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Risk Preferences of EV Fleet Aggregators in Day-Ahead Market Bidding: Mean-CVaR Linear Programming Model

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Abstract: This paper introduces a mean profit- conditional value-at-risk (CVaR) model for purchasing electricity on the day-ahead market (DA) by electric vehicles fleet aggregator (EVA). EVA controls electric vehicles (EVs) during their workplace parking, enabling smart charging and cost savings by accessing market prices that are potentially lower than flat rates available during home charging. The proposed stochastic linear programming model leverages market price scenarios to optimize aggregated charging schedules, which serve as templates for constructing effective DA bidding curves. It integrates an aspiration/reservation-based formulation of the mean profit-risk criteria, specifically Conditional Value at Risk (CVaR) to address the EVA's risk aversion. By incorporating interactive analysis, the framework ensures adaptive and robust charging schedules and bids tailored to the aggregator's risk preferences. Its ability to balance profitability with risk is validated in case studies. This approach provides a practical and computationally efficient tool for EV aggregators of global companies that can benefit from the workplace charging their fleets thanks to buying energy in the DA market.

Keywords: aggregator; smart charging; bid curve; CVaR; stochastic linear programming

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1. Introduction

The rapid adoption of electric vehicles (EVs) has brought new opportunities and challenges to energy markets, particularly in managing EV charging at parking lots by aggregators (EVA) [1]. This paper considers centrally managed and fully controlled EVs (e.g., employees' cars) by EVA during their workplace parking to enable smart charging within the accurately predicted availability and flexibility of EVs [2]. One of the main challenges are the operating costs of charging, which can be significant and require optimization [3]. EVA has access to market prices that can be potentially lower in the daily valley compared to flat rates available for charging at home [4]; thus, the main focus is on maximizing the benefits of purchasing electricity on the day-ahead market (DA). Several papers considered similar smart charging possibilities assuming free access to photovoltaic power at workplace parking; see, e.g., [5]. Recent trends in extreme market prices resulting from excess renewable production, see, e.g., [6] confirm the validity of investigating low-cost opportunities enabled by DA participation.

The main research question of this work is how to support a new energy market participant, as EVA considered in this paper, with its operational decisions regarding bidding and smart charging. Specifically, we aim to investigate a relatively simple setting, suitable for inexperienced market participants that do not consider V2G, that is, discharging, and are not interested in more advanced market opportunities, i.e., ancillary service or real-time markets. Anyway, even if the EVA undertakes a relatively simple, basic form

of electricity trading, that is, buying energy in the DA market to charge the fleet at the workplace, its decision problem is non-trivial. The challenge comes from significant uncertainties EVA faces due to DA market rules and volatile prices. To address this challenge, we aim to develop an optimization model in the linear programming form, making it solvable with easily accessed, i.e., open-source solvers. With the proposed model, EVA can intuitively indicate profit and risk criteria preferences.

Several works emphasize EVAs' participation in DA markets, assuming different modes of operation, i.e., charging/discharging [7–11], as well as different strategic models regarding other market opportunities, i.e., ancillary services markets [12–15]. In such a case, more realistic, possibly nonlinear charging characteristics and battery degradation costs need to be considered [11]. Here, we consider the EVAs to procure the energy required for charging EVs, avoiding speculative trading activities. Ref. [16] allows EV charging at the lowest cost while complying with technical constraints required by the system operators, assuming that the EVA predicts the overall EV load curve. The framework to coordinate the electricity exchange between the two parking lots located at different areas of pricing is presented in [9]; the initial state of charge (SoC) of the EVs is taken into account by stochastic programming, and the problem is modeled by mixed-integer quadratic conic programming (MIQCP). Many studies tend to consider the possible RT clearing scenarios to make DA bidding decisions by employing stochastic programming (SP) approaches, i.e., [14,17]. Here, we concentrate on cost savings enabled by purchasing electricity only on the day-ahead market (DA) for the sake of simplicity, like in [18]. The main focus is to provide a more detailed understanding of the impacts of price uncertainties and risk preferences on the charging-bidding results.

Bidding strategies for EVAs in electricity markets are typically formulated based on the stochastic optimization of charging/discharging schedules [12]. Many studies equate bidding strategies with the planned energy quantities to be purchased/sold, which leads to single block hourly bids and offers formulation. However, a more comprehensive approach is to consider the whole bidding curve, which allows one to take advantage of favorable price realization and adjust planned schedules to unpredicted market conditions [19]. A comprehensive approach to developing the DA optimal bidding model for a retailer with flexible EVs was proposed in [17]. However, the optimization model is complex since it involves the multiplication of variables indicating the bidding power and prices and also the nonlinear usage of binary variables defining the affiliation to one of the steps of the bidding curve. An interesting approach is presented in [10] where the demand curves of individual EVs are translated into the marginal benefits to determine the relation between the opportunity costs of charging energy and the lost benefit; EVA bids are identified with optimized energy schedules, though. Most recently, ref. [20] proposes a stochastic adaptive robust optimization approach to build the bidding curves of EVs aggregator participating in DA. The general model indicating constraints on monotonically decreasing bidding curves is reformulated into the three-level optimization structure. However, the resulting equivalent formulation does not incorporate bidding prices. Probably, similarly to [18] authors use these scenario-dependent variables and the corresponding scenario-market prices to build the bidding curves. Here, we follow the same approach.

Risk management is another critical aspect of EVA bidding models, particularly in the case of stochastic optimization problems with scenarios of market prices and EV behavior [21]. One significant issue is to ensure the feasibility of the optimized plan in all the uncertain realizations that were not covered in the scenarios, and the answer is robust optimization that may lead to too conservative solutions, see discussion in [20]. One answer to this problem may be to consider energy purchases only within the available charging flexibility [22]. Still, the profit risk is inevitable in stochastic models, while in [22]

prices are result of the lower-level problem representing the market clearing with assumed bids of other market participants. However, the "price-taker EVA" assumption seems more realistic and is accepted in the majority of studies [23]. Various approaches have addressed the downside risk with the CVaR criterion, particularly in settings where worst-case price scenarios could severely impact profitability [10,12,13,15,17]. By focusing on the tail-end risks, CVaR helps EVAs achieve more balanced risk-profit trade-offs. Still, the EVA preferences regarding these trade-offs may not be easily incorporated. [10] uses weights in the objective function together with CVaR confidence level. [20] models risk preferences by allowing to determine the number of time periods in which the uncertain variables may deviate from its forecast value. Others perform sensitivity analysis only with regards to CVaR confidence level, but this criterion alone may not provide decision-makers with control toward both risk and profit [24].

Studies that show the advantages of using an interactive framework to incorporate specific decision makers' risk preferences into the optimization process have been known for years in the electricity market context [25]. They are successfully applied in different problems, see [26], yet to the best of our knowledge, none of the approaches formulated EVA's preferences-based multi-criteria problem. This paper proposes a novel approach to address the EVA's risk aversion.

Summarizing the contribution, this paper presents a stochastic linear programming model designed to provide a centralized charging plan for EVs expected in a parking lot during work hours. The resulting charging scenarios serve as templates for constructing effective bidding curves, ensuring strategic alignment with the aggregator's risk aversion level. An intuitive aspiration/reservation-based interactive framework is used to balance expected profit and risk described by the CVaR measure and to ensure that the generated charging schedules are both computationally efficient and robust against price uncertainties. The novelty of this research lies in its adaptive approach, where charging schedules and the resulting final SoC for each EV are determined not only by EV technical requirements but also by the prevailing bids and electricity prices, as well as intuitively modeled risk preferences.

