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A Time-of-use Pricing Strategy for Managing Electric Vehicle Clusters

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Abstract

A demand response program for electric vehicles (EV) is proposed to control the charging decision process in EV clusters. This approach corresponds to a time-of-use solution which is an indirect method, based on prices, for inducing demand modifications on consumers. An aggregator of EV fleet acts as a dealer between an electricity market and consumers. The EV aggregator is a price-taker agent from the wholesale electricity market viewpoint and price designer when selling energy to consumers. A game-theoretical model based on a Stackelberg formulation is proposed to capture the interactions between the fleet operator and electric vehicle owners, avoiding the requirement of a price elasticity model for the EV clusters. The interaction between the agents is formulated as a bi-level optimization problem: At the upper-level, the aggregator maximizes its benefits whereas the lower-level represents the dynamic behaviour of rational drivers as a fleet. The EV operator faces uncertainty in wholesale prices when buying energy and when forecasting consumption behaviour, then random parameters are modelled in a scenario framework. The model performance is evaluated through a case study using historical data from car-sharing services in Italy, comparing the result with a fixed-prices model. It is shown that the proposed price-based scheme allows to increment the aggregator profit with respect to a fixed-price contract, producing also a load shifting effect in the charging profile of the fleet.

Keywords: Aggregator, bi-level optimization, demand side management, electric vehicles, time-of-use, stochastic optimization.

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Nomenclature

Abbreviations

DR	Demand response.
EV	Electric vehicle.
MPEC	Mathematical programming with equilibrium constraints.
SO	System operator.
TOU	Time-of-use.
MILP	Mixed-integer linear programming.
LSE	Load-serving entity.
KKT	Karush–Kuhn–Tucker.

Indices

t	index for time ($t = 1, 2, ..., nt$).
w	index for clusters of electric vehicles ($w \in \pi(w)$).
v	index for market prices.

Parameters

H	charging efficiency.
Δ	time-step duration [h].
$\overline{E_t^s}, \underline{E_t^s}$	upper/lower bound on the energy content (state of charge) of the virtual battery of the EV aggregation [kWh].
$\overline{P_t}$	upper bound for the maximum charging power of EV aggregation [kW]
$\hat{\Gamma}$	average daily dynamic price charged to EV owners [€/kWh].
$\overline{\Gamma}, \underline{\Gamma}$	maximum/minimum dynamic price charged to EV owners [€/kWh].
E_w^0	initial condition of the virtual battery representing the EV aggregation [kWh].

Stochastic parameters

$E_{t,w}^T$	energy demand of the electric fleet in scenario w at time t [kWh].
$\Lambda_{t,v}$	energy price at the spot market [€/kWh] according to the scenario v at the time t.

Optimization variables

$e^s_{t,w}$ energy content (state-of-charge) of the virtual battery of the EV aggregation [kWh].

$p_t, \mathbf{p}_t$ expectation of charging power required by EV fleet (optimal solution in bold) [kW].

$p_{t,w}, \mathbf{p}_{t,w}$ charging power of the virtual battery depicting the EV aggregation in scenario w (optimal solution in bold) [kW].

γ_t dynamic price charged to the EV owner [€/kWh].

Dual variables

The dual variables below are associated with the following constraints:

$\alpha_{t,w}$ state-space model of the electric vehicle fleet.

$\mu^a_{t,w}, \mu^b_{t,w}$ upper/lower bound of stored energy.

$\mu^c_{t,w}$ upper bound of charging power.

Binary variables

The binary variables below are associated with the following constraints:

$z^a_{t,w}, z^b_{t,w}$ upper/lower bound of stored energy.

$z^c_{t,w}$ upper bound of charging power.

1. Introduction

The penetration of electric vehicles in the transportation sector has been expanding quickly in recent years. For example, taxis and car-sharing companies are introducing EVs as a part of their solutions. However, for the electricity distribution systems, the increment in demand generated by the enlarging EV fleet can cause problems in the operation, such as lines congestion and peak demand increment. Several studies go in this direction evaluating the potential risk that can derive from the uncoordinated connection of vehicle to the grid [1, 2]. These studies start from the measurement and analysis of behaviour of users ad their modelling [3].

To deal with the envisaged challenges in network operation caused by the EVs, it becomes necessary to implement a new market participant known as demand aggregator or EV fleet operator [4]. The aggregator has to address two main different problems. First, it must design prices that satisfy both consumers and EV fleet operator needs; second, the aggregator must drive EV users to modify their charging behaviour, in order to support the grid's requirements in terms of operational constraints, environmental objectives, costs reduction, among others. A convenient charging schedule planning is required to fulfill the grid objectives [5].

