

Optimal charge scheduling of electric vehicle fleets through dynamic pricing and intraday market trading

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We consider an electricity supplier for a large commercial electric vehicle (EV) fleet. The supplier uses a dynamic pricing scheme for buying and selling energy from and to the fleet, enabling the supplier to trade any deviations from the agreed day-ahead (DA) position in the intraday auction (IDA) market, while taking into account the behavior of the fleet and its participation in vehicle-to-grid (V2G) services. We propose a bilevel optimization model to capture the hierarchical interaction between the two agents. At the upper level, the supplier maximizes its profit, whereas at the lower level, the EV fleet owner minimizes its total energy cost under a predetermined trip schedule. Because the follower model includes complementarity constraints, we use McCormick envelope relaxation to linearize them, and we prove that the linear relaxation of the lower-level problem is equivalent to the original formulation. We reformulate the model into an equivalent single-level formulation and solve it using an off-the-shelf solver. The model is evaluated through a case study on the Iberian electricity market, comparing results with a baseline that follows the agreed DA position with no adjustments in the IDA market and no V2G. The results confirm that the proposed model improves the economic position of both supplier and fleet owner.

Keywords: Bilevel optimization, Dynamic pricing, Electric vehicle flexibility, Intraday auction market, Vehicle-to-Grid

1 Introduction

In recent years, due to various economic and social incentives, there has been a significant growth in the use of electric vehicles (EVs). Logistics service providers, driven by the urgency of climate change and government policies, have started integrating EVs into their fleets to achieve carbon neutral operations. For example, Amazon has committed to having at least 100,000 electric delivery vans on the road by 2030 [1], while other logistics companies, such as FedEx [2] and DHL [3] have announced similar goals.

Although the rapid increase in the number of EVs brings new challenges to the power system [4], EVs can also be a flexible resource, when managed effectively, and help overcome challenges raised by large volumes of intermittent loads and renewable sources in electricity generation. To use this flexibility effectively, business models play an important role in incentivizing market participation. However, under market rules, a single vehicle has limited energy and power capacity, so it does not meet the minimum power requirements to partic-

ipate in the energy markets. For example, in the Iberian electricity market, the minimum buy or sell order size in the intraday auction market is 0.1 MW [5].

In this paper, we focus on commercial EV fleets, as operated by transportation and delivery companies, among others, that have predictable, or even predetermined, trip schedules and allow flexible charging between routes. Leveraging this flexibility in energy markets can create revenue opportunities for electricity suppliers and reduce fleet operational costs.

Commercial EV fleet owners can also benefit from vehicle-to-grid (V2G) services, which enable them to generate revenue and increase their participation in energy markets. V2G technology enables bidirectional energy exchange between EVs and the power grid when the cars are parked and plugged into the charging stations for EV charging or grid support. Therefore, EVs can function as mobile energy storage resources to support the power grid and offer financial benefits to EV owners [6–8].

We propose a mathematical optimization model that captures the interaction between an electricity supplier and a commercial EV fleet owner. The idea is to leverage EV flexibility and set dynamic retail-level prices that encourage the fleet to adjust its day-ahead position in order to exploit arbitrage opportunities in the intraday auction market and maximize profit. At the same time, the fleet owner aims to determine a charging schedule that enables all vehicles to complete their routes at minimal cost, incorporating V2G options. The supplier must account for the charging decisions of the fleet when setting prices. Hence, this hierarchical interaction between the two agents motivates the use of a bilevel optimization model.

The rest of the paper is organized as follows. Section 2 provides background on bilevel optimization and briefly introduces electricity spot markets. We also review the literature on EV charging flexibility and trading in different electricity markets. In Section 3, we introduce the proposed business model. In Section 4, we present the bilevel optimization model. Section 5 describes the single-level reformulation used to solve the problem. In Section 6, we present and analyze computational results for the Iberian electricity market. Conclusions and potential directions for future research are given in Section 7. Finally, the mathematical details are explained in Appendix.

2 Background and literature review

2.1 Bilevel optimization

Bilevel optimization is a framework for non-cooperative hierarchical decision-making processes involving at least two decision makers, a leader and a follower, whose decisions are made sequentially with the aim of optimizing their respective objectives. The leader makes a decision first, and then the follower observes the leader’s decision and responds by optimizing its own objective. Consequently, the outcome of the leader’s objective depends on the follower’s reaction. Therefore, the leader must account for the follower’s anticipated response in order to optimize its own objective. As the name suggests, a bilevel problem involves two different optimization problems, with the lower-level (or follower) problem nested within the upper-level (or leader) problem.

In this paper, we focus on linear bilevel optimization problems, which can be expressed as:

$$\begin{aligned} \min_{x, \tilde{y}} \quad & a^T x + b^T \tilde{y} \\ \text{s. t.} \quad & Ax + B\tilde{y} \geq c, \\ & \tilde{y} \in \mathcal{S}(x), \end{aligned} \tag{1}$$

where $\mathcal{S}(x)$ is the set of optimal solutions of the x -parameterized linear problem:

$$\begin{aligned} \min_y \quad & d^T y \\ \text{s. t.} \quad & Cx + Dy \geq f, \end{aligned} \tag{2}$$

and $A, B, C, D, a, b, c, d, f$ are constant matrices and vectors of appropriate dimensions. Problem (1) represents the upper-level problem, where the upper-level decision variables (or leader's decisions) are denoted by x . The lower-level problem is defined by (2), with y denoting the lower-level decision variables (or follower's decisions).

We point out that the above formulation yields the so-called optimistic bilevel optimal solution [9]. Under the optimistic approach, when the lower-level problem has multiple optimal solutions, that is, when the lower-level solution set $\mathcal{S}(x)$ is not a singleton, the follower selects that solution $\tilde{y} \in \mathcal{S}(x)$ that leads to the best upper-level objective function value. This formulation assumes some level of cooperation between the two players, to the extent that the follower selects an optimal solution that also benefits the leader.

Bilevel problems are intrinsically hard to solve. Even when both the upper- and lower-level problems are linear, bilevel problems are strongly NP-hard [10]. The most common solution approach for linear bilevel problems is to reformulate the bilevel model as a single-level problem. This is typically done by replacing the lower-level problem with its necessary and sufficient Karush–Kuhn–Tucker (KKT) conditions. The linear bilevel problem can therefore be reformulated as:

$$\min_{x,y,\lambda} \quad a^T x + b^T y \tag{3a}$$

$$\text{s. t.} \quad Ax + By \geq c, \tag{3b}$$

$$Cx + Dy \geq f, \tag{3c}$$

$$\lambda \in \Omega_D := \{\lambda \geq 0 : D^T \lambda = d\}, \tag{3d}$$

$$\lambda^T (Cx + Dy - f) = 0, \tag{3e}$$

where λ are the dual variables associated with the inequality constraints of the lower-level problem. The resulting single-level optimization problem is nonconvex because of the complementarity conditions in (3e), which state that either the corresponding primal constraint is active or the dual variable is zero. In particular, problem (3) is a mathematical program with complementarity constraints (MPCC). We note that the linear bilevel problem is equivalent to the corresponding MPCC (3) in terms of global optimal solutions, but local optimal solutions of (3) are not necessarily local optimal solutions of the bilevel problem [11].

The difficulty in solving problem (3) arises from the KKT complementarity constraints (3e). Two possible ways to handle these constraints are to linearize them using the big-M approach or to model them as special ordered sets of type 1 (SOS1).

Under the big-M approach, we introduce auxiliary binary variables $\sigma \in \{0, 1\}^m$, where m denotes the number of lower-level constraints, to model the disjunctive nature of the complementarity constraints. The complementarity conditions can then be rewritten in the following mixed-integer linear form [12]:

$$Cx + Dy - f \leq (1 - \sigma) M_P, \quad \lambda \leq M_D \sigma,$$

where M_P and M_D are sufficiently large positive constants. The resulting mixed-integer linear reformulation of the KKT reformulation (3) can then be solved using standard mixed-integer solvers. However, this method has some major drawbacks. As explained in [13], the resulting formulation is equivalent to the MPCC (3), provided that M_P and M_D are valid upper bounds. This requires that M_P and M_D do not cut off any vertex of the primal

and dual feasible regions, respectively. Choosing them too small can result in suboptimal solutions [13], whereas large values of M_P and M_D may cause numerical instabilities [14]. In fact, validating the correctness of a given big-M is NP-hard in general [15]. Hence, this approach should be used only when valid constants can be obtained from problem-specific knowledge.

An alternative is to model complementarity constraints using SOS1 constraints, which allows the resulting problem to be solved to global optimality using modern mixed-integer solvers without choosing any big-Ms [14, 16]. An SOS1 constraint defines a set of nonnegative variables for which at most one variable in the set may take a nonzero value. We introduce surplus variables $s_i \geq 0$ and reformulate the complementarity conditions as follows:

$$s_i = (Cx + Dy - f)_i, \quad \{s_i, \lambda_i\} \text{ is SOS1}, \quad i = 1, \dots, m.$$

Bilevel problems may also involve integer decision variables. In mixed-integer linear bilevel problems, even checking whether a given point is feasible is NP-hard [17]. In addition, the existence of an optimal solution strongly depends on whether integrality constraints are imposed at the upper level, lower level, or both levels. In [18], Vicente et al. discuss the existence of optimal solutions for three cases of bilevel MILPs: (a) only upper-level variables are discrete, (b) all upper- and lower-level variables are discrete, and (c) only lower-level variables can take discrete values. They show that, under some additional assumptions analogous to the linear case, an optimal solution always exists for cases (a) and (b). However, for case (c), it seems that the existence of an optimal solution is a more difficult task. Vicente et al. provide an example that demonstrates this complication, in which, under similar assumptions, the bilevel-feasible set may not be closed and, therefore, an optimal solution may not exist [18]. A thorough overview of algorithmic techniques in bilevel optimization can be found in [17, 19].

Our proposed bilevel model has non-KKT complementarity constraints in the lower level. To avoid introducing binary variables in the lower level, we relax the complementarity constraints using McCormick inequalities [20] and prove that this formulation is equivalent to the original lower-level model.

2.2 Electricity spot markets

Generally, wholesale electricity markets can be classified into three broad categories based on the product or service traded: capacity, energy, and ancillary services markets [21]. Not surprisingly, electricity market design differs across regions. Focusing on energy markets, there are, for instance, key differences between Europe and the United States. In most European countries, energy markets include forward markets, spot markets, which include the day-ahead (DA) and intraday (ID) markets, and balancing-energy markets [22]. In much of the United States, Regional Transmission Organizations and Independent System Operators operate two basic types of energy markets: the DA and real-time (RT) markets [23]. Each market fulfills a different purpose and operates at a different point in time relative to physical delivery. In addition, each market offers market participants a different degree of flexibility, which refers to the ability to adjust consumption or production patterns in response to new information. In this work, we focus on electricity markets across Europe, particularly spot markets, while the main characteristics of the other energy markets are outlined for context. For more information on the electricity market design in the United States, see [24].

As mentioned, spot markets include the DA and ID markets, in which trading takes place from one day up to a few minutes before physical delivery.

The forward market complements the spot markets by allowing participants to trade electricity from several years up to two days ahead of the real-time electricity consumption

and production [25]. Forwards and futures are contracts traded in the forward market that lock in a price today, either for the physical delivery of a specified volume of electricity (physical contract) or for the payoff based on the difference between the agreed contract price and the specified index (financial contract) at an agreed time in the future [26, 27]. These contracts allow buyers and sellers to hedge against unwanted price movements and mitigate their exposure to spot price volatility.

Any deviations between scheduled and actual consumption or generation between the ID market closure and real-time are addressed in the balancing market to ensure the safe operation of the power system [28]. Balancing markets are operated by transmission system operators (TSOs) within their respective control areas to correct any imbalances and prevent potential blackouts.

Focusing now on the spot markets, the DA market is where electricity is traded for delivery on the following day. Market participants submit buy or sell orders for the following day before gate closure, which is noon market time on the day before delivery in most markets [29]. The price of a buy order indicates the highest price a buyer is willing to pay, while the price of a sell order indicates the lowest price at which a seller is willing to sell [30]. The market clears through a blind auction, with a uniform price determined for each market time unit (MTU) of the following day based on the merit-order principle [31]. Hence, all accepted orders are settled at the market-clearing price under the pay-as-clear pricing scheme.

DA markets across 27 European countries are part of the Single Day-Ahead Coupling (SDAC), a mechanism that couples the DA markets of the involved bidding zones into a single cross-zonal day-ahead electricity market [32]. It enables trading between these bidding zones through a common price-coupling algorithm, PCR EUPHEMIA, which matches supply and demand across bidding areas and implicitly allocates available cross-border transmission capacity [33]. The algorithm determines a single market-clearing price for each bidding zone based on input from all nominated electricity market operators (NEMOs) and TSOs: orders collected and submitted by NEMOs and network capacities and constraints provided by TSOs. SDAC transitioned from hourly to 15-minute MTUs on 1 October 2025, in line with Article 8 of Regulation (EU) 2019/943 [34, 35].

After the DA market-clearing process, the ID market opens, allowing market participants to adjust their positions closer to real time based on new forecasts and price signals. It plays a primary role in addressing short-term imbalances and providing flexibility. In particular, it allows participants to manage forecast errors and unforeseen events, such as unplanned power unit outages or unexpected demand variations, and set up arbitrage trades. Without ID trading, real-time deviations of scheduled market positions will be spilled into the balancing market. A sufficiently liquid ID market allows market participants to lower their exposure to imbalance risks and financial penalties [36]. Market participants can either trade continuously on the continuous intraday (CID) market, which runs up until very close to delivery, or via intraday auctions on the intraday auction (IDA) market.