This paper is organized as follows: Section 2 describes in detail the problem assumptions and proposed stochastic linear programming framework. It also discusses the aspiration/reservation-based interactive analysis for risk preference modeling. Section 3 presents the results of the case studies, and Section 4 discusses the findings and their implications. Section 5 concludes with insights and directions for future research.

This research provides a comprehensive solution for parking lot aggregators, enabling them to dynamically adapt to price forecasts and manage risks effectively in the rapidly evolving energy market landscape.

2. Materials and Methods

2.1. Nomenclature

All the nomenclature is provided in the Abbreviations list at the end of the paper.

2.2. Assumptions

This paper assumes the following features of the EVA problem.

- Each EV owner drives an EV as a company car. Charging facilities are available at the workplace for free, and also a flat rate for home charging is covered by employer. EVs will arrive to workplace parking at a particular time in a day with some starting SoC level, and will departure after several hours with some final SoC. Battery capacities, and trip energy requirements are known to EVA.

- EVA controls charging only during workplace parking. It purchases energy in the DA electricity market to benefit from lower prices.
- Participation in the DA market involves the submission of non-ascending bidding curves that are defined independently for each hour of the trading period and consist of offered price-energy pairs. DA is cleared before the operation day to determine in each period the DA energy purchase price and the purchased power volume.
- The bid is accepted only if the offered price is attractive, i.e., higher than the DA price. Thus, EVA predicts the next-day stochastic DA prices under the "price-taker" assumption accepted in the majority of studies [23].
- Plans determined with the models in this paper are robust in the sense that user driving requirements of EV are met.

2.3. Aggregation Model

EVA acts as an intermediary between electricity market and EV users. In such a setting, an aggregate battery model based on a virtual battery concept is useful [23], as it allows full exploitation of the EVs charging flexibility, see also [22,27].

The parameters used in aggregation phase are determined for each vehicle k. EV k is assigned an arrival hour h_k^a and departure hour h_k^d defining the availability period A_k.

Charging power in each hour from the availability period is limited within maximum $\overline{p}_k$ voltage limitations. Battery capacity is denoted as B_k, with the safe operating range between $\underline{\delta}_k$ and $\overline{\delta}_k$ (typically between 20% and 90% of battery capacity [28]). The initial state of charging is denoted as SoC_k. These battery-specific parameters determine the minimum required energy level E_k^{min} and maximum energy levels E_k^{max} as follows:

$$E_k^{min} = \min\left\{E_k^{trip}; E_k^{trip} - SoC_k + \underline{\delta}_k \cdot B_k\right\} \geq 0, \tag{1}$$

$$E_k^{max} = \overline{\delta}_k \cdot B_k - SoC_k \geq 0. \tag{2}$$

The definition of minimum and maximum required energy levels allows flexibility: any load level within these limits is acceptable and can be indirectly controlled with the bidding prices. The minimum energy level E_k^{min} may be considered as a purely shiftable but non-decreasable load, while the difference between E_k^{max} and E_k^{min} defines a purely flexible load, which can be shifted and/or shed.

Equation (1) refers to trip energy E_k^{trip} which may be partially supported by initial SoC_k that must exceed lower safe limit of battery capacity $\underline{\delta}_k \cdot B_k$, however, it is possible that EV arrives depleated—in such a case trip energy must be charged in workplace.

Energy that can be charged by EV in each hour is also restricted by maximum power $\overline{p}_k$. Aggregation of individual k characteristics involves simple summing:

$$\tilde{p}_h = \sum_k \overline{p}_k, \forall h \in A_k. \tag{3}$$

If the aggregated power limit is smaller than minimum load `EMIN` accepted in the auction (typically 1MW, but in smaller markets it could be for example 10 kW) in first arrival hours and last departure hours, it means that a shorter common availability period of the fleet must be considered. We denote it with h^a, h^d, where $h^a = \min\{h : \tilde{p}_h \geq \texttt{EMIN}\}$, and $h^d = \max\{h : \tilde{p}_h \geq \texttt{EMIN}\}$.

During common availability period $\langle h^a, h^d \rangle$ following aggregated characteristics are considered by EVA:

- minimum daily energy level: $E^{\min} = \sum_k E_k^{\min}$;
- maximum daily energy level: $E^{\max} = \sum_k E_k^{\max}$;
- maximum hourly energy level: $\overline{p}_h = \tilde{p}_h, \forall h \in \langle h^a, h^d \rangle$.

2.4. Smart Charging Stochastic Model

EVA predicts the next-day stochastic DA prices modeled with s scenarios, see, e.g., [15,27]. Price scenarios c_{sh}, together with aggregated parameters of EVs considered in availability period $\langle h^a, h^d \rangle$, as discussed in the previous section, are used to develop a robust charging plan.

We define nonnegative stochastic charging variables p_{sh} together with two robust variables $P_h^{\min}$ and $P_h^{\max}$. Stochastic variables allow for considering zero, $P_h^{\min}$ or $P_h^{\max}$ volumes of energy to be purchased, depending on prices, while preserving the overall requirements. The variable $P_h^{\min}$ denotes the amount of energy offered to buy regardless of price, i.e., with the highest alternative price (i.e., price expected in the real-time market). The second variable, $P_h^{\max}$, denotes the potential maximum amount of energy that can be purchased without violating the capacities of batteries. The following operational constraints are formulated:

$$z_{sh} \leq (c^f - c_{sh}) \cdot p_{sh}, \quad \forall s, h, \tag{4}$$

$$p_{sh} \geq P_h^{\min}, \quad \forall s, h, \tag{5}$$

$$\sum_h P_h^{\min} \geq E^{\min}, \tag{6}$$

$$p_{sh} \leq P_h^{\max}, \quad \forall s, h, \tag{7}$$

$$\sum_h P_h^{\max} \leq E^{\max}, \tag{8}$$

$$P_h^{\max} \leq \overline{p}_h, \quad \forall h. \tag{9}$$

Stochastic benefit modeled in (4) is dependent on the market prices, as stochastic charging variables p_{sh} may be zero in adverse scenarios when price c_{sh} exceeds flat rate c^f—otherwise a negative benefit will be obtained. Anyway, at some hours charging must be no less than minimum amount $P_h^{\min}$, regardless of scenario price (5). These minimum values must fullfill minimum energy requirement (6). Similarly, to prepare for any possibility, maximum possible purchase is indicated by highest purchase in any scenario (7), so the maximum energy that can be charged does not exceed the capacities of EVs (8). Moreover, it should not exceed the maximum power limit (9).

2.5. Aspiration/Reservation-Based Mean-CVaR Optimization

Let us consider the overall benefit under a given scenario of energy prices, using hourly scenario benefits from (4):

$$z_s = \sum_h z_{sh}, \quad \forall s. \tag{10}$$

Variable z_s represents the overall profit under a given scenario of energy prices. The stochastic benefit realizations z_s are used to define profit and risk criteria, namely mean profit q_1 and CVaR q_2. Similarly to [25] following linear constraints are stated:

$$q_1 = \sum_s p_s z_s, \tag{11}$$

where p_s denotes probability of scenario s (in simplest approach equally probable scenarios are assumed).

$$q_2 = y^\beta - \frac{1}{\beta} \sum_s p_s z_s^\beta, \tag{12}$$

$$y^\beta - z_s^\beta \leq z_s, \quad \forall s, \tag{13}$$

where β is a specified confidence level, most often value 0.05 representing the 5th quantile is used, y^β is a free auxiliary variable, and z_s^β is a nonnegative auxiliary variable, see, e.g., [25].

