H, Wu J, Liu Z, Lv Y. Trip chain based usage patterns analysis of the round-trip carsharing system: A case study in Beijing. Transp Res A Policy Pract 2020;140:190–203. https://doi.org/10.1016/j.tra.2020.08.017.
[37] Wang S, Dong ZY, Chen C, Fan H, Luo F. Expansion planning of active distribution networks with multiple distributed energy resources and EV sharing system. IEEE Trans Smart Grid 2020;11:602–11. https://doi.org/10.1109/TSG.2019.2926572.
[38] Fan VH, Wang S, Meng K, Dong ZY. Optimal shared mobility planning for electric vehicles in the distribution network. IET Gener Transm Distrib 2019;13:2257–67. https://doi.org/10.1049/iet-gtd.2018.6900.
[39] Wei J, Zhang Y, Wang J, Wu L. Distribution LMP-based demand management in industrial park via a Bi-level programming approach. IEEE Trans Sustain Energy 2021;12:1695–706. https://doi.org/10.1109/TSTE.2021.3062044.
[40] Patnam BSK, Pindoriya NM. DLMP calculation and congestion minimization with EV aggregator loading in a distribution network using bilevel program. IEEE Syst J 2021;15:1835–46. https://doi.org/10.1109/JSYST.2020.2997189.
[41] Wang X, Li F, Dong J, Olama MM, Zhang Q, Shi Q, et al. Tri-level scheduling model considering residential demand flexibility of aggregated HVACs and EVs under distribution LMP. IEEE Trans Smart Grid 2021;12:3990–4002. https://doi.org/10.1109/TSG.2021.3075386.
[42] Lin M-H, Carlsson JG, Ge D, Shi J, Tsai J-F. A review of piecewise linearization methods. Math Probl Eng 2013;2013:1–8. https://doi.org/10.1155/2013/101376.
[43] Wu W, Tian Z, Zhang B. An exact linearization method for OLTC of transformer in branch flow model. IEEE Trans Power Syst 2017;32:2475–6. https://doi.org/10.1109/TPWRS.2016.2603438.
[44] Wei W, Shen Z, Wu L, Li F, Ding T. Estimating DLMP confidence intervals in distribution networks with AC power flow model and uncertain renewable generation. IET Gener Transm Distrib 2020;14:1467–75. https://doi.org/10.1049/iet-gtd.2019.0958.
[45] Huang S, Wu Q, Wang J, Zhao H. A sufficient condition on convex relaxation of AC optimal power flow in distribution networks. IEEE Trans Power Syst 2016:1. https://doi.org/10.1109/TPWRS.2016.2574805.
[46] Ben-Tal A, Nemirovski A. On polyhedral approximations of the second-order cone. Mathematics of OR 2001;26:193–205. https://doi.org/10.1287/moor.26.2.193.10561.
[47] Danping Z, Juan L, Yuchun C, Zhongjian C, Liping L. Research on electric vehicle charging stations planning based on traffic destination heat data and charger usage data. 2020 IEEE 5th International Conference on Intelligent Transportation Engineering (ICITE), Beijing, China: IEEE; 2020, p. 407–10. https://doi.org/10.1109/ICITE50838.2020.9231480.
[48] Kobashi T, Yoshida T, Yamagata Y, Naito K, Pfenninger S, Say K, et al. On the potential of "Photovoltaics + Electric vehicles" for deep decarbonization of Kyoto's power systems: Techno-economic-social considerations. Appl Energy 2020;275:115419. https://doi.org/10.1016/j.apenergy.2020.115419.
[49] Vita V. Development of a decision-making algorithm for the optimum size and placement of distributed generation units in distribution networks. Energies 2017;10:1433. https://doi.org/10.3390/en10091433.
[50] GAMS. CPLEX. WwwGamsCom 2022. https://www.gams.com/36/docs/S_CPLEX.html (accessed March 30, 2022).