The CID market enables orders to be matched continuously throughout the trading period, with participants submitting orders to a central platform. The order book, accessible to all participants, contains all submitted orders available for matching. Once an entered order matches an order already in the order book, the trade is executed anonymously, with partially fulfilled orders amended and fulfilled orders removed from the order book [37]. Orders are matched based on a price-time priority principle, that is, orders are matched based on the attractiveness of their price, with the time of submission to the central platform acting as a tiebreaker when two or more orders have the same price limit [30]. Consequently, the CID market may yield different prices for individual trades.

Complementing continuous intraday trading, intraday auctions provide additional opportunities for market participants to adjust their positions before delivery, since capacity in

the CID market is allocated on a first-come, first-served basis. The IDA market operates similarly to the DA market, with all orders cleared simultaneously based on the merit-order principle.

Most European countries participate in the Single Intraday Coupling (SIDC), which enables cross-border intraday electricity trading among its members, based on continuous cross-border trading and complemented by three intraday implicit auctions [38, 39]. The SIDC currently couples the intraday markets of 25 countries. IDAs, implemented across Europe on 13 June 2024, take place as three European-wide auctions held at 15:00 (D-1), 22:00 (D-1), and 10:00 (D) [32]. Lastly, SIDC uses the same price-coupling algorithm as SDAC to clear intraday auctions.

The products supported by SDAC and SIDC IDAs are equivalent. In detail, the mandatory products available for trading under SDAC and SIDC IDAs are MTU orders, period orders and simple block orders, while several optional products may also be supported [40, 41]. Mandatory products are products that, as a minimum legal requirement, must be accommodated by the price coupling algorithm [42]. MTU orders are curve orders that cover a single MTU, while period orders are 30-minute and 60-minute curve orders that cover multiple MTUs with identical quantities for all periods. Simple block orders cover multiple MTUs and consist of a fixed price limit, a minimum acceptance ratio specifying the minimum proportion of the offered volume that must be matched, expressed as a percentage from 0 to 100 inclusive, and a volume profile for each selected MTU.

The majority of energy traded in the spot market is traded in the DA market. In 2025, the volume traded in SDAC was around 1900 TWh, while total trading activity in SIDC amounted to approximately 387 TWh, of which around 100 TWh was traded in the three daily auctions and 286.85 TWh in the continuous market [32]. Despite this, trading on the intraday market has increased significantly, partly due to the increasing penetration of renewable energy, but also due to storage options, such as batteries, which enable available flexibility to be traded in the short term.

In this work, we focus on the Iberian DA and IDA markets, with more details provided in Section 6.1.1.

2.3 Related literature

EVs are among the most flexible loads, as their charging can be coordinated and shifted over time in response to external factors, such as electricity price signals. EV charging flexibility has received significant attention for its potential to enhance grid stability and facilitate the integration of renewable energy through smart and bidirectional charging. Time-varying pricing is an important tool to influence charging behavior and unlock EV flexibility.

A number of studies have been carried out to optimize the charging schedule of electric vehicle fleets in order to minimize their operational costs. Pelletier et al. [43] propose a model to optimize the depot charging schedule for electric freight fleets under time-dependent energy prices, considering battery degradation and facility-related demand charges that depend on the maximum charging power retrieved from the grid during the billing period. The model assumes a sufficient number of chargers during long layovers, with fast charging available. A similar study is that of Abdelwahed et al. [44], in which they optimized the charging of electric transit-bus networks during layovers between trips under time-varying energy prices and a limited number of chargers, while ensuring feasible operations under a predetermined trip schedule. In [45], an optimization algorithm is developed to jointly solve the charging and routing problem of a commercial EV fleet, considering depot and on-route public charging stations, time-of-use prices, and peak-demand charges, under the assumption of sufficient depot capacity. To account for limited depot charging capacity, Al-Hanahi et al. [46] propose a charging strategy for large commercial EV fleets.

Blatiak et al. [47] propose a framework to optimize the charging schedule and trip start time of a commercial EV fleet with known transportation requirements on a day-ahead basis. Their objective is to maximize potential revenues for the commercial fleet owner from providing upward balancing service while meeting the EV trip energy requirements. Other studies investigated how to take advantage of the flexibility EVs have to offer from an energy supplier or aggregator perspective. These studies looked at the benefits of trading EV charging flexibility in electricity markets, for example, to maximize profits and mitigate financial risks arising from inaccuracies in forecasts of charging behavior.

Authors in [48–50] focused on the trading of EV flexibility in both DA and RT/ID markets. Sánchez-Martín et al. [48] propose a two-stage stochastic optimization model to address uncertainty in vehicle staying patterns in order to minimize the expected electricity procurement costs of the energy supplier while trading in the DA and ID markets. First-stage decisions determine the DA schedule (V2G/G2V energy), while second-stage decisions adjust the DA position in the ID market under several possible vehicle staying scenarios. Jin et al. [50] propose an optimization model to minimize the operational costs of EV aggregators participating in DA and RT markets, using V2G-compatible vehicles to provide auxiliary services to the power grid while accounting for uncertainty in EV charging behavior.

A rolling-horizon optimization framework is proposed in [49,51] to facilitate EV flexibility trading in the CID market, allowing trading and charging decisions to adapt dynamically to market conditions. Chemudupaty et al. [49] propose trading strategies within the DA and CID markets to manage the power needs of a fleet of residential EVs under uncertainty in EV flexibility forecasts and CID prices, while leveraging EV charging flexibility for arbitrage opportunities in the CID market, using Germany as a case study. A two-step linear optimization framework was developed: first, DA procurement costs are optimized, and then the charging schedule is re-optimized using an updated EV flexibility forecast, with different strategies proposed for this readjustment. Naharudinsyah and Limmer [51] developed an MILP model to minimize the EV charging costs of a charging station operator, allowing the operator to purchase energy either from an energy supplier at a fixed price or from the CID market, with the option to resell the purchased energy back to the market. The German market is used as a reference, using currently available CID prices.

However, to implement business models that use EVs as flexible assets, the aggregator or supplier needs to offer EV owners financial rewards. In particular, both the aggregator and EV owners are motivated to participate in such business models only if they are economically feasible: how much profit the energy supplier makes and how much money the EVs save [52]. In addition, dynamic pricing is a promising approach to unlock EV flexibility as prices are dynamically adjusted by the charging provider to changes in the operating conditions [53–55]. Hence, a dynamic pricing strategy can provide different benefits, such as lower charging costs for EV users, increased power grid stability, and reduced operational costs for public charging stations.

Anjos et al. [56] present a single-leader multi-follower bilevel optimization model for an electric vehicle charging station pricing problem that takes customer preferences into account. An EV charging provider operates a network of charging stations serving multiple disjoint customers and uses a discrete dynamic pricing strategy to maximize profit and reduce the negative impact on the grid and queues at charging stations. A non-parametric ranking-based consumer choice model is considered, in which the customer selects the place and time to charge according to an incomplete preference list and a reserve price.

Vuelvas et al. [57] propose a stochastic bilevel optimization framework that models the interactions between an EV aggregator and EV owners. The aggregator designs retail prices under uncertainty in demand and DA prices to induce users to modify their energy consumption, assuming unidirectional charging, and maximize its benefits. The dynamics of the fleet are modeled as a virtual battery at the lower level.

Our work differs from related studies in the following aspects: a strategic bilevel model is proposed to model the interaction between an electricity supplier and a commercial EV fleet to design retail prices that encourage the fleet to adjust its agreed DA position, enabling the supplier to participate in the IDA market and exploit energy arbitrage opportunities. The supplier uses a dynamic pricing scheme to maximize profit while taking into account the behavior of the fleet and its participation in V2G. Table 1 summarizes our main contributions with respect to the literature reviewed in this section.

Table 1: Overview of related literature.

Research paper	Bilevel model	Economic benefits optimized		V2G	Dynamic pricing	Modelling individual EV behavior	Participation in the IDA market
		supplier/ aggregator	EV fleet owner				
Abdelwahed et al. [44]	✗	✗	✓	✗	✗	✓	✗
Al-Hanahi et al. (2022) [45]	✗	✗	✓	✗	✗	✓	✗
Al-Hanahi et al. (2024) [46]	✗	✗	✓	✗	✗	✓	✗
Anjos et al. (2025) [56]	✓	✓	✓	✗	✓	✓	✗
Blatiak et al. [47]	✗	✗	✓	✓	✗	✓	✗
Chemudupaty et al. [49]	✗	✓	✗	✗	✗	✗	✓
Jin et al. [50]	✗	✓	✗	✓	✗	✓	✓
Naharudinsyah and Limmer [51]	✗	✓	✗	✗	✗	✓	✓
Pelletier et al. [43]	✗	✗	✓	✗	✗	✓	✗
Sánchez-Martín et al. [48]	✗	✓	✗	✓	✗	✓	✓
Vuelvas et al. [57]	✓	✓	✓	✗	✓	✗	✓
This paper	✓	✓	✓	✓	✓	✓	✓

3 Proposed business model

We consider an electricity supplier for a large commercial EV fleet. The supplier uses a dynamic pricing scheme to maximize profit by trading EV flexibility in the IDA market. In return, the fleet benefits from lower prices and participation in V2G services, reducing its overall charging costs. The idea is to set prices that encourage the fleet to adjust its agreed DA position, enabling the supplier to participate in the IDA market. If the block order is accepted, the EV fleet must follow the new consumption pattern; otherwise, it must adhere to the position agreed in the DA market clearing. We note that the agreed DA position is obtained through cost-optimal EV charge scheduling based on indexed electricity rates, with a constant supplier margin assumed (see Section 4.1). The proposed business model could therefore improve the economic outcomes of both participants.

The interactions between the supplier and the fleet owner are illustrated in Figure 1 as a decision sequence diagram. First, the supplier designs the retail prices. Then, the fleet optimizes its consumption profile based on its driving requirements and the new pricing scheme. In turn, the supplier observes the new consumption pattern and participates in the IDA market to adjust the consumption schedule. The hierarchical interaction between the two decision-makers motivates the use of a single-leader single-follower bilevel optimization model.

4 Bilevel optimization model

We propose a bilevel optimization model that captures the interactions between the electricity supplier (upper-level decision maker) and the EV fleet owner (lower-level decision maker). The electricity supplier determines the retail prices over the planning horizon to encourage the fleet to adjust its agreed DA position e^{DA} in order to trade in the IDA market.

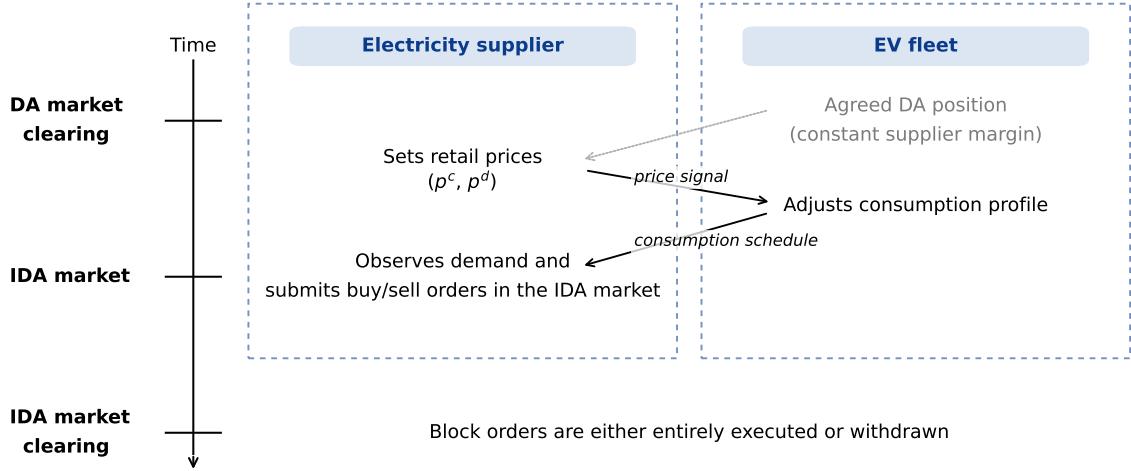


Figure 1: Decision-making framework of the electricity supplier and the EV fleet.

Let I be the set of EVs and T be the set of periods in the given day. We consider a set of homogeneous EVs in a commercial fleet. Each vehicle has a battery with an energy capacity of $E^{\max}$ (nominal capacity). We define the state of charge (SoC) of a battery as the ratio of the remaining available capacity to the nominal capacity [58]. Here, $E^{\max}$ stands for the maximum amount of energy that can be stored in the battery. The fleet trip schedule is known in advance, with the vehicles parked at the station between trips. We assume a sufficient number of chargers of the same type are available at the station, so that all vehicles can plug in whenever they are there. To describe vehicle availability for grid connection, we introduce the binary parameter $w_{i,t}$, which takes the value 1 if EV i is at the station during period t and 0 otherwise. When at the station, we allow vehicles to charge, discharge, or remain idle. Finally, we consider energy losses due to the system round-trip efficiency over a charge-discharge cycle.