Moreover, as in [25], we apply the aspiration/reservation-based interactive framework to find an efficient solution (operational schedule) to the mean-CVaR problem. The efficient solutions are called also Pareto-optimal solutions to the multiple criteria problem—they consist of nondominated outcome vectors. Instead of trying to identify the entire set of efficient solutions, the aspiration/reservation-based interactive framework helps the decision maker (EVA in our case) to select one efficient solution most close to her preferences. This technique, described for the first time by Wierzbicki [29] transforms the multicriteria problem to the maximization of the minimum partial achievement problem. Examples of achievement function a_i based on aspiration q_i^a and reservation points q_i^r provided by the decision maker that is, EVA in our case, are shown in Figure 1.

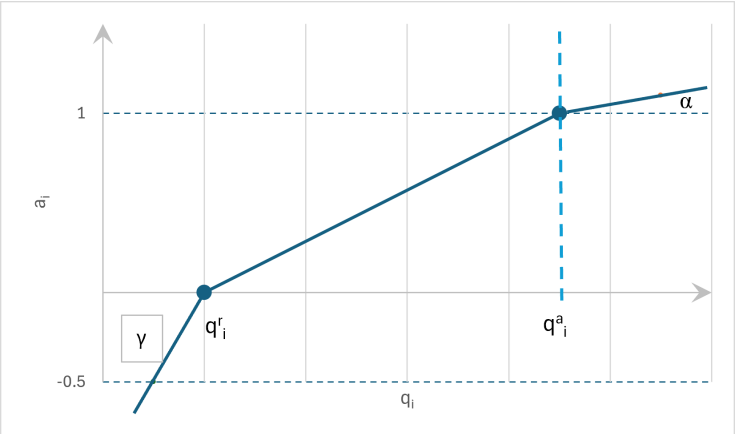


Figure 1. Exemplary achievement function a_i based on aspiration q_i^a and reservation points q_i^r provided by EVA with regards to maximized criterion q_i.

Achievement functions show normalized satisfaction of EVA when the value q_i of specific i criterium reaches a level above aspiration, i.e., when $q_i \geq q_i^a$, or below reservation, i.e., when $q_i \leq q_i^r$. Specifically, the following linear constraints are stated:

$$a_i \leq \gamma(q_i - q_i^r)/(q_i^a - q_i^r) \qquad \forall i = 1, \ldots, m, \tag{14}$$

$$a_i \leq (q_i - q_i^r)/(q_i^a - q_i^r) \qquad \forall i = 1, \ldots, m, \tag{15}$$

$$a_i \leq \alpha(q_i - q_i^a)/(q_i^a - q_i^r) + 1 \qquad \forall i = 1, \ldots, m, \tag{16}$$

$$a_i \geq \underline{a} \qquad \forall i = 1, \ldots, m, \tag{17}$$

where α and γ are parameters $0 < \alpha < 1 < \gamma$ representing additional satisfaction/dissatisfaction.

Constraint (17) determines the worst achievement $\underline{a}$, maximized in the objective:

$$\max \underline{a} + \rho \sum_i a_i. \tag{18}$$

Second term in (18) is used for regularization, introduced only to guarantee the solution efficiency in a non-unique optimal solution.

The first step of the optimization problem analysis performed by EVA may be to examine the so-called pay-off possibilities, i.e., extreme solutions obtained with regards to only one of the criteria: mean benefit (risk neutral solution) or CVaR (risk averse solution). Extreme solutions are computed by optimizing each criterion separately. To be exact, the regularized criteria $q_i + \epsilon \sum_j q_j$ are optimized to guarantee the efficiency in a non-unique

optimal solution. The extreme solutions can help to understand the conflicts between criteria. In the following steps, the EVA may explore trade-offs by providing reference points of aspiration and reservation. An exemplary process is examined in the Section 3.

The proposed LP model takes into account the EVA's preferences toward profit and risk and guarantees the efficiency of the solution. The formulation requires only $4m$ additional constraints and $m + 1$ additional variables, where m is the number of criteria subject to optimization. Notice that the model can be easily enhanced with any number of additional criteria.

3. Results

Data of EVs are essentially based on the case study of [30], which is itself a modification of the numerical example of [31]. In their case study, EVs are aggregated into five fleets based on similar driving characteristics, i.e.,: locations and availability periods. Here, we consider fleets no 2 and 3 that arrive at the same workplace parking and are available for charging from 8:00 to 16:00. Altogether, there are 3000 vehicles with the same charging power capacity considered as 7.3 kW, and the battery capacity as 27.4 kWh. The average energy required for driving each EV home is 5.29 kWh. The aggregated maximum and minimum capacity, charging power, and the required trip energy for the whole fleet managed by EVA are given in Table 1.

Similarly to [30], we consider three situations regarding the starting SoC level of EVs in the fleet.

Case 1: initial SoC is equal to the minimum capacity of batteries, i.e., the batteries are almost depleted. The EVs must charge before leaving the workplace.

Case 2: initial SoC is 60%, which is enough to make the trip home without charging.

Case 3: EVs left home fully charged, so the initial SoC is close to the maximum level in workplace parking.

Depending on the case, different levels of minimum and maximum energy requirements are determined according to Equations (1) and (2). Note that in Cases 2 and 3 no minimum energy is required to be charged, i.e., $E^{min} = 0$, thus, to save space they were not reported in Table 1.

Table 1. Parameters describing the fleet managed by EVA at workplace.

Aggregated Fleet Characteristcs				**Case 1**		**Case 2**	**Case 3**
Min Capacity $\sum_k \overline{\delta}_k \cdot B_k$ [MWh]	Max Capacity $\sum_k \underline{\delta}_k \cdot B_k$ [MWh]	Max. Charge $\overline{p}_h$ [MW]	Trip Energy $\sum_k E_k^{trip}$ [MWh]	Min Energy E^{min} [MWh]	Max Energy E^{max} [MWh]	Max Energy E^{max} [MWh]	Max Energy E^{max} [MWh]
16.44	82.2	21.87	15.87	15.87	65.76	32.88	15.87

Furthermore, we compare our results with two benchmark charging strategies, which assume uncoordinated charging as soon as EVs arrive at work:

Base scenario: only the minimum required amount of energy is charged;

BaseMax scenario: EVs are charged to the maximum capacity.

In both baseline scenarios, EVA pays the DA prices for charged energy. To be specific, we assume that uncoordinated charging starts at hour 9, i.e., the next hour after the arrival of EVs, because prices in scenarios considered in our case study are very high at hour 8, which would cause disproportionate losses for EVA.

The scenarios of DA prices are generated using the same technique, as described in [27]. It uses the Iberian Electricity Market prices [32] from the year 2020 to generate 1000 scenarios reduced to 10 by applying the K-means method, which is a widely recognized and frequently used algorithm [33]. In Figure 2 it can be observed that we achieved similar price scenario characteristics to the ones shown in [27]. One should notice, however, that price scenarios are considered as input parameters to our model, thus any other scenario generation and reduction technique could also be applied, i.e., recursive method most recently applied in [11]. All price scenario data are provided in the Appendix A.

The flat rate for charging vehicles at home is considered as 50 €/MWh.

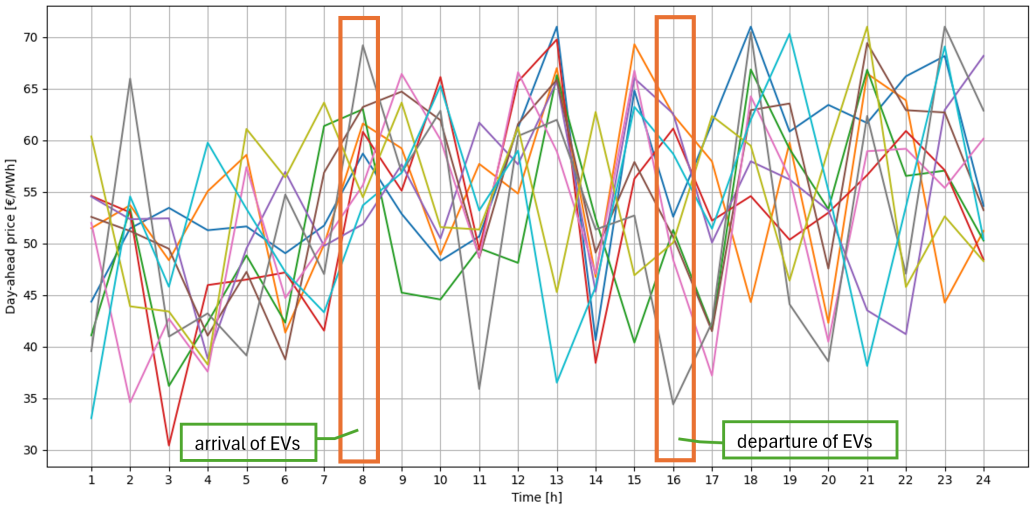


Figure 2. 10 scenarios of DA prices, each represented with different line color. Hours of arrival and departure of EVs indicate the availability period for smart charging.

3.1. Case 1—Depleted Batteries

In this case study EVs arrive at the workplace with depleted batteries, so they need to charge at least the amount of energy required to travel back home, i.e., 15.87 MWh. If the prices are favorable, the fleet may charge more energy, up to the maximum capacity equal to 65.76 MWh in the considered case.

The exemplary process of the interactive search for the most satisfying and efficient solution, together with the extreme risk neutral, and risk averse solutions is shown in Figure 3. It shows three iterations of providing preferences, and obtaining the solution. Each iteration is denoted as P1, P2, and P3.

It can be observed that there is a considerable risk of negative profits, since EVA is obliged to buy the minimum amount of energy. However, the most conservative approach guarantees positive profits. The EVA uses aspiration and reservation levels to control the interactive analysis. First, it specifies the preferences close to the risk neutral solution. With each iteration, a lower mean profit is obtained, but a higher CVaR is obtained. Solutions are always better than the specified reservation levels and worse than aspiration levels. Final solution P3 allows to obtain positive CVaR with a moderately lower than the maximum level mean profit.

Figure 4 illustrates the schedules obtained with respect to different sets of preferences. Generally, purchases are planned in the same hours, i.e., 11, 13, and 14. The minimum energy level should be charged regardless of the cost in hours 11 and 14, but different levels are planned depending on risk preferences. The most safe plan P3 distributes the minimum energy equally between those two hours, while the most profitable plan proposes charging mainly in hour 14. Interestingly, the safe plan P3 distributes also the maximum amount of energy planned for purchase from hour 11 to hour 15. Plans P1 and P2 are exactly the same

regarding the maximum amount of energy planned to purchase—they assume buying the maximum possible amount of energy in hours 11, 13, and 14. The differences between plans P1 and P2 appear only in planned minimum levels of energy.

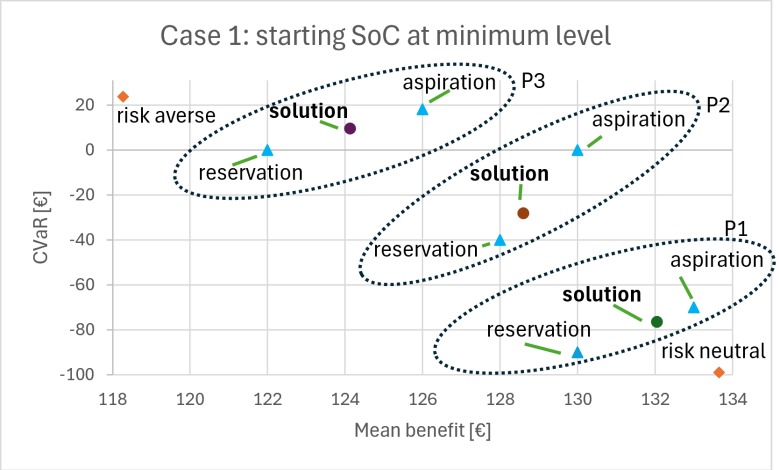


Figure 3. Paretosolutions obtained with three different preferences toward mean benefit and CVaR in Case 1.

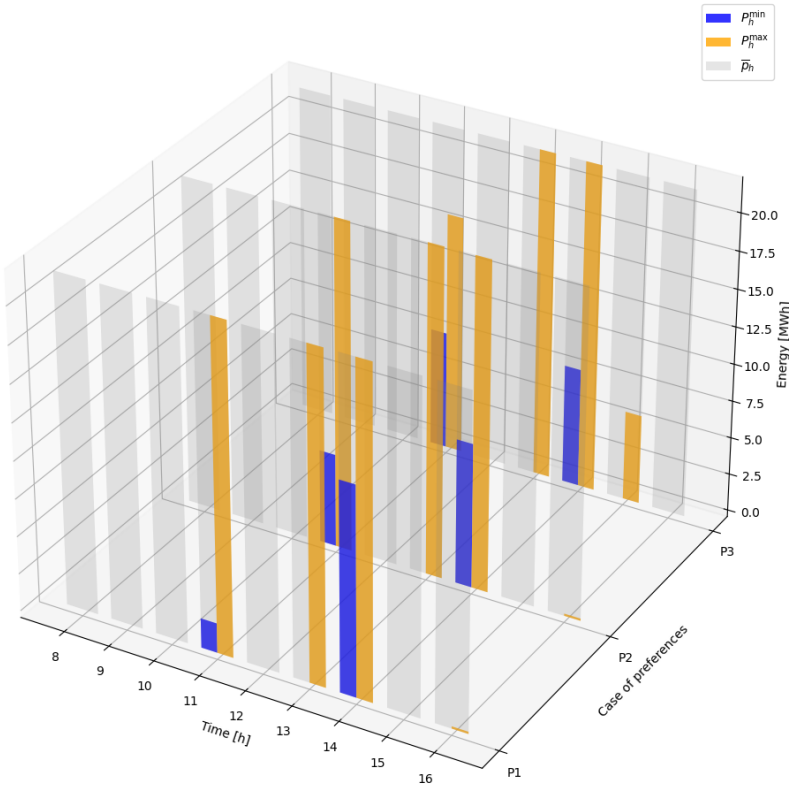


Figure 4. Case 1: Schedules of minimum amount $P_h^{\min}$ and maximum amount $P_h^{\max}$ of energy planned for purchase in each hour under different risk preferences, as provided in Figure 3.