We start by describing the upper-level problem, defined as follows:

$$\begin{aligned} \max_{\substack{p_t^c, p_t^d, m_t, \\ e_{i,t}^{c*}, e_{i,t}^{d*}, S_{i,t}^*}} & - \sum_{t \in T} p_t^{\text{DA}} e_t^{\text{DA}} + \sum_{t \in T} \sum_{i \in I} p_t^{\text{DA}} e_{i,t}^{c*} + \sum_{t \in T} \sum_{i \in I} m_t e_{i,t}^{c*} \\ & - \sum_{t \in T} \sum_{i \in I} p_t^d e_{i,t}^{d*} + \sum_{t \in T} \bar{p}_t^{\text{IDA}} \left(e_t^{\text{DA}} - \sum_{i \in I} (e_{i,t}^{c*} - e_{i,t}^{d*}) \right) \end{aligned} \quad (4a)$$

$$\text{s. t. } p_t^c = (p_t^{\text{DA}} + p_t^{\text{N}} + p_t^{\text{L}} + m_t) (1 + \tau) \quad \forall t \in T \quad (4b)$$

$$\left(1 - 2 \operatorname{sgn} \left(\sum_{i \in I} w_{i,t} \right) \right) m^{\text{const}} \leq m_t \leq m^{\text{const}} \quad \forall t \in T \quad (4c)$$

$$0 \leq p_t^d \leq \operatorname{sgn} \left(\sum_{i \in I} w_{i,t} \right) |\bar{p}_t^{\text{IDA}}| \quad \forall t \in T \quad (4d)$$

$$p_t^c \geq \lambda^2 p_t^d + \epsilon \quad \forall t \in T \quad (4e)$$

$$(e_{i,t}^{c*}, e_{i,t}^{d*}, S_{i,t}^*) \in \mathcal{S}(p_t^c, p_t^d) \equiv \arg \min L(p_t^c, p_t^d)$$

where $L(p_t^c, p_t^d)$ is the lower-level problem.

The electricity supplier aims to maximize its profit, as formulated in (4a). The first term details the cost of purchasing energy in the DA market, where p_t^{DA} is the DA market-clearing

price in period t . The parameter e_t^{DA} represents the DA position for period t after market clearing, obtained through cost-optimal EV charge scheduling based on indexed electricity rates $p_t^{c,\text{base}}$, with a constant supplier margin of m^{const} (see Section 4.1). The second term represents the payment received from the fleet for its new charging pattern, valued at the DA market price. Here, $e_{i,t}^c$ is a lower-level decision variable for the energy charged, in kWh, to EV i during period t . We note that the fleet pays the wholesale cost for its final consumption. Therefore, any deviations from the agreed DA position are borne by the leader and may result in either a loss or a profit.

The third and fourth terms represent the revenue made from providing charging services to the fleet and the compensation paid to the fleet for discharging energy, respectively. The decision variables for supplier margin per kWh and the unit price paid to the fleet for discharging are denoted by m_t and p_t^d , respectively. The lower-level decision for the energy discharged, in kWh, from EV i during period t is denoted by $e_{i,t}^d$.

Finally, the fifth term represents the predicted profit from trading in the IDA market by buying and selling energy to adjust the agreed DA position. Here, $\bar{p}_t^{\text{IDA}}$ is the IDA price forecast for period t . We note that intraday prices can be negative, which can lead to unconventional pricing outcomes in which the supplier is paid when the fleet consumes more energy than the agreed DA position and pays when the fleet consumes less.

Constraint (4b) defines the indexed charging price p_t^c , which comprises the energy and supply component, represented in the model by the DA market price and supplier margin, network charges, and other levies and charges, with applicable taxes added on top [59]. Here, p_t^{N} represents network charges, which mainly comprise transmission and distribution costs, and p_t^{L} represents other applicable levies and charges, such as those related to renewable energy support and other system charges. The supplier margin m_t contributes to the final electricity price and is added by the supplier to cover its operating and commercialization costs and generate a return from its activity. The parameter τ represents the applicable non-recoverable tax rate for non-household final customers.

The supplier can adjust its margin within an acceptable range, as enforced by constraint (4c). In periods when all vehicles are on the road, the charging price becomes irrelevant from an operational perspective, as no charging can occur. In such cases, constraint (4c) ensures that the charging price is set equal to $p_t^{c,\text{base}}$. Constraint (4d) sets a price cap on the amount the supplier pays the fleet owner per unit of discharged energy. Similarly, when all vehicles are on trips, the discharging price becomes irrelevant and is therefore set to 0. Lastly, constraint (4e) ensures that the price setting discourages an EV from charging and discharging simultaneously within the same period by making such behavior costly for the fleet after accounting for energy losses due to the system round-trip efficiency over a charge-discharge cycle, whose square root is denoted by λ . Here, ϵ is a sufficiently small positive constant used to enforce the strict inequality constraint. Note that constraint (4e) is redundant for preventing simultaneous charging and discharging, as this is already enforced at the lower level. Nevertheless, it will be useful when solving the bilevel problem.

Constraints (4b), (4d), and (4e) imply the following lower bound on the supplier margin in each period t :

$$m_t \geq - (p_t^{\text{DA}} + p_t^{\text{N}} + p_t^{\text{L}}) + \frac{\epsilon}{1 + \tau} =: m_t^{\min}.$$

Since $m_t \leq m^{\text{const}}$, model feasibility requires $m^{\text{const}} \geq m_t^{\min}$. Hence, m^{const} must satisfy:

$$m^{\text{const}} \geq m_{\min}^{\text{const}}, \quad (5)$$

where

$$m_{\min}^{\text{const}} := \max_{d \in D} \max_{t \in T} \left\{ - (p_{d,t}^{\text{DA}} + p_{d,t}^{\text{N}} + p_{d,t}^{\text{L}}) + \frac{\epsilon}{1 + \tau} \right\}. \quad (6)$$

Here, D denotes the set of days in the period of interest. The additional index d is introduced only in this expression to distinguish prices across days.

We recall that this formulation establishes the so-called optimistic solution. If the follower has multiple optimal solutions, it is assumed that the follower selects a lower-level solution that yields the highest profit for the leader. The follower problem is embedded in the constraints of the leader's problem and is therefore parameterized by the leader's decision variables p_t^c and p_t^d . We next describe the follower problem, defined as:

$$\min_{e_{i,t}^c, e_{i,t}^d, S_{i,t}} \sum_{t \in T} \sum_{i \in I} \left(p_t^c e_{i,t}^c - p_t^d e_{i,t}^d \right) \quad (7a)$$

$$\text{s. t. } e_{i,t}^c \leq e_{\text{cd}}^{\max} w_{i,t} \quad \forall i \in I, t \in T \quad (7b)$$

$$e_{i,t}^d \leq e_{\text{cd}}^{\max} w_{i,t} \quad \forall i \in I, t \in T \quad (7c)$$

$$e_{i,t}^c e_{i,t}^d = 0 \quad \forall i \in I, t \in T \quad (7d)$$

$$S^{\min} \leq S_{i,t} \leq S^{\max} \quad \forall i \in I, t \in T \setminus \{|T|\} \quad (7e)$$

$$S_{i,0} = S_i^{\text{init}} \quad \forall i \in I \quad (7f)$$

$$S_{i,|T|} = S_i^{\text{init}} \quad \forall i \in I \quad (7g)$$

$$S_{i,t} = S_{i,t-1} + \lambda \frac{e_{i,t}^c}{E^{\max}} - \frac{1}{\lambda} \frac{e_{i,t}^d}{E^{\max}} - (1 - w_{i,t}) S^{\text{out}} \quad \forall i \in I, t \in T \quad (7h)$$

$$e_{i,t}^c, e_{i,t}^d \geq 0 \quad \forall i \in I, t \in T. \quad (7i)$$

The EV fleet owner aims to optimize its charging and discharging activities under a predetermined trip schedule in order to minimize the overall cost (7a) defined as the difference between the cost of charging the fleet and the revenue generated from discharging the stored energy.

Equations (7b) and (7c) ensure that a vehicle can charge or discharge only when it is at the station and only up to the maximum allowable amount. Constraint (7d) prevents the simultaneous performance of both actions within the same period. Constraint (7e) ensures that the SoC of a vehicle remains within safe operational limits. In addition, equation (7f) implies that the SoC of each vehicle at the beginning of the time horizon is S_i^{init} , and (7g) ensures that by the end of the planning horizon, the vehicle has the same SoC value as at the beginning. This ensures conservation of the energy stored in EVs by the end of the optimization time horizon. Constraint (7h) is used for updating the battery level of a vehicle from one period to the next based on its availability status and its decision to charge, discharge or stand by during its visit to the station. This constraint assumes that the SoC decreases by a fixed rate of S^{out} per period if the vehicle is on a trip. When a vehicle is connected to a charger, part of the dispatched energy during this process is lost due to the system round-trip efficiency. Finally, constraint (7i) defines the domain of the decision variables.

All the notation introduced in this section is summarized in Table 2.

4.1 Agreed day-ahead position

We obtain the DA schedule by solving a similar version of the lower-level problem (7) that considers only unidirectional charging. The indexed electricity prices $p_t^{c,\text{base}}$ are defined as in (4b), but with a constant supplier margin m^{const} and perfect foresight of DA prices. The value of m^{const} is chosen to satisfy the feasibility condition in (5). Thus, the agreed DA

Table 2: List of sets, parameters, and variables used in the bilevel model.

Sets	
I	set of EVs, indexed by i
T	set of time periods over the planning horizon, indexed by t^1
Parameters	
ϵ	sufficiently small positive tolerance constant
τ	applicable non-recoverable tax rate on electricity [%]
p_t^N	network charges for period t [€/kWh]
p_t^L	other applicable levies and electricity-system charges for period t [€/kWh]
p_t^{DA}	DA price for period t [€/kWh]
$\bar{p}_t^{\text{IDA}}$	IDA price forecast for period t [€/kWh]
e_t^{DA}	energy purchased in the DA market for charging activities during period t [kWh]
$w_{i,t}$	availability status: 1 if EV i is at the station during period t ; 0 if on a trip
$e_{\text{cd}}^{\text{max}}$	maximum charging or discharging energy of an EV during period t [kWh per period]
S^{min}	minimum value of SoC [%]
S^{max}	maximum value of SoC [%]
S_i^{init}	initial value of SoC for EV i [%]
S^{out}	rate of decrease in the SoC when a vehicle is on a trip during period t [%]
m^{const}	supplier margin used to determine the agreed DA position [€/kWh]
λ	square root of the system round-trip efficiency [%]
E^{max}	maximum battery capacity (nominal capacity) [kWh]
Upper-level decision variables	
m_t	supplier margin in period t [€/kWh]
p_t^c	energy unit price of charging during period t [€/kWh]
p_t^d	energy unit price of discharging during period t [€/kWh]
Lower-level decision variables	
$S_{i,t}$	SoC of EV i at the end of period t [%]
$e_{i,t}^c$	energy charged to EV i during period t [kWh]
$e_{i,t}^d$	energy discharged from EV i during period t [kWh]

¹ The initial time period $t = 0$ is not included in the set T . We consider the notation $T_0 = \{0\} \cup T$.

position is obtained by solving the following linear optimization problem:

$$\min_{e_{i,t}^c, S_{i,t}} \sum_{t \in T} \sum_{i \in I} p_t^{c, \text{base}} e_{i,t}^c \quad (8a)$$

$$\text{s. t.} \quad 0 \leq e_{i,t}^c \leq e_{\text{cd}}^{\text{max}} w_{i,t} \quad \forall i \in I, t \in T \quad (8b)$$

$$S^{\text{min}} \leq S_{i,t} \leq S^{\text{max}} \quad \forall i \in I, t \in T \setminus \{|T|\} \quad (8c)$$

$$S_{i,0} = S_{i,|T|} = S_i^{\text{init}} \quad \forall i \in I \quad (8d)$$

$$S_{i,t} = S_{i,t-1} + \lambda \frac{e_{i,t}^c}{E^{\text{max}}} - (1 - w_{i,t}) S^{\text{out}} \quad \forall i \in I, t \in T. \quad (8e)$$

It is important to note that the bilevel model is independent of the DA optimization procedure, as the DA charging schedule serves only as a reference position for trading in the IDA market. The DA charging optimization model (8) provides one way to obtain a DA position. Alternative cost-minimization formulations for determining a DA position are presented in [60–62].

5 Solution approach

The model introduced in Section 4 is a single-leader single-follower bilevel problem with a lower level that is a linear program with complementarity constraints (LPCC). This implies that the bilevel problem cannot be directly transformed into an MPCC, following the solution approach described in Section 2.1. For this reason, we first relax the complementarity constraints using McCormick envelopes and then replace the relaxed lower-level problem with its necessary and sufficient KKT conditions.