To assess the plans obtained, we compare each solution with baseline schedules in Figure 5. It shows the benefits that EVA would have achieved if a specific price scenario were realized. One can observe that uncoordinated charging causes significant losses in every price scenario except 2, in which the actual benefit is even higher than the one achieved with plans P1–P3. The difference is even higher in the BaseMax scenario when more energy is purchased uncoordinatedly in hours 9, 10, and 11. It happens because one scenario assumes a very low price in hours 9 and 10 (they equal 45.23 €/MWh and 44.57 €/MWh,

respectively). However, losses incurred in every other scenario worsened this solution based on each of the criteria analyzed. When comparing benefits obtained with plans P1, P2, and P3, they are close in each scenario. Still, the most risky plan, P1, generates slightly higher or equal benefits in each scenario except the ones in which losses are incurred, i.e., in scenarios 3 and 9. Let us examine prices in these scenarios in hour 14 when the total minimum amount of energy is planned for purchase in more risky plans—they equal 52.41 €/MWh and 62.74 €/MWh, respectively. That is why small losses are inevitable in the more risky but more profitable plan P1.

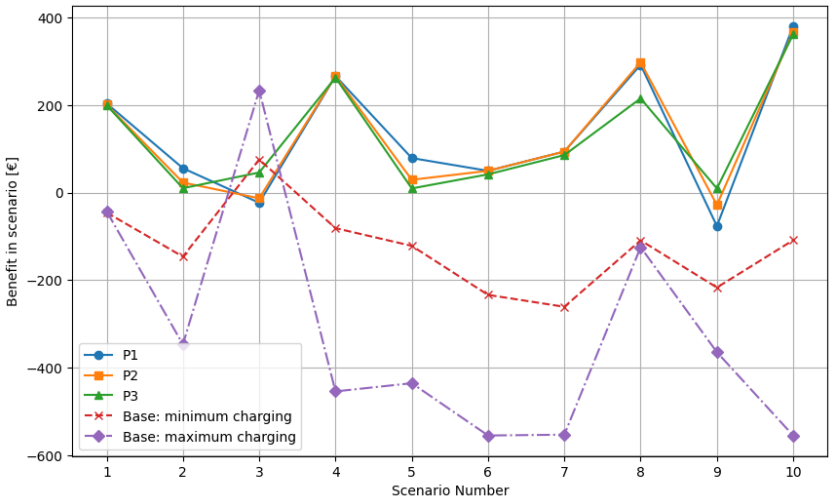


Figure 5. Case 1: Profits obtained under each scenario with different plans P1, P2, P3, or with baseline uncoordinated charging.

Finally, bids that EVA should submit to DA in hours 11, 13, and 14 are shown in Figure 6. Different mean-CVaR preferences impact bidding strategies in hours 11 and 14. In hour 13, it is always profitable to buy energy if prices are lower than 50 €/MWh. Looking at the price scenarios in Figure 2, we can see two scenarios in hour 13 when considerably low prices may occur. By submitting the bid at that hour, EVA will take advantage of the low price and avoid high prices which are probable to occur, since average price in that hour is very high (60.83 €/MWh). In hours 11 and 14, different levels of minimum energy purchased are planned depending on risk preferences. Each plan guarantees that EVA will buy the minimum required energy because the first step of the bid defines a very high price. On the other hand, the purchased energy would never exceed the fleet's capacity because the summary embedded energy is equal to the maximum energy level in each plan P1, P2, and P3.

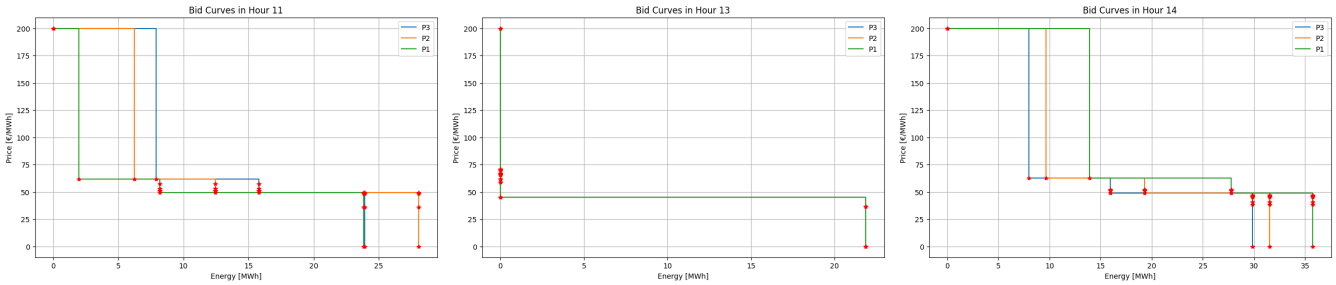


Figure 6. Case 1: Bidding curves obtained under different risk preferences should be submitted within hours of planned purchases.

3.2. Case 2—Initial SoC at 60% of Capacity

Next, we examine the same process, assuming more flexible availabilities to charging the fleet: batteries are not depleted, and still, there is some spare capacity to charge energy in favorable market conditions.

Figure 7 shows the process of providing preferences and examining solutions. First, one can observe that EVA may expect only positive benefits as it is not obliged to buy any energy if prices are too high. Safety comes at the expense of mean benefits, as EVA can buy less energy despite possibly low prices. Comparing Figures 3 and 7, we can see that CVaR is considerably higher in Case 2, while the mean benefit is significantly lower. Again, by changing preferences toward risk, EVA can explore the most suitable balance between criteria. It can be interesting to observe steps P1 and P2, where EVA provided quite conservative reservations and aspirations levels, and the final solution is better than the preferences in terms of both criteria.

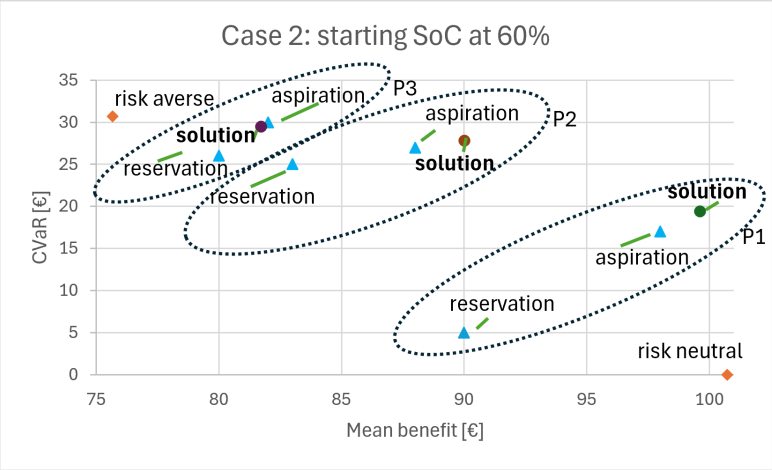


Figure 7. Pareto solutions obtained with three different preferences toward mean benefit and CVaR in Case 2.

If we examine the schedules related to each plan P1, P2, and P3 shown in Figure 8, we can see that they resemble plans obtained in Case 1—charging is planned in the same hours, i.e., 11, 13, and 14, plus additionally 15. Also, the same dependencies between the riskness of plans and amounts of energy planned for purchase in hours 11 and 14 are observed. However, this time, less energy is assigned for buying in hour 13, as less capacity is available overall.

A comparison of benefits that EVA can expect under each scenario in the considered case is shown in Figure 9. Obviously, the baseline results in zero benefits as EVs are not charging at all. However, again, in the BaseMax case, huge losses must be expected if any price scenario except 2 would be realized. Interestingly, more significant differences between outcomes of each plan P1, P2, and P3 can be observed in Case 2, especially regarding scenarios 1, 4, and 8. The explanation is mainly in plans for hour 11—the safer plan, the higher amount of energy is planned in that hour than in hour 14, which assumes a lower mean price (47.96 €/MWh vs. 49.79 €/MWh) but higher volatility. Moreover, a very low price of 35.90 €/MWh is expected in hour 11 in scenario 8.

Finally, the bids are presented in Figure 10. They consist of only one step with a price of 50 €/MWh and different amounts of energy, depending on the risk preferences.

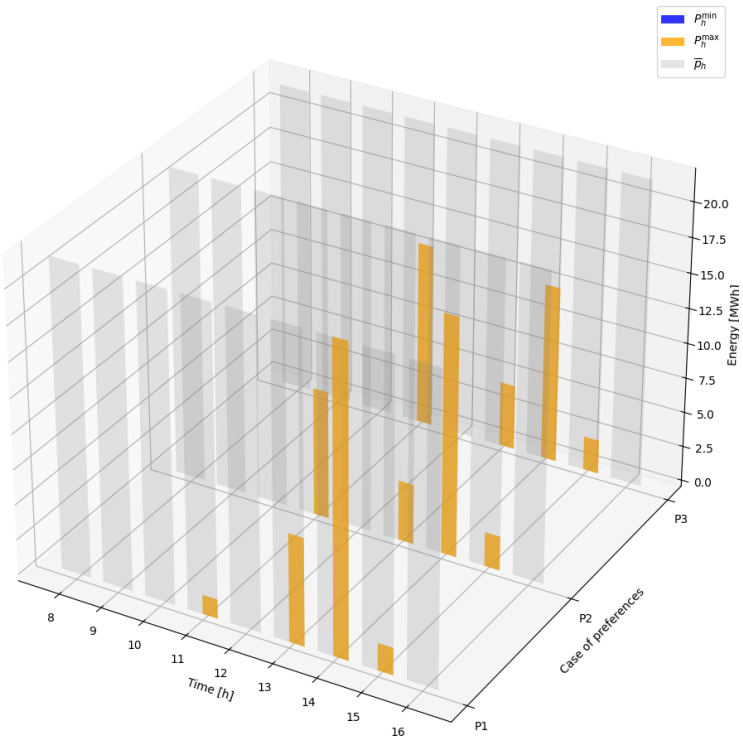


Figure 8. Case 2: Schedules of minimum amount $P_h^{\min}$ and maximum amount $P_h^{\max}$ of energy planned for purchase in each hour under different risk preferences, as provided in Figure 7.

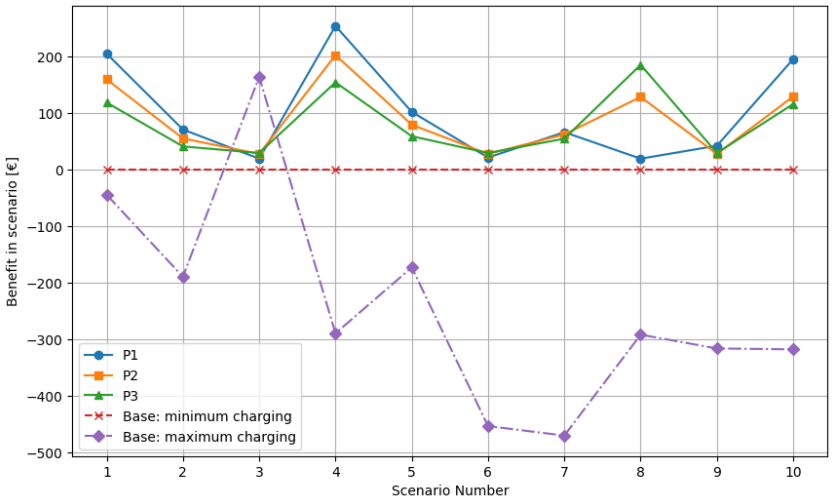


Figure 9. Case 2: Profits obtained under each scenario with different plans P1, P2, P3, or with baseline uncoordinated charging.

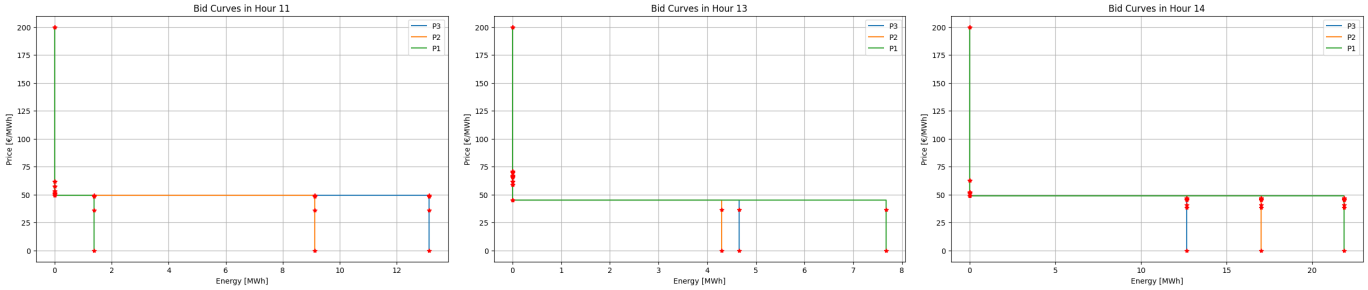


Figure 10. Case 2: Bidding curves obtained under different risk preferences should be submitted within hours of planned purchases.

3.3. Case 3—EVs Leave Home Fully Charged

In the final Case considered, the fleet arrives with almost full batteries, and they can only possibly recharge the amount used for driving to work. Thus, the advantage of accessing DA prices at the workplace is significantly limited, but, just like in Case 2, there is no risk of negative profits. The process of exploring optimal opportunities can be examined in Figure 11. Mean profits and CVaR are considerably lower than in Case 1 and much less dispersed. To maintain the exact structure of the analysis as in previous cases, here we also report three possible plans, P1, P2, and P3, even if the objective difference between the criteria values is slight. What is worth pointing out is that the safest solution, P3, considerably improves mean benefit, compared to the CVaR-only maximizing solution (denoted in Figure 11 as 'risk averse').

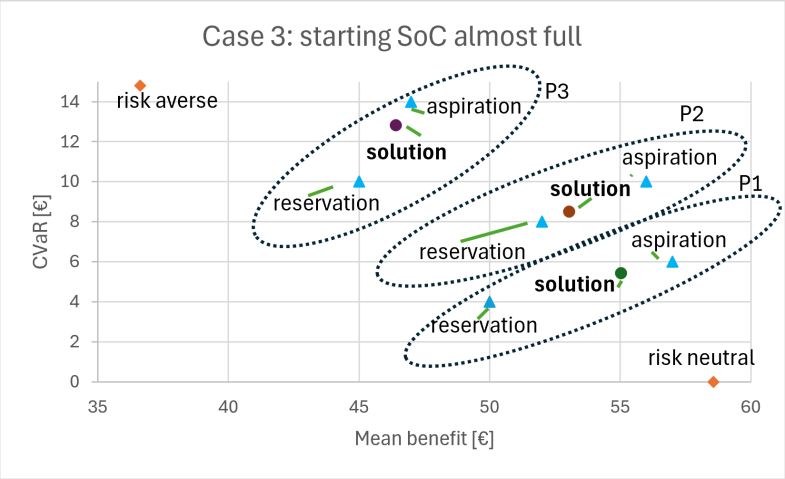


Figure 11. Pareto solutions obtained with three different preferences toward mean benefit and CVaR in Case 3.

Schedules obtained in each plan are shown in Figure 12. Again, the main charging activity is concentrated in hour 14, with the lowest mean price. Here, we can clearly observe how the distribution of charging dilates between consecutive hours while CVaR increases.