5.1 Model simplification

The lower-level problem (7) is an LPCC because of the nonconvex complementarity constraint (7d) ensuring that a vehicle can charge or discharge, but cannot perform both actions simultaneously. To address this difficulty, we employ the McCormick envelope relaxation in which we approximate the bilinear terms using convex underestimators and concave overestimators over the specified domain [20]. We replace each bilinear term $e_{i,t}^c e_{i,t}^d$ by a new auxiliary variable $z_{i,t}$ and four linear inequalities:

$$\begin{aligned} z_{i,t} &\geq 0 \\ z_{i,t} &\geq e_{\text{cd}}^{\max} w_{i,t} e_{i,t}^c + e_{\text{cd}}^{\max} w_{i,t} e_{i,t}^d - (e_{\text{cd}}^{\max} w_{i,t})^2 \\ z_{i,t} &\leq e_{\text{cd}}^{\max} w_{i,t} e_{i,t}^c \\ z_{i,t} &\leq e_{\text{cd}}^{\max} w_{i,t} e_{i,t}^d. \end{aligned} \tag{9}$$

Substituting $z_{i,t} = 0$ into (9) yields, after simplification:

$$\begin{aligned} e_{i,t}^c, e_{i,t}^d &\geq 0 & \forall i \in I, t \in T, \\ e_{i,t}^c + e_{i,t}^d &\leq e_{\text{cd}}^{\max} w_{i,t} & \forall i \in I, t \in T. \end{aligned} \tag{10}$$

Condition (10) describes the convex hull of the complementarity set:

$$\{(e_{i,t}^c, e_{i,t}^d) \mid e_{i,t}^c e_{i,t}^d = 0, 0 \leq e_{i,t}^c, e_{i,t}^d \leq e_{\text{cd}}^{\max} w_{i,t}\},$$

and also implies (7b) and (7c). The resulting problem is an LP relaxation of the lower-level problem (7) defined as follows:

$$\begin{aligned} \min_{e_{i,t}^c, e_{i,t}^d, S_{i,t}} \quad & (7a) \\ \text{s. t.} \quad & (7e)-(7i) \\ & e_{i,t}^c + e_{i,t}^d \leq e_{\text{cd}}^{\max} w_{i,t} \quad \forall i \in I, t \in T. \end{aligned} \tag{7_r}$$

Under the McCormick relaxation, an EV is allowed to charge and discharge simultaneously. This is why we introduce constraint (4e) at the upper level. By doing so, we ensure that the price setting discourages an EV from performing both actions in the same period by making such behavior costly for the fleet.

Proposition. *For each vehicle i , an optimal solution for the relaxed lower-level problem (7_r) is also optimal for the lower-level problem (7) if the following constraints are satisfied:*

$$p_t^c \geq \lambda^2 p_t^d + \epsilon \quad \forall t \in T,$$

with $\lambda \in (0, 1)$ and $\epsilon > 0$.

Proof. Suppose, for a contradiction, that there exists an optimal solution (e^{c*}, e^{d*}) of problem (7_r) such that $e_{j,\tau}^{c*} > 0$ and $e_{j,\tau}^{d*} > 0$ for some vehicle $j \in I$ and period $\tau \in T$. We denote the feasible set of (7_r) as $\mathcal{F}_r$.

Let $e_{j,\tau}^{c*} = \alpha + \bar{e}_{j,\tau}^c$ and $e_{j,\tau}^{d*} = \lambda^2 \alpha + \bar{e}_{j,\tau}^d$ where $\alpha = \min\{e_{j,\tau}^{c*}, e_{j,\tau}^{d*}/\lambda^2\}$ and $\bar{e}_{j,\tau}^c \bar{e}_{j,\tau}^d = 0$ (i.e., $\bar{e}_{j,\tau}^c$ and $\bar{e}_{j,\tau}^d$ describe the net charged energy and net discharged energy, respectively). This formulation covers all possible cases:

- (a) $e_{j,\tau}^{c*} = \alpha$ and $e_{j,\tau}^{d*} = \lambda^2 \alpha$,
- (b) $e_{j,\tau}^{c*} > \alpha$ and $e_{j,\tau}^{d*} = \lambda^2 \alpha$, and
- (c) $e_{j,\tau}^{c*} = \alpha$ and $e_{j,\tau}^{d*} > \lambda^2 \alpha$.

Since we consider energy losses due to the system round-trip efficiency over a charge-discharge cycle, when a vehicle is connected to a charger, its battery level is updated from one period to the next as follows:

$$S_{i,t} = S_{i,t-1} + \frac{1}{E^{\max}} \left(\lambda e_{i,t}^c - \frac{e_{i,t}^d}{\lambda} \right).$$

Therefore, in case (a), charging α and discharging $\lambda^2 \alpha$ leave the SoC unchanged. This is equivalent to setting $\bar{e}_{j,\tau}^c = \bar{e}_{j,\tau}^d = 0$. In cases (b) and (c), the SoC from period $t-1$ to period t increases by $\lambda \bar{e}_{j,\tau}^c / E^{\max}$ and decreases by $\bar{e}_{j,\tau}^d / \lambda E^{\max}$, respectively. The same SoC updates are obtained by charging $\bar{e}_{j,\tau}^c$ with no discharging and by discharging $\bar{e}_{j,\tau}^d$ with no charging, respectively. Therefore, $(\bar{e}^c, \bar{e}^d) \in \mathcal{F}_r$, where $\bar{e}_{i,t}^c = e_{i,t}^{c*}$ and $\bar{e}_{i,t}^d = e_{i,t}^{d*}$ for each $(i,t) \neq (j,\tau)$. Moreover, $\bar{e}_{i,t}^c \bar{e}_{i,t}^d = 0$ for each $i \in I$ and for each $t \in T$.

The optimal objective value of problem (7_r) is:

$$\sum_{t \in T} \sum_{i \in I} (p_t^c e_{i,t}^{c*} - p_t^d e_{i,t}^{d*}) = p_\tau^c e_{j,\tau}^{c*} - p_\tau^d e_{j,\tau}^{d*} + \sum_{\substack{t \in T \\ t \neq \tau}} \sum_{\substack{i \in I \\ i \neq j}} (p_t^c e_{i,t}^{c*} - p_t^d e_{i,t}^{d*}).$$

It follows that:

$$\begin{aligned} p_t^c e_{j,\tau}^{c*} - p_t^d e_{j,\tau}^{d*} &= p_t^c (\alpha + \bar{e}_{j,\tau}^c) - p_t^d (\lambda^2 \alpha + \bar{e}_{j,\tau}^d) \\ &= \alpha (p_t^c - \lambda^2 p_t^d) + p_t^c \bar{e}_{j,\tau}^c - p_t^d \bar{e}_{j,\tau}^d \\ &\geq \alpha \epsilon + p_t^c \bar{e}_{j,\tau}^c - p_t^d \bar{e}_{j,\tau}^d \\ &> p_t^c \bar{e}_{j,\tau}^c - p_t^d \bar{e}_{j,\tau}^d, \end{aligned}$$

contradicting our hypothesis. Therefore, any optimal solution of problem (7_r) satisfies the complementarity condition. $\square$

5.2 Single-level reformulation

For the remainder of the paper, we consider the following formulation:

$$\begin{aligned} &\max_{\substack{p_t^c, p_t^d, m_t, \\ e_{i,t}^{c*}, e_{i,t}^{d*}, S_{i,t}^*}} && (4a) \\ &\text{s. t.} && (4b)-(4e) \\ &&& (e_{i,t}^{c*}, e_{i,t}^{d*}, S_{i,t}^*) \in \arg \min && (7a) \\ &&& \text{s. t.} && (7e)-(7i) \\ &&& e_{i,t}^c + e_{i,t}^d \leq e_{\text{cd}}^{\max} w_{i,t} \quad \forall i \in I, t \in T. && (\text{LLF}) \end{aligned}$$

Since (LLF) is an LP-LP bilevel problem, we reformulate it using an equivalent single-level optimization problem. We replace the lower-level problem with its necessary and sufficient KKT conditions that consist of primal feasibility (A.1), dual feasibility (A.2) and complementary slackness (A.3).

The resulting single-level optimization problem is nonconvex because of the complementary slackness conditions. We express these constraints using SOS1 constraints. We note that (LLF) has bilinear terms of the form $p_t^c e_{i,t}^c$ and $p_t^d e_{i,t}^d$ in the objective function. We leave these terms unchanged, as Gurobi can handle them directly.

The final step before solving the single-level reformulation is to add the strong duality cut of the lower-level problem, as introduced in [14], to (LLF) in order to reduce the total computational time of the algorithm.

6 Computational case study

We present the results of a computational case study to evaluate the potential of the proposed business model and the capabilities of (LLF). In Section 6.1, we describe the data used and the computational setup. In Section 6.2, we demonstrate the economic feasibility of the proposed business model by calculating the profit derived from trading EV flexibility in the IDA market, and comparing the proposed strategy with the optimal fleet behavior under a constant supplier margin when no trading in the IDA market or V2G is considered.

6.1 Data and implementation

Section 6.1.1 outlines the Iberian electricity market used as a reference. Section 6.1.2 details the price data used in our study, and Section 6.1.3 describes the main characteristics of the EV fleet and the vehicle availability patterns considered in the experiments. Finally, Section 6.1.4 provides details of our computational implementation.

6.1.1 Related aspects of the Iberian electricity market

Our study uses the Iberian DA and IDA markets as a reference. OMIE is the NEMO for the Iberian Peninsula’s DA and ID markets [63]. Since 13 June 2024, the Iberian IDA market is structured into three auction sessions coupled at the European level as part of the EU implementation of IDAs [64, 65]. IDA1 and IDA2 are held on day D-1, alongside the DA session, and cover all MTUs of day D, with gate closure times at 15:00 and 22:00 on day D-1, respectively. IDA3 takes place on day D and covers only the hours from 12:00 to 24:00, with gate closure at 10:00 on the same day. Figure 2 presents the schedule of the Iberian DA and IDA markets.

To enhance market efficiency and support the integration of intermittent renewable energy sources, the Iberian DA and ID markets transitioned from 60-minute to 15-minute MTUs, resulting in 96 quarter-hourly periods per day (48 for IDA3). In more detail, 15-minute products were introduced in the Iberian ID market on 18 March 2025 [66]. The DA market adopted the 15-minute MTU on the trading day of 30 September 2025, for delivery on 1 October 2025, as part of a Europe-wide coordinated launch under the SDAC project [67]. A detailed analysis of the Iberian ID market can be found in the study by Maiz et al. [65].

6.1.2 Price data

We obtain all DA and IDA market data from the OMIEData platform [68]. The forecast of electricity prices in the IDA market is outside the scope of this work. Hence, we assume perfect foresight of IDA market prices. However, we note the importance of accurately forecasting IDA prices to obtain reliable results in real scenarios of the proposed model.

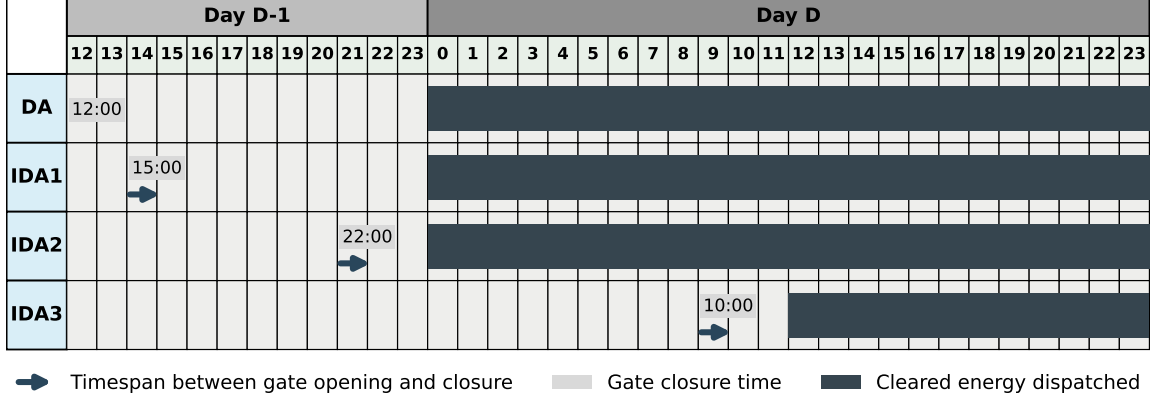


Figure 2: Schedule of the Iberian DA and IDA markets.

We run simulations for all seasons in 2025-2026, covering the period from 1 March 2025 to 28 February 2026. We omit any days with missing or invalid dynamic price data. Complete price data are available for 341 out of 365 days. In all cases, we assume a 24-hour planning horizon and consider hourly blocks to ensure consistency throughout the analysis, since the transition from 60-minute to 15-minute MTUs occurred during the study period. For days after the transition, we average the corresponding quarter-hourly prices to derive hourly prices.

Acknowledging that EV charging needs across consecutive hours are not fully independent, we consider block orders with a minimum acceptance ratio of 100%, implying that the block order will either be entirely executed or withdrawn.

In Spain, the final indexed price comprises the supplier margin, energy costs, regulated network tolls and system charges, and applicable taxes [69]. The energy component includes wholesale energy procurement costs and other costs, such as ancillary-service costs and system and market operator fees. In this study, we consider only the DA market price (OMIE price) and omit the remaining costs.

The constant supplier margin m^{const} is chosen to satisfy the feasibility condition in (5), with the corresponding lower bound given by (6). For the period March 2025 – February 2026, the lower bound $m_{\min}^{\text{const}}$ is 0.010470 €/kWh. We therefore set m^{const} to 0.011 €/kWh, rounded up to the next tenth of a euro cent.

The main taxes are value-added tax (VAT) and the excise duty on electricity. As VAT is generally recoverable on expenses incurred for business activities, it is excluded from the price formulation. Therefore, the only non-recoverable tax considered in this study is the excise duty on electricity. The tax rate is 5.11269632%, as regulated by Law 38/1992 of December 28 on Excise Duties (Ley 38/1992, de 28 de diciembre, de Impuestos Especiales) [70]. Hence, we set the parameter τ to 5.11%.