Individual benefits in every price scenario are shown in Figure 13. Similar dependencies, as in Case 2, can be observed. Also, in Case 3, there are no benefits in the baseline case (so we don't report it in the Figure). At the same time, BaseMax yields precisely the same benefits as the Base scenario in Case 1—the same amount of 15.87 MWh is expected to be charged uncoordinated. Benefits expected when realizing plans P1, P2, and P3 are close and about double lower than those reported in Case 2, Figure 9.

Bids are shown in Figure 14, just like in Case 2, consisting of only one step with a price of 50 €/MWh and different amounts of energy, depending on the risk preferences. In Case 3, only the risk-averse EVA that would choose to implement plan P3 will buy energy in hour 11, and the highest amount in hour 13, compared to plans P2 and P3. EVA will purchase most energy in hour 14 according to each plan—if the market price settles below 50 €/MWh, that is the level of flat rate for home charging. Recall that in hour 14, we expect the lowest mean price in all scenarios.

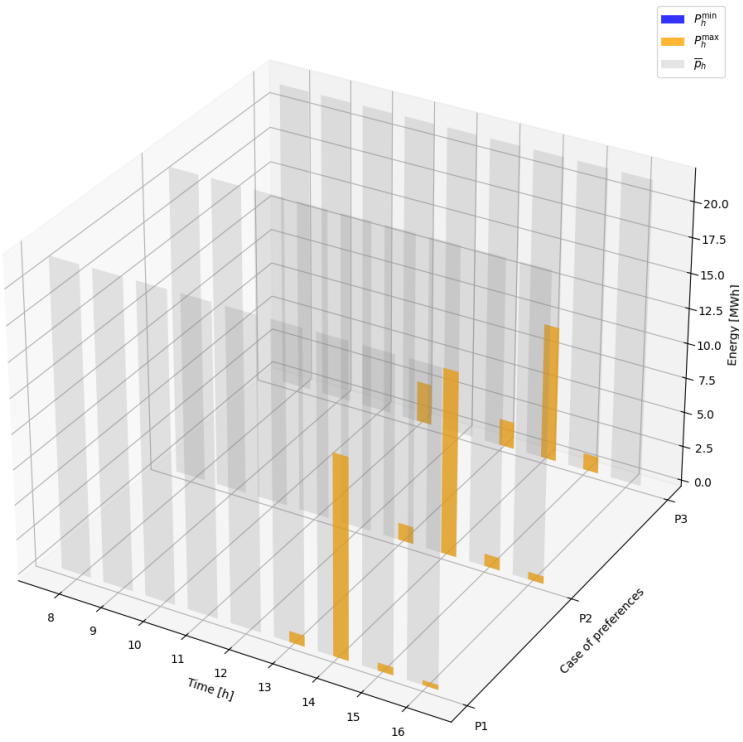


Figure 12. Case 3: Schedules of minimum amount $P_h^{\min}$ and maximum amount $P_h^{\max}$ of energy planned for purchase in each hour under different risk preferences, as provided in Figure 11.

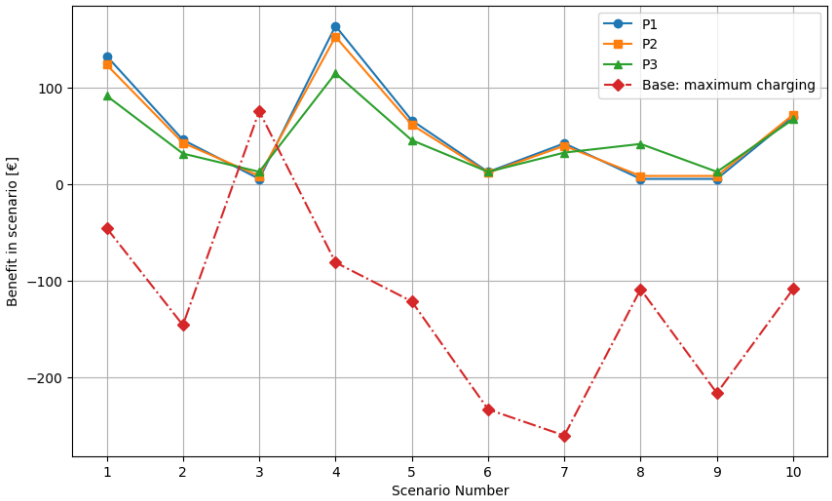


Figure 13. Case 3: Profits obtained under each scenario with different plans P1, P2, P3, or with baseline uncoordinated charging.

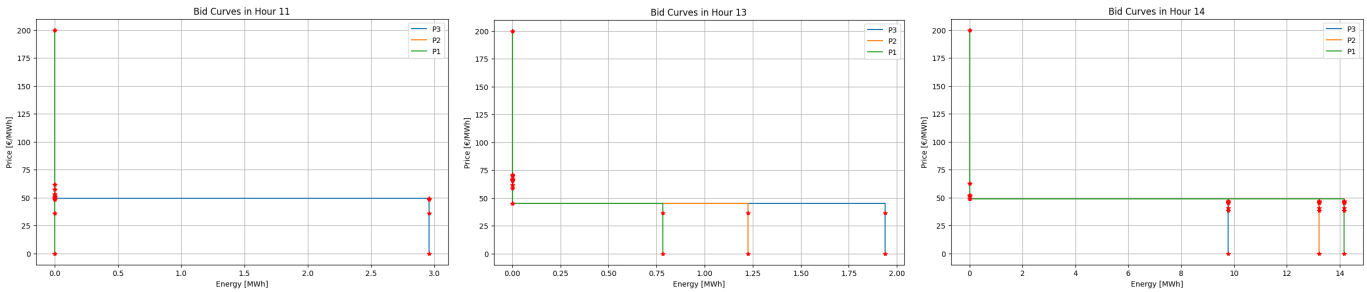


Figure 14. Case 3: Bidding curves obtained under different risk preferences should be submitted within hours of planned purchases.

4. Discussion

The findings reported in case studies demonstrate that the charging schedules generated by the proposed framework adapt effectively to forecasted electricity prices and the aggregator's risk attitude. Specifically, including profit-risk criteria, such as Conditional Value at Risk (CVaR) and expected profit, provides a comprehensive basis for decision-making. These criteria enable aggregators to balance maximizing profits and minimizing exposure to unfavorable market conditions. With the proposed model, EVA indicates preferences toward criteria by declaring reservation and aspiration levels, which are defined in terms of the values of criteria; such an approach is very straightforward, in contrast to control parameters used e.g., in [18] which need to be defined for each hour and scenario separately. The results validate that schedules tailored to these criteria can be reliable templates for constructing bidding strategies. In contrast to [17] or [20], we obtained these results by solving problem formulated in a linear programming form, which make it solvable with easily accessed, i.e., open-source solvers.

This study's results align with prior research emphasizing the significance of uncertainty management and strategic risk consideration in energy markets. However, the interactive aspiration/reservation-based multi-criteria approach distinguishes this work by offering a flexible and computationally efficient tool that adjusts to diverse risk attitudes and market conditions. The demonstrated adaptability underlines the potential for practical implementation in real-world aggregator operations. It should be noted that considering the opposite criterion is recommended when the decision-making situation is favorable for the assessment against this criterion—when losses dominate the results, CVaR becomes more critical. In contrast, when profits are expected, it is worth being guided by the mean profit criterion. Considering both criteria with clearly indicated preferences toward them allows for flexible adjustment of the optimization goal to market conditions.