Government-regulated costs include access tolls for electricity transmission and distribution networks, as well as system charges linked to renewable energy costs and other system expenses [71]. We consider publicly accessible EV charging points with contracted power exceeding 15 kW and connected at voltages above 1 kV and below 30 kV [72]. Hence, the relevant tariff segments are 6.1 TDVE for access tolls and 3 VE for system charges. Both access tolls and system charges are broken down into contracted power and energy terms and follow a six-period time-of-use pricing system. This system divides the hours of the year into six tariff periods (P1 to P6) based on the season, day of the week, and hour of the day, with a different tariff rate for each period [73]. We consider the pricing system defined for Peninsular Spain, which is discussed in more detail later in this section.

Tables 3 and 4 present the access tolls and system charges, respectively, applicable to

publicly accessible EV charging points connected at a voltage above 1 kV and below 30 kV for 2025 and 2026.

Table 3: Access tolls (6.1TDVE) for publicly accessible high-voltage EV charging points [74, 75].

Power term of access tolls (€/kW year)						
	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
2025	5.460600	2.887083	1.083564	0.763585	0.016143	0.014376
2026	5.523814	2.926765	1.095280	0.770513	0.016375	0.014472

Energy term of access tolls (€/kWh)						
	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
2025	0.162917	0.071484	0.028390	0.016448	0.000733	0.000174
2026	0.161150	0.073878	0.030860	0.016704	0.000718	0.000176

Table 4: System charges (tariff segment 3 VE) for publicly accessible high-voltage EV charging points [76, 77].

Power term of system charges (€/kW year)						
	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
2025	0	0	0	0	0	0
2026	0	0	0	0	0	0

Energy term of system charges (€/kWh)						
	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
2025	0.055640	0.041215	0.022254	0.011129	0.007134	0.004451
2026	0.061354	0.045446	0.024440	0.012271	0.007867	0.004908

The energy component of the regulated part of the bill is given by [72, 73]:

$$C^{\text{en}} = \sum_{j=1}^6 \left(\tau_{P_j}^{\text{en,toll}} + \tau_{P_j}^{\text{en,chg}} \right) E_{P_j},$$

where $\tau_{P_j}^{\text{en,toll}}$ and $\tau_{P_j}^{\text{en,chg}}$ are the energy-term rates of the access tolls and system charges, respectively, for tariff period P_j , expressed in €/kWh, and E_{P_j} denotes the energy consumed in tariff period P_j , expressed in kWh. In the model formulation, $\tau_{P_j}^{\text{en,toll}}$ and $\tau_{P_j}^{\text{en,chg}}$ correspond to the network charges p_t^{N} and other levies and system charges p_t^{L} , respectively, based on the tariff period to which period t belongs:

$$p_t^{\text{N}} = \tau_{P_j}^{\text{en,toll}} \text{ and } p_t^{\text{L}} = \tau_{P_j}^{\text{en,chg}} \text{ for } t \in P_j.$$

Similarly, the power component of the regulated part of the bill is given by [72, 73]:

$$C_{\text{daily}}^{\text{pow}} = \frac{\sum_{j=1}^6 \left(\tau_{P_j}^{\text{pow,toll}} + \tau_{P_j}^{\text{pow,chg}} \right) P_{P_j}^{\text{contr}}}{365},$$

where $\tau_{P_j}^{\text{pow,toll}}$ and $\tau_{P_j}^{\text{pow,chg}}$ are the power-term rates of the access tolls and system charges, respectively, for tariff period P_j , expressed in €/kW year, and P_j^{contr} denotes the contracted power in tariff period P_j , expressed in kW. We assume the same contracted power across all six tariff periods:

$$P_{P_j}^{\text{contr}} = P^{\text{contr}}, \quad j = 1, \dots, 6,$$

where

$$P^{\text{contr}} = \frac{e_{\text{cd}}^{\text{max}}}{\Delta t} \max_{t \in T} \sum_{i \in I} w_{i,t}.$$

Here, Δt denotes the duration of each time period t . Since we consider hourly blocks, $\Delta t = 1$ hour. For tariff segment 3 VE, the power-term rates of the system charges are zero in all tariff periods. Therefore,

$$C_{\text{daily}}^{\text{pow}} = \frac{P^{\text{contr}} \sum_{j=1}^6 \tau_{P_j}^{\text{pow,toll}}}{365}.$$

Since the power term depends on the contracted power rather than energy consumption, and the contracted power is determined by the fleet availability profile rather than charging decisions, $C_{\text{daily}}^{\text{pow}}$ is constant and does not affect the optimal solution. We simply include it when calculating the total fleet cost.

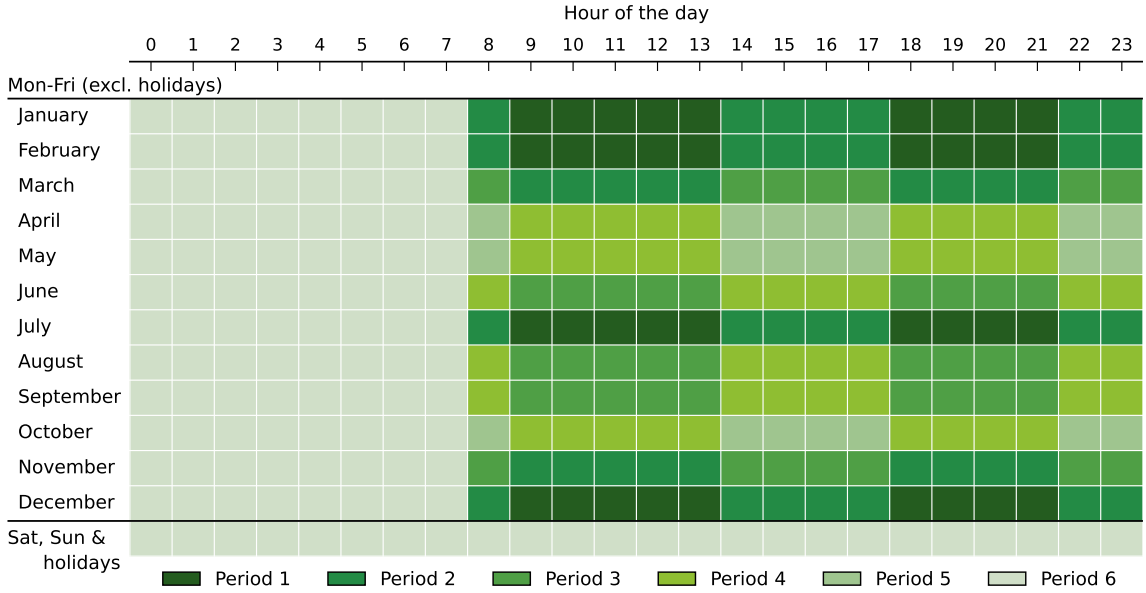


Figure 3: Six-period time-of-use pricing system in Peninsular Spain.

For Peninsular Spain, the six tariff periods (P1 to P6) are defined as follows. According to [73], the year is divided into four seasons: (i) high season: January, February, July and December, (ii) mid-high season: March and November, (iii) mid-season: June, August and September, and (iv) low season: April, May and October. In addition, day types are classified as follows: weekdays, excluding holidays, are classified as Type A in the high season, Type B in the mid-high season, Type B1 in the mid-season, and Type C in the low season. Saturdays, Sundays, and holidays are classified as Type D. Here, holidays refer to national public holidays as defined in the official calendar of the corresponding year. For 2025, the holidays falling within the period of interest are 18 April, 1 May, 15 August, 1 November, 6

December, 8 December, and 25 December [78]. For 2026, the corresponding holidays are 1 January and 6 January [79]. Figure 3 shows the six time-of-use periods applicable to access tolls and system charges in Peninsular Spain, depending on the month, day type, and hour.

6.1.3 Characteristics of the EV fleet

We consider a commercial fleet of V2G-compatible vehicles, each with a battery capacity of 87 kWh [80,81]. We assume a sufficient number of AC Level 2 bi-directional charges at the depot, each with a maximum power rate of 22 kW. The system round-trip efficiency is 87%, in accordance with the average value reported in [82]. We assume this same efficiency across all SoC levels. Since we consider energy losses over a charge-discharge cycle, we set the parameter λ to 0.93. We set $S^{\min}$ to 10% and $S^{\max}$ to 100%. Moreover, we assume an average travel distance of approximately 20 km per period, which, based on a WLTP range of 460 km, corresponds to an average energy consumption of 3.915 kWh per period [80]. This implies that, when a vehicle performs its route, the battery SoC decreases by 4.5% per period. Lastly, we assume that all EVs start with the same battery level. The initial SoC varies between 10% and 90% in steps of 5%, that is $\{10\%, 15\%, 20\%, \dots, 90\%\}$. The main characteristics of the EV fleet are provided in Table 5. We consider instances with fleet sizes of (a) 5 EVs and (b) 20 EVs. The corresponding daily availability schedules are shown in Figure 4.

Table 5: Characteristics of EVs in the fleet.

param.	value	param.	value	param.	value
$e_{cd}^{\max}$	22 kWh per hour	$S^{\min}$	10%	$S^{\max}$	100%
$E^{\max}$	87 kWh	S^{out}	4.5%	λ	0.93

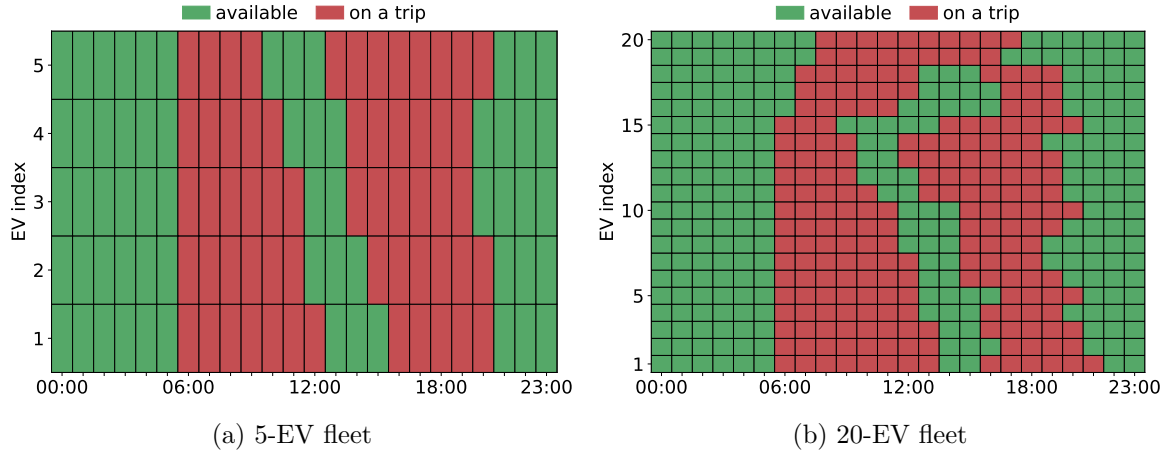


Figure 4: Daily availability schedule of (a) 5-EV fleet and (b) 20-EV fleet.

6.1.4 Computational implementation

All experiments were performed on a server with two Intel(R) Xeon(R) Gold 6234 CPUs at 3.30 GHz and 503 GiB of RAM. The single-level reformulation was implemented in Python and solved using Gurobi 13.0.0. All graphs are created using Python and the libraries Matplotlib, Seaborn, and NumPy. For each problem instance in this chapter, we set the relative MIP gap tolerance to 1×10^{-3} and allowed a maximum solve time of 3600 seconds.

Lastly, we set the tolerance ϵ in equation (4e) to 1×10^{-5} . This choice allows us to enforce the strict inequality given that the default value for feasibility tolerance in Gurobi is 1×10^{-6} .

6.2 Results and discussion

In this section, we demonstrate the profitability of the proposed business model. Our base-case model is (8) as described in Section 4.1, which determines the DA position with no further adjustments in the IDA market and no V2G. The proposed business model described in Section 4, solved using the reformulation (LLF) in Section 5.2, is referred to as the bilevel V2G model.

6.2.1 Results for the 5-EV fleet instance

We study the financial benefits of the proposed model for both participants using a small-instance case with a fleet of 5 EVs, whose availability schedule is shown in Figure 4a. Figures 5a and 5b show the annual leader profit and follower cost, respectively, under the base-case and bilevel V2G models for different initial SoC levels. The results reveal clear economic benefits for both agents under the bilevel V2G model across all considered SoCs. These benefits are generally larger at lower initial SoC levels, particularly for the electricity supplier. Moreover, the additional profit obtained by the leader does not come at the expense of the follower, as the follower also benefits from reduced annual costs.