5. Conclusions

This study introduced a multi-criteria stochastic linear programming framework to support electric vehicle parking lot aggregators (EVPLAs) in optimizing their charging schedules and constructing strategic bidding curves for participation in day-ahead electricity markets. By integrating forecasted price scenarios, user availability data, battery constraints, and risk preferences, the proposed model offers a robust, adaptive approach to maximize profitability while managing price uncertainty.

The main aim of this work was to explore the simplest, basic form of electricity trading, that is, buying the charging energy in the DA market. Results show that even in this relatively simple setting it is not a trivial task to decide when, and how much to bid, due to uncertainties that EVA faces regarding the DA market rules (bids are submitted in each hour independently) and volatile prices. The profits that may be achieved by accessing DA prices should not be considered without accounting for the risk preferences of EVA. Moreover, as we indicate in the case study, different criteria become more significant in different market conditions—when losses dominate the results, CVaR becomes more critical. In contrast, when profits are expected, it is worth being guided by the mean profit criterion. Considering both criteria allows for flexible adjustment of the optimization goal to market conditions. With the proposed model, EVA indicates preferences toward criteria by declaring reservation and aspiration levels, which are defined in terms of the values of criteria; such an approach is very straightforward. Last but not least, our model is stated in the linear programming form, which makes it solvable with easily accessed, i.e., open-source solvers.

While this study offers valuable insights, several avenues for future research remain open. Expanding the framework's scope to incorporate real-time market dynamics and

ancillary service markets could further enhance its applicability. Additionally, incorporating more granular data, such as user behavior patterns or localized grid constraints, would allow for even more precise scheduling and bidding strategies.

Exploring the model's scalability to larger aggregations of EVs and testing its performance under varying regulatory environments and renewable energy penetration levels would also provide valuable extensions. Lastly, integrating advanced machine learning techniques for price forecasting could further improve the accuracy of bidding strategies.

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Nomenclature

Indices

k	Index of individual EV
h	Index of time periods (hours)
s	Index of scenario
i	Index of criterion

Parameters

α	Parameter representing additional increase of the EVA's satisfaction when a criterion generates outcomes better than the corresponding aspiration level; $0 < \alpha < 1$.
β	Confidence level of CVaR.
$\underline{\delta}_k$	Minimum safe operating range of EV k battery.
$\overline{\delta}_k$	Maximum safe operating range of EV k battery.
γ	Parameter representing additional decrease of the EVA's satisfaction when a criterion generates outcomes worse than the corresponding reservation level; $\gamma \geq 1$.
A_k	Availability period for smart charging of EV k
B_k	Battery capacity of EV k
c^f	Flat rate/unit price for charging vehicles at home
c_{sh}	DA price in scenario s, hour h
E_k^{min}	Minimum energy level required to be charged in workplace by EV k
E^{min}	Minimum energy level required to be charged in workplace by whole fleet
E_k^{max}	Maximum energy level that can be safely charged in workplace by EV k
E^{max}	Maximum energy level that can be safely charged in workplace by whole fleet
E_k^{trip}	Trip energy required by EV k at departure
SoC_k	Initial battery State of Charge of EV k
h_k^a	Hour of arrival of EV k to workplace
h^a	First hour of possible smart charging of the whole fleet at workplace
h_k^d	Hour of departure of EV k from workplace
h^d	Last hour of possible smart charging of the whole fleet at workplace
q_i^a	Aspiration target value of criterion i
q_i^r	Reservation target value of criterion i
$\overline{p}_k$	Maximum charging power of EV k
$\tilde{p}_h$	Aggregated potential charging power of the fleet in hour h
$\overline{p}_h$	Aggregated maximum smart charging power of the fleet in hour h
p_s	Probability of scenario s

Variables

a_i	Partial achievement measure of the criterion q_i, with respect to the corresponding aspiration and reservation levels (q_i^a and q_i^r, respectively); free.

$\underline{a}$	The worst partial achievement among all a_i; free.
q_1	Mean benefit—maximized criterion of average scenario benefits; free.
q_2	CVaR—maximized criterion of average β-quintile worst scenario benefits; free.
p_{sh}	Charging energy planned in scenario s, hour h; nonnegative.
$P_h^{\min}$	Charging energy purchased regardless of price in hour h; nonnegative.
$P_h^{\max}$	Charging energy purchased only if price is advantageous in hour h; nonnegative.
z_{sh}	Benefit obtained charging energy p_{sh} in scenario s, hour h; free.
z_s	Total benefit that can be obtained according to scenario realization s; free.
z_s^β	Auxiliary variable used to determine if benefit in scenario s falls into β-quintile of all scenario benefits; nonnegative.
y^β	Auxiliary variable used to determine β-quintile level of all scenario benefits; free

Appendix A. Scenario Prices

Table A1. Values of hourly DA market prices in each scenario shown with average (avg.) prices in each hour [€/MWh], used in case studies.

h/s	1	2	3	4	5	6	7	8	9	10	Avg.
1	44.35	51.48	41.10	54.60	54.53	52.57	51.99	39.57	60.36	33.07	48.36
2	51.45	53.70	53.34	53.00	52.35	51.20	34.60	65.96	43.91	54.55	51.41
3	53.45	48.37	36.19	30.42	52.43	49.48	42.70	40.98	43.41	45.81	44.32
4	51.28	55.06	42.35	45.96	38.84	41.06	37.58	43.22	38.26	59.76	45.34
5	51.65	58.58	48.83	46.50	49.52	47.25	57.39	39.14	61.09	53.34	51.33
6	49.05	41.37	42.33	47.19	56.93	38.76	44.72	54.74	56.40	47.23	47.87
7	51.73	49.90	61.38	41.55	49.76	56.87	50.11	47.02	63.65	43.33	51.53
8	58.70	61.62	63.00	60.81	51.86	63.22	55.64	69.19	54.47	53.69	59.22
9	52.87	59.21	45.23	55.11	57.66	64.71	66.42	56.87	63.65	56.84	57.86
10	48.33	48.90	44.57	66.12	50.48	61.94	60.06	62.85	51.58	65.25	56.01
11	50.68	57.70	49.53	49.41	61.70	48.62	48.67	35.90	51.35	53.20	50.68
12	61.21	54.83	48.12	65.68	57.66	61.57	66.59	60.41	61.25	58.98	59.63
13	71.00	66.99	66.30	69.76	65.73	65.85	58.92	61.97	45.28	36.52	60.83
14	40.63	46.76	52.41	38.43	45.34	49.11	47.05	51.35	62.74	45.80	47.96
15	64.81	69.29	40.40	56.27	65.99	57.89	66.74	52.70	46.92	63.23	58.42
16	52.59	62.46	51.30	61.13	62.57	50.61	48.41	34.41	50.08	58.69	53.23
17	61.65	57.94	41.68	52.21	50.08	41.50	37.20	42.34	62.35	51.43	49.84
18	71.00	44.32	66.85	54.58	57.96	62.91	64.25	70.46	59.47	61.98	61.38
19	60.84	59.77	59.15	50.36	56.19	63.56	56.38	44.11	46.4	70.31	56.71
20	63.42	42.30	53.32	52.98	53.19	47.56	40.47	38.57	59.13	55.14	50.61
21	61.67	66.45	66.82	56.62	43.52	69.42	58.93	62.35	71.00	38.13	59.49
22	66.19	63.87	56.54	60.90	41.21	62.91	59.17	47.06	45.77	53.56	55.72
23	68.16	44.26	57.05	57.09	62.93	62.69	55.38	71.00	52.62	69.08	60.03
24	53.64	51.21	50.28	48.44	68.17	53.23	60.15	62.87	48.28	50.40	54.67

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