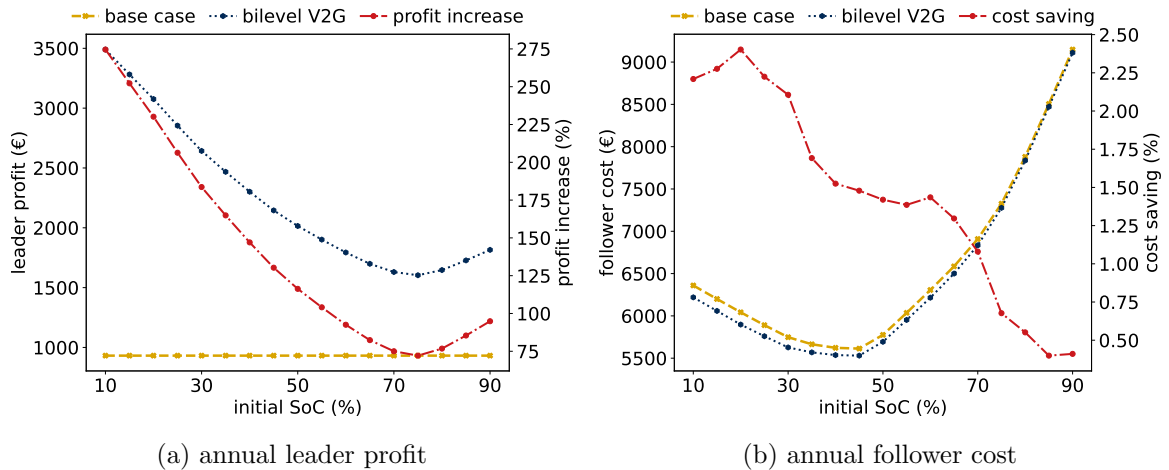


Figure 5: Annual leader profit and follower cost (including the power term) under base-case and bilevel V2G models with different initial SoCs.

Under the base-case model, the leader profit comes solely from the supplier margin, which is constant across the different initial SoC levels, while the follower cost comes from charging activities plus a fixed charge based on the contracted power. Note that the total daily energy requirement of the fleet under the base-case model is the same across all considered SoCs (248.37 kWh) because the fleet follows the same daily schedule in all cases (Figure 4a) and the final SoC is constrained to be equal to the initial SoC level. Hence, with a fixed supplier margin and a predetermined daily energy requirement, the leader profit remains constant across the different initial SoCs.

However, the initial SoC affects when EVs can charge and, therefore, the follower cost. At low initial SoC levels, EVs can charge early in the day but have limited flexibility to charge toward the end of the day, since the final SoC must match the low initial SoC. The opposite happens at high initial SoC levels, with little or no room to charge before the first block of delivery periods, so charging is shifted to later periods once part of the stored energy

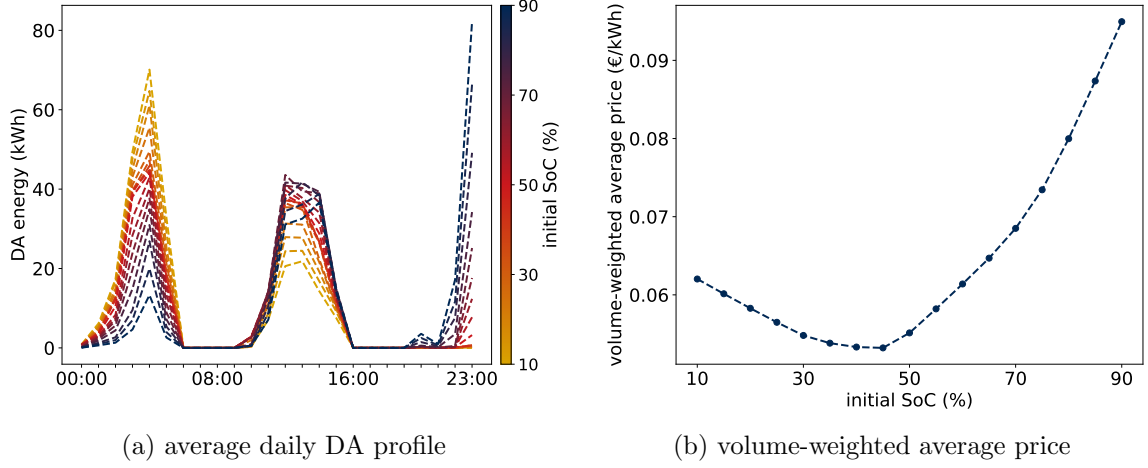


Figure 6: Average daily DA energy profiles and volume-weighted average base-case charging prices for different initial SoCs over the period March 2025 – February 2026.

has been consumed. This can be observed in Figure 6a, which shows the average daily DA energy profile over the study period for different initial SoCs. Because charging prices are generally higher later in the day (see Figure 7), the fleet incurs higher costs at high initial SoC levels as it shifts charging toward these more expensive periods. At medium initial SoC levels, EVs have more flexibility in when to charge, with charging opportunities in both earlier and later periods, hence, the fleet incurs lower overall costs, as shown in Figure 5b. This is further reflected in Figure 6b, which shows the volume-weighted average base-case charging price over the study period for the different SoC levels considered.

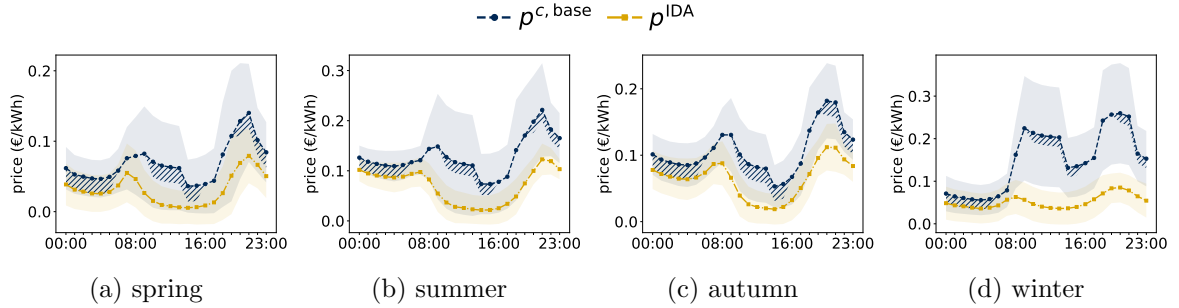


Figure 7: Seasonal average hourly profiles of base-case charging and IDA prices. Shaded areas represent ± 1 standard deviation of hourly prices within each season. The hatched area shows the admissible charging price range under the bilevel V2G model at a supplier margin of 0.011 €/kWh.

As shown in Figure 5, the follower cost under the bilevel V2G model follows a pattern similar to that of the base case across all considered initial SoC levels. A similar argument applies, considering also that V2G services are available under the bilevel V2G model. The average daily charging and discharging profiles are shown in Figure 8.

We note that discharging is profitable for the fleet only if the revenue from discharging at least covers the cost of restoring the discharged energy, after accounting for energy losses due to the system round-trip efficiency over a charge-discharge cycle. As shown in Figure 7, IDA prices are relatively low in the middle of the day across all seasons. Since discharging prices, as set by the leader, cannot exceed IDA prices, the fleet has little or no incentive to discharge during these periods, even when the supplier sets discharging prices at the highest

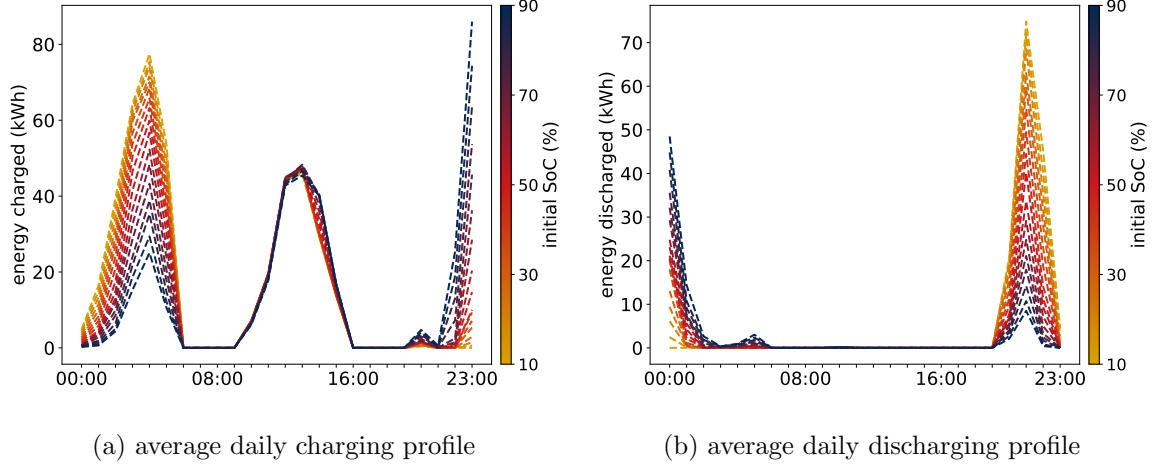


Figure 8: Average daily (a) charging and (b) discharging energy profiles for different initial SoCs over the period March 2025 – February 2026.

possible value (the corresponding IDA price), resulting in almost zero discharge, as shown in Figure 8b. In contrast, IDA prices are relatively high toward the end of the day compared with the possible charging prices in other periods (hatched area in Figure 7). This allows the supplier to set higher discharging prices, as shown, for example, by the optimal prices with 50% initial SoC in Figure 7. In turn, these higher prices can make discharge profitable for the fleet and therefore incentivize it to discharge during these later periods.

The ability to discharge when profitable depends on the initial SoC level of the vehicles. In particular, at low initial SoC levels, EVs can benefit from the high discharge prices toward the end of the day, as shown in Figure 8b. At medium initial SoC levels, EVs have less flexibility to discharge toward the end of the day, when discharge prices are higher, because the final SoC must match the moderate initial SoC value, while at high initial SoCs, vehicles have no room to discharge during these periods.

Under the bilevel V2G model, the fleet charges at discounted or unchanged prices, since charging prices can be set below or at the base-case prices, with V2G revenue further reducing the total cost. Therefore, in the worst-case scenario, the follower incurs the same daily cost as under the base-case model. In particular, the annual follower cost can be reduced from 0.4% to 2.4% compared to following the consumption schedule determined at the DA market clearing, as shown in Figure 5b, with the largest cost reduction occurring at low initial SoC levels. This is clearly influenced by the pricing scheme considered (see Figure 7) and the flexibility vehicles have to respond to price signals in each case, as explained above.

The supplier also has an incentive to encourage discharging when IDA prices are high, as this may create a surplus relative to the agreed DA position that must be corrected by submitting a sell block order in the IDA market. By selling the excess energy, the supplier generates additional profit while buying back the required energy at lower IDA prices in other periods. Therefore, since discharging is mainly profitable toward the end of the day and EVs can exploit these opportunities when starting with low SoC, as shown in Figure 8b, the supplier earns higher profits at low initial SoC levels. This is because the additional profit under the bilevel V2G model comes mainly from trading in the IDA market, with IDA revenue accounting for a significant share of total profit, as illustrated in Figure 9a. In addition, with low initial SoC levels, the fleet could exploit more profitable price differences across periods during the day (more arbitrage opportunities), resulting in larger deviations from the agreed DA position and therefore increased participation in the IDA market by the supplier. Figure 9b shows the annual energy volumes for different initial SoCs, with both

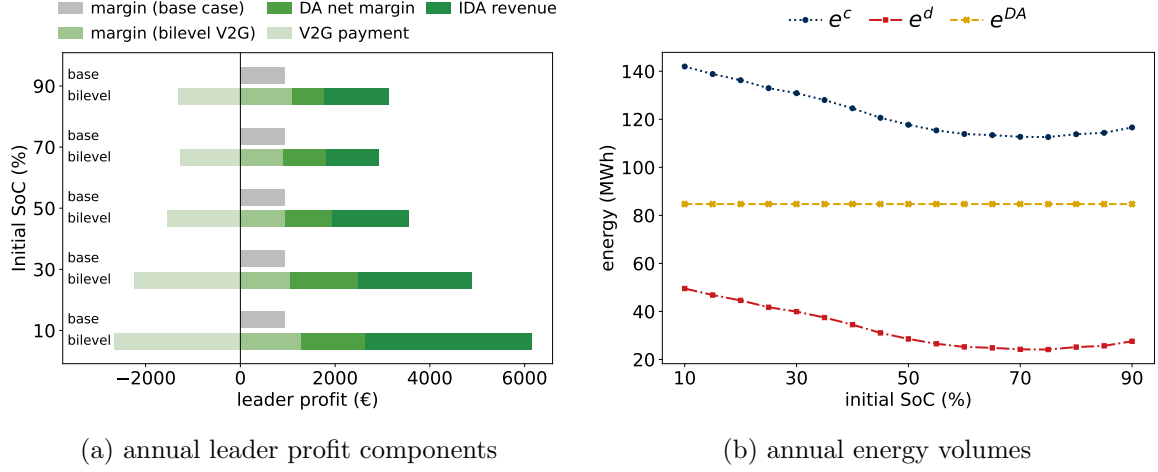


Figure 9: (a) Breakdown of annual leader profit and (b) annual energy volumes for different initial SoCs under the base-case and bilevel V2G models.

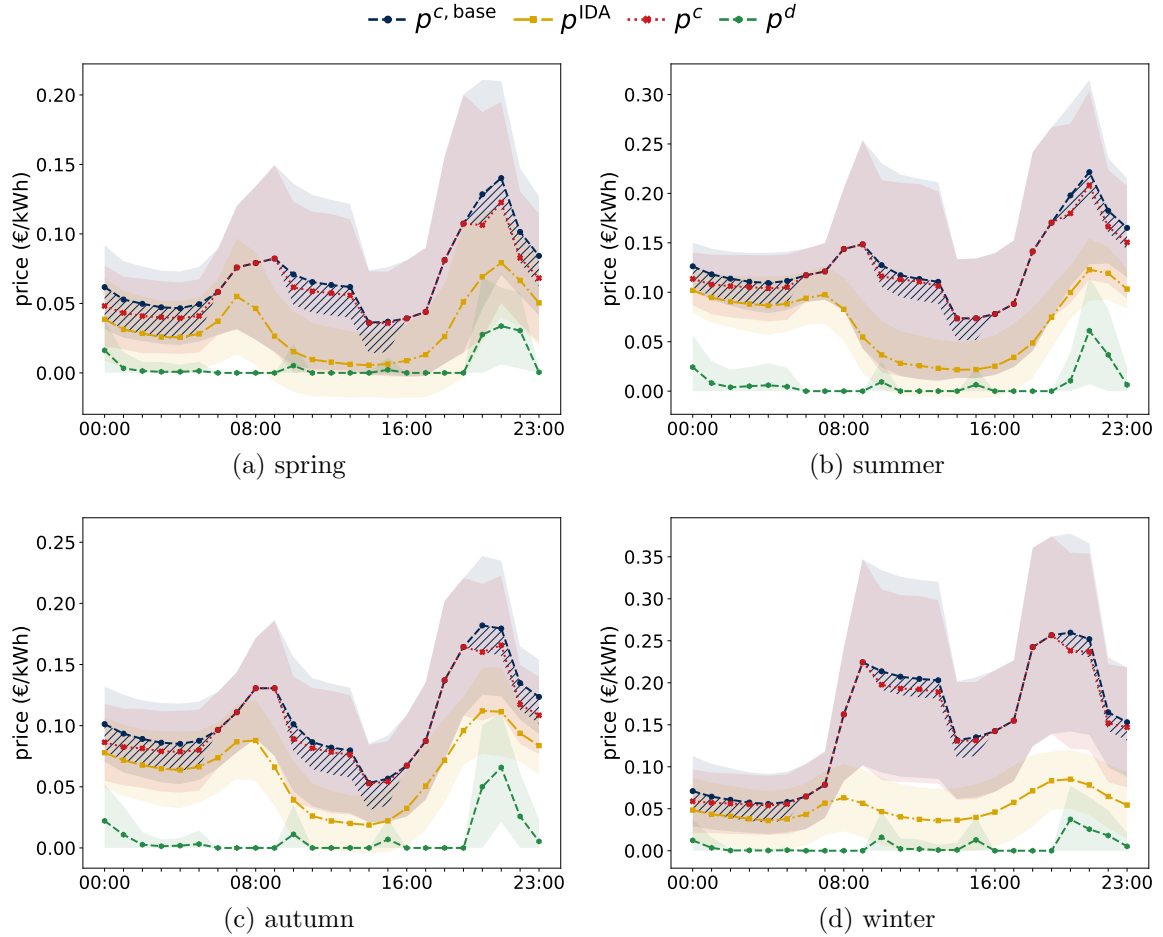


Figure 10: Seasonal average hourly profiles of base-case charging and IDA prices, and optimal charging and discharging prices with 50% initial SoC. Shaded areas represent ± 1 standard deviation of hourly prices within each season. The lower bound for discharging prices is set to zero, as imposed by constraint (4d). The hatched area shows the admissible charging price range under the bilevel V2G model at a supplier margin of 0.011 €/kWh.

charging and discharging energy being higher at low initial SoC levels, as expected.

Figure 9a reveals the breakdown of the annual leader profit under the base-case and bilevel V2G models. We present only five SoC values to capture the main trends across low, medium, and high initial SoC levels.

The DA net margin represents the difference between the revenue received from the fleet for the energy charged under the new consumption pattern, valued at the DA price, and the energy procurement cost in the DA market. We note that the daily DA net margin may be negative. Without discharge in the new consumption pattern, this can happen only when charging is shifted to periods with lower charging prices due to a reduction in the supplier margin, where, overall, the corresponding DA prices are lower. When discharging takes place, the same argument holds, while an additional scenario of negative DA net margin arises when additional charging happens in periods with negative DA prices. In this case, the supplier bears the cost associated with the additional energy consumed by the fleet, with negative DA prices reversing the usual outcome. Since the supplier maximizes its profits, it will set the new prices in this way only if the IDA market revenue is sufficient to offset the negative DA net margin and other costs. However, cases where the daily DA net margin is negative are limited, and therefore, the annual DA net margin contributes positively to the profit, as illustrated in Figure 9a.

With the supplier margin being the only adjustable component of the charging price under its control, the supplier may sacrifice some margin revenue to incentivize changes in the agreed DA position and enable trading in the IDA market. For example, with 70% initial SoC, the annual supplier margin is approximately €932 under the base-case model and €918 under the bilevel V2G model, while approximately 33.1% more energy is charged under the latter model.

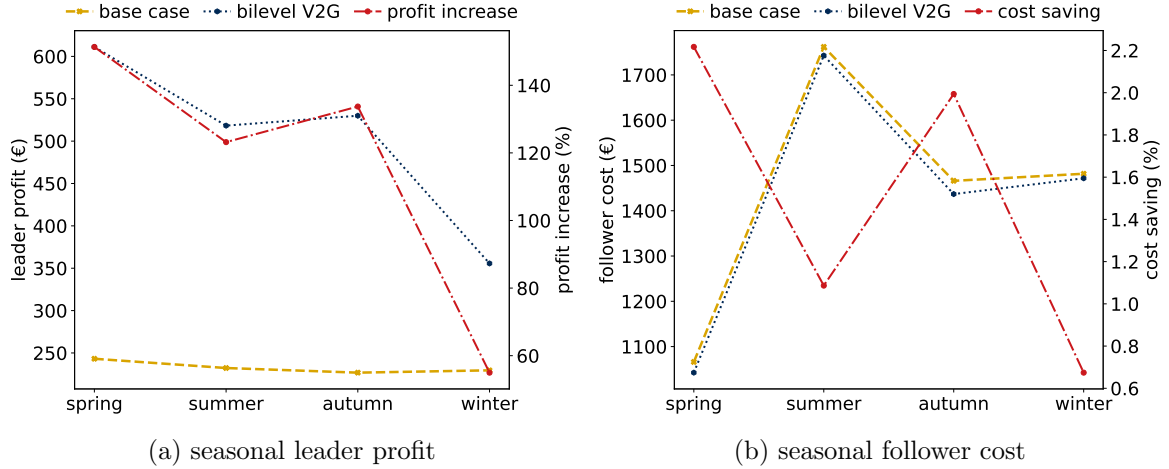


Figure 11: Seasonal leader profit and follower cost (including the power term) under base-case and bilevel V2G models with 50% initial SoC.

In order to demonstrate the profitability of the proposed model across seasons, we consider an initial SoC of 50% for the vehicles. This selection was made based on the annual follower cost, as the fleet achieves its minimum cost at moderate initial SoC levels (see Figure 5b). Figure 11 illustrates the total leader profit and follower cost for the different seasons over the study period, with the optimal charging and discharging prices shown in Figure 10. We note that the differences in the leader profit across seasons under the base case are due to the number of days considered for each season because of missing or invalid price data. In particular, we consider 89 days for spring, 85 for summer, 83 for autumn, and 84 for winter, which explains the differences in the total profit across seasons under the base-case model.

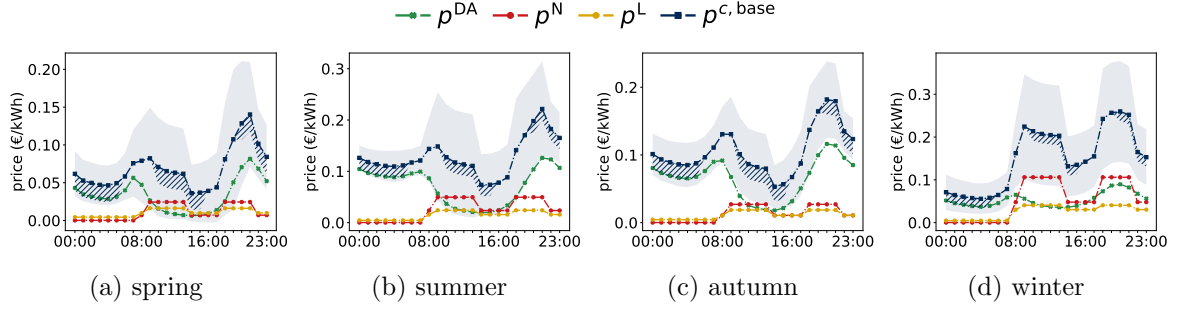


Figure 12: Seasonal average hourly profiles of charging prices under the base-case model at a supplier margin of 0.011 €/kWh and their components. The blue area represents ± 1 standard deviation of hourly charging prices within each season. The hatched area shows the admissible charging price range under the bilevel V2G model.

The economic benefits for both participants under the bilevel V2G model are lower in winter. This is because IDA prices vary less across periods and are lower relative to charging prices, as shown in Figure 10, creating fewer opportunities to deviate from the agreed DA position and, therefore, fewer opportunities for the supplier to trade in the IDA market. In addition, the total follower cost in summer and winter is generally higher because of higher DA prices and government-regulated costs, which result in higher charging prices. Figure 12 shows the breakdown of the average base-case prices along with the feasible region of charging prices under the bilevel V2G model over the study period.

6.2.2 Results for the 20-EV fleet instance

Similarly to all the results presented thus far, a similar economic benefit is obtained for both participants with a larger EV fleet, whose availability schedule is shown in Figure 4b. We consider moderate initial SoC levels, that is $\{30\%, 40\%, 50\%, 60\%, 70\%\}$, as this choice results in a lower total fleet cost under the base-case model. Figure 13 presents the annual leader profit and follower cost for the different initial SoCs considered.

With low initial SoC levels, EVs can benefit from the higher discharging prices set by the supplier toward the end of the day. This is because, when IDA prices are high, the supplier can set higher discharging prices and has an incentive to do so to encourage V2G, as it benefits from selling excess energy at high IDA prices and buying it back at lower prices in other periods. Hence, by discharging toward the end of the day and charging earlier, when prices are more favorable, EVs can exploit profitable price differences across periods and, therefore, deviate from their agreed DA position, enabling the supplier to trade in the IDA market to adjust the DA position and generate additional revenue. Thus, as shown in Figure 13, both participants benefit under the bilevel V2G model, with greater economic benefits at low initial SoC levels. In detail, trading in the IDA market and allowing V2G can increase the supplier revenue by up to 236.5% and decrease fleet costs by up to 3.7%. This means that a supplier serving a fleet of 20 EVs can make additional revenue of up to €8178 while the fleet can save up to €799.

The fleet achieves a minimum cost with moderate initial SoC under both models. A similar argument applies as in the 5-EV fleet case. In particular, under the base case, EVs with medium initial SoC are more flexible about when to charge and can therefore benefit more from the dynamic prices across the day. With V2G available under the bilevel V2G model and with charging prices set below or at the base-case prices, the fleet can further reduce its costs. However, the economic benefit is not the highest with moderate initial SoC levels, as the requirement for the final SoC to match the moderate initial SoC prevents the

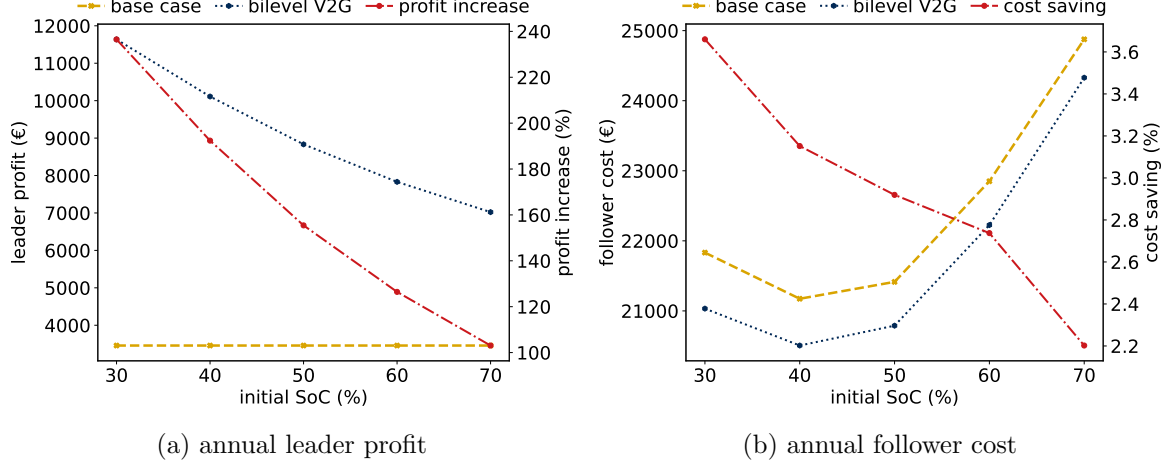


Figure 13: Annual leader profit and follower cost (including the power term) under base-case and bilevel V2G models with different initial SoC values.

fleet from fully exploiting the high discharging prices in later periods.

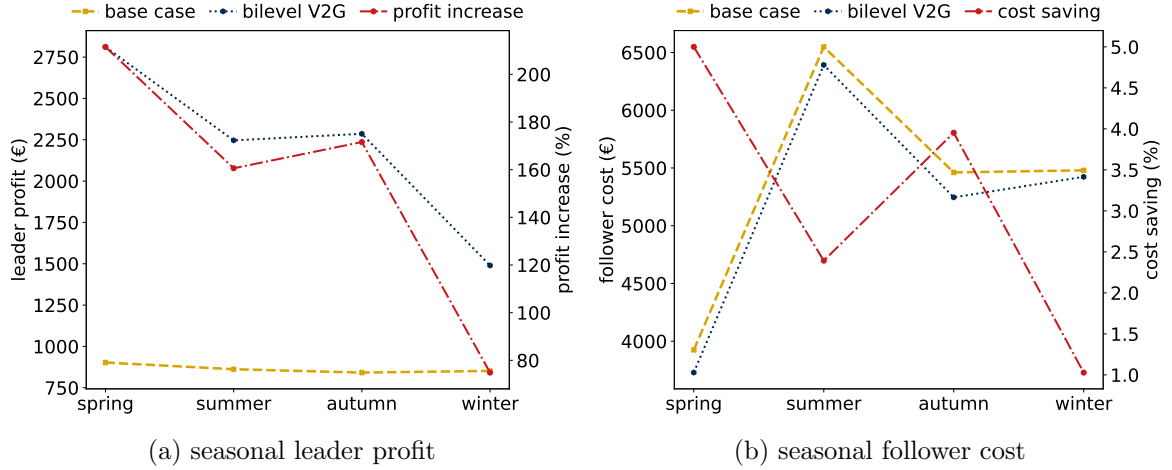


Figure 14: Seasonal leader profit and follower cost (including the power term) under base-case and bilevel V2G models with 50% initial SoC.

Finally, as in the 5-EV fleet case, we can estimate how much the proposed model benefits both participants each season. Figures 14a and 14b show the economic benefits for the supplier and fleet, respectively, for each season with 50% initial SoC. Similar to previous results, spring and autumn yield higher economic benefits. This is because IDA prices fluctuate drastically throughout the day, creating more opportunities for the supplier to trade in the IDA market. As shown in Figure 15, the highest economic benefit is associated with higher discharging energy. In winter, IDA prices vary less across periods and are lower overall than the charging prices, so opportunities to profitably deviate from the DA position are limited, and therefore the economic benefit for both the supplier and the fleet owner is lower.

Any deviation from the DA position results in either a profit or a cost for the supplier. In particular, focusing solely on the charging behavior of the fleet, we consider two cases: (a) when the fleet charges less than the agreed DA position, the supplier sells the excess energy in the IDA market, and (b) when the fleet charges more than the agreed DA position, the supplier buys the additional energy in the IDA market at the IDA price. Whether a

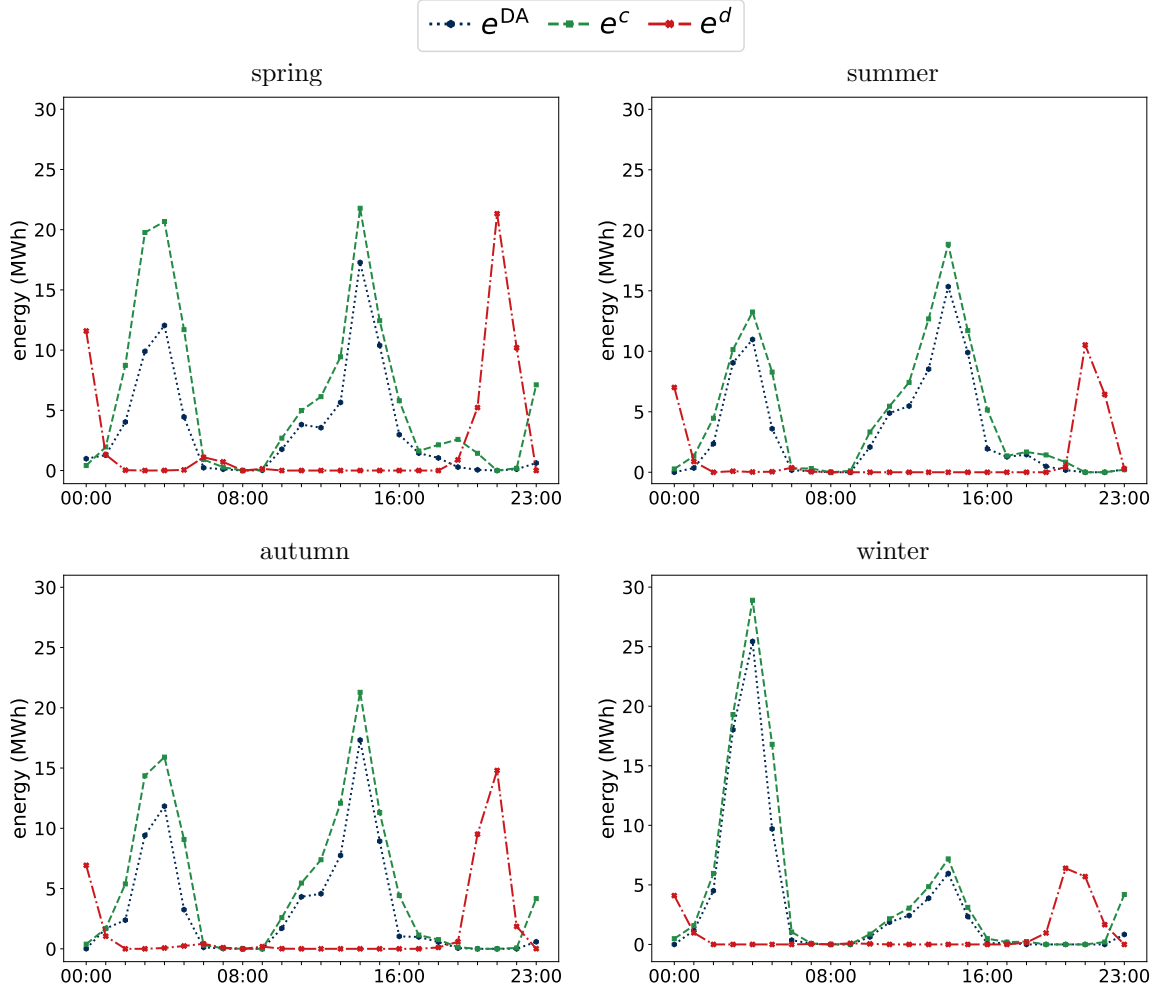


Figure 15: Seasonal average hourly profiles of charging and discharging consumption with 50% initial SoC.

deviation is profitable also depends on the relationship between the DA and IDA prices. When the supplier sells excess energy in the IDA market, the fleet pays the DA component of the energy price for its actual consumption, while the supplier has already paid for more energy. So, this deviation is profitable only if the revenue from selling the excess energy at least covers the DA procurement cost borne by the supplier. This implies that the supplier profits only when the DA price is lower than the corresponding IDA price, as shown by the following term from its objective function:

$$\sum_{t \in T} (p_t^{\text{IDA}} - p_t^{\text{DA}}) \left(e_t^{\text{DA}} - \sum_{i \in I} e_{i,t}^{c*} \right).$$

A similar argument holds when the supplier buys additional energy in the IDA market. In this case, any deviation is profitable for the supplier only if the DA price is higher than the IDA price so that the additional revenue received from the fleet for the DA component of the energy price on the additional energy at least covers the cost of buying the additional energy in the IDA market.

In spring, both participants obtain the highest economic benefit. The price structures in spring and autumn are similar. However, as shown in Figure 15, the fleet charges and discharges more in spring than in autumn. This is due to the price differences between the

DA and IDA markets. In particular, the relationship between the DA and IDA prices, along with when the fleet deviates from the DA position, is more favorable for the supplier in spring.

7 Conclusions and future research

We proposed a business model that leverages EV charging flexibility to exploit arbitrage opportunities in the IDA market. In this model, an electricity supplier for a large commercial EV fleet designs a dynamic pricing scheme to maximize profit by participating in the IDA market while taking into account the behavior of the fleet, in exchange for lower prices and V2G participation.

We have formulated a single-leader single-follower optimistic bilevel optimization model that captures the hierarchical interaction between the two participants, with the lower-level problem formulated as an LPCC.

We used McCormick relaxation to linearize the non-KKT complementarity constraints at the lower-level problem, and proved that the linear relaxation of the lower level is equivalent to the original formulation. We then reformulated the model into an equivalent single-level formulation by replacing the lower-level problem with the necessary and sufficient KKT conditions of its linear relaxation, along with SOS1 constraints.

The computational results confirm the economic potential of the proposed business model. Based on price data from the Iberian electricity market, both participants achieve a better economic position under the proposed strategy. Under the new price formulation, in which the supplier adjusts its supplier margin and is willing to sacrifice some revenue from providing charging services, the fleet deviates from the agreed DA position, enabling the supplier to trade in the IDA market. Hence, our findings suggest that the additional profit and cost savings, for the leader and follower, respectively, result from the opportunity to generate extra revenue through the IDA market and to take advantage of price differences across periods and between the DA and IDA markets. In comparison with the base case, which follows the agreed DA position with no adjustments and no V2G, under the proposed model, the supplier increases its profit by around 72% to 275%, and the follower reduces its cost by around 0.4% to 3.7% over the year, with winter presenting the lowest economic potential for both participants.

In future research, we plan to extend this model to account for changes in the profile schedule of the fleet to enhance flexibility. The current model assumes a fixed, predefined EV availability pattern. Therefore, one could look into the possibility of embedding the availability pattern as a decision variable in order to integrate time window-shiftable trips into the model. In addition, it would be interesting to account for uncertainty in the arrival and departure times of EVs and the energy required to charge them. Lastly, the model could be extended to consider trading in the CID market.

Acknowledgments

E.M. was supported by the EPSRC Centre for Doctoral Training in Mathematical Modelling, Analysis and Computation (MAC-MIGS) funded by the UK Engineering and Physical Sciences Research Council (EPSRC) grant EP/S023291/1, Heriot-Watt University and the University of Edinburgh.

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Appendix. KKT conditions of lower-level problem

We first apply the transformation $\bar{S}_{i,t} = S_{i,t} - S^{\min}$ so that all lower-level decision variables are constrained to be nonnegative.

The primal feasibility constraints of the relaxed lower-level problem (7_r) are:

$$\begin{aligned}
e_{i,t}^c + e_{i,t}^d &\leq e_{\text{cd}}^{\max} w_{i,t} & \forall i \in I, t \in T, \\
\bar{S}_{i,t} &\leq S^{\max} - S^{\min} & \forall i \in I, t \in T \setminus \{|T|\}, \\
\bar{S}_{i,0} &= S_i^{\text{init}} - S^{\min} & \forall i \in I, \\
\bar{S}_{i,|T|} &= S_i^{\text{init}} - S^{\min} & \forall i \in I, \\
\bar{S}_{i,t} &= \bar{S}_{i,t-1} + \lambda \frac{e_{i,t}^c}{E^{\max}} - \frac{1}{\lambda} \frac{e_{i,t}^d}{E^{\max}} - (1 - w_{i,t}) S^{\text{out}} & \forall i \in I, t \in T, \\
e_{i,t}^c, e_{i,t}^d, \bar{S}_{i,t} &\geq 0 & \forall i \in I, t \in T.
\end{aligned} \tag{A.1}$$

The dual feasibility is given by:

$$\begin{aligned}
-\mu_i^t - \frac{\lambda}{E^{\max}} \delta_i^t &\leq p_i^c & \forall i \in I, t \in T, \\
-\mu_i^t + \frac{1}{\lambda} \frac{1}{E^{\max}} \delta_i^t &\leq -p_i^d & \forall i \in I, t \in T, \\
\alpha_i - \delta_i^1 &\leq 0 & \forall i \in I, \\
\gamma_i + \delta_i^{|T|} &\leq 0 & \forall i \in I, \\
-\zeta_i^t + \delta_i^t - \delta_i^{t+1} &\leq 0 & \forall i \in I, t \in T \setminus \{|T|\}, \\
\mu_i^t &\geq 0 & \forall i \in I, t \in T, \\
\zeta_i^t &\geq 0 & \forall i \in I, t \in T \setminus \{|T|\}, \\
\delta_i^t &\in \mathbb{R} & \forall i \in I, t \in T, \\
\alpha_i, \gamma_i &\in \mathbb{R} & \forall i \in I.
\end{aligned} \tag{A.2}$$

Complementary slackness is given by the following nonlinear equations:

$$\begin{aligned}
(e_{\text{cd}}^{\max} w_{i,t} - e_{i,t}^c - e_{i,t}^d) \mu_i^t &= 0 & \forall i \in I, t \in T, \\
(S^{\max} - S^{\min} - \bar{S}_{i,t}) \zeta_i^t &= 0 & \forall i \in I, t \in T \setminus \{|T|\}, \\
(p_t^c + \mu_i^t + \frac{\lambda}{E_{\max}} \delta_i^t) e_{i,t}^c &= 0 & \forall i \in I, t \in T, \\
(-p_t^d + \mu_i^t - \frac{1}{\lambda} \frac{1}{E_{\max}} \delta_i^t) e_{i,t}^d &= 0 & \forall i \in I, t \in T, \\
(-\alpha_i + \delta_i^1) \bar{S}_{i,0} &= 0 & \forall i \in I, \\
(-\gamma_i - \delta_i^{|T|}) \bar{S}_{i,|T|} &= 0 & \forall i \in I, \\
(\zeta_i^t - \delta_i^t + \delta_i^{t+1}) \bar{S}_{i,t} &= 0 & \forall i \in I, t \in T \setminus \{|T|\}.
\end{aligned} \tag{A.3}$$