In general terms, two load management strategies can be recognized: direct control and indirect methods [6]. In direct control approaches the aggregator manages the charging profile of each EV directly [7]. The advantage and disadvantage of this methods can be resumed as: demand management becomes a robust centralized solution, guaranteeing power system security but as drawback there is the large investment required to implement bidirectional communication with each EV. Another issue highlighted in the literature is related to the consumer acceptance of such as approaches.

On the other hand, indirect programs for demand side management are based on prices or incentive signals aimed to influence the consumer behaviour (EV owners decisions) [8]. The main benefit of this solution is that the infrastructure costs can be reduced since it is an unidirectional approach. However, it is necessary to properly design the pricing scheme to achieve an optimal response from the user and this imposes the requirement of an appropriate model of the demand [9].

In order to investigate in this direction it is worth to note that in the context of EV charging, some indirect schemes have been proposed aimed to curtail load at peak time periods while rising EV penetration level in the electricity sector. Time-Of-Use (TOU) tariffs have been employed in EV demand management models. In [6] drivers pursue to minimize their costs concerning battery capacity, charging power level, energy needs and constraints in a decentralized framework. In [10], TOU tariffs are studied in the context of EV charging profiles. That work claims the importance of designing appropriate rates to motivate demand response. Also, TOU pricing is proposed in [11], where a social experiment is suggested to estimate the price response of the EV charging process. Models based on game-theoretic models have been investigated in [12] focusing on the Nash equilibrium of the charging problem of large populations of EVs. Furthermore, dynamic price signals are proposed to avoid transformer overloads in [13]. Additionally, distribution locational marginal pricing is developed to manage network congestion in [14]. Nevertheless, more research in price response model is required to achieve the appropriate performance in the grid [4]. Note that the previous works rely on consumer models based on demand functions where the elasticity is a key factor.

Stackelberg games have also been employed in literature to represent markets with hierarchical structure in EV charging management. In [15], an MPEC formulation is developed to find optimal bidding strategies of EV aggregators in day-ahead energy and ancillary services markets with variable wind energy, in which the upper-level problem is the aggregator conditional value at risk maximization, while the lower-level problem represents the system operation cost minimization. Similarly, [16] proposed an MPEC approach of a price-maker aggregator for bidding into the day-ahead electricity market with the aim of minimizing charging costs while satisfying the EV flexible demand. In that approach, the upper-level problem corresponds to the charging cost minimization of the aggregator, whereas the lower-level problem represents the market clearing. Furthermore, a stochastic robust optimization formulation is presented in [17], where a bidding strategy of an EV aggregator that participates in the

day-ahead energy market is developed. The model output corresponds to the bidding curves that are submitted to the System Operator (SO). Additionally, a bi-level programming approach or MPEC between a parking lot and a SO is developed in [18]. In that model, the upper-level problem represents the operation cost minimization of the SO while the lower-level problem corresponds to the scheduling of energy and reserves with the aim of minimizing the parking operation cost. Moreover, a profit-maximizing EV aggregator is developed in [19], it participates as a price-taker agent into day-ahead energy and reserve markets, which include compensation for battery degradation. The previous works adopt a centralized direct control framework where the aggregator has access to the charging infrastructure.

Stackelberg games have also been employed to design prices in indirect methods for EV DR. In [20] is proposed a bi-level mechanism to determine TOU prices to incentive EV behaviour to elicit load levelling. Particularly, the top-level solves the problem to minimize the system load variance, and the lower level the charging cost of every EV. In [21] is developed a distributed charging strategy based on day-ahead prices, with the aim of increasing the operating profits based on a Stackelberg game. The authors present a heuristic algorithm to obtain a sub-optimal solution for the EV operator and each smart charger. In [22] is highlighted the benefits of employing dynamic pricing to induce demand response in EVs, the authors propose a bi-level formulation for the interaction between between the SO and EV parking lots to reduce energy consumption under price spikes. Furthermore, an aggregator is considered for buying energy in the day-ahead market while accounting for technical aspects of each EV [23]. In [24], an optimal pricing and charging scheduling model is developed for a car-sharing company, considering EV mobility to capture the spatial translations without tracking every single vehicle. A bi-level program for EV aggregation using indirect load control is designed to minimize the personal mobility cost while maximizing the aggregator profit. The previous works rely on consumer models based on price elasticity of demand that must be estimated from historical behaviour data.

Starting from these consideration, our work proposes a tool to design prices in indirect DR programs for EV charging users. Starting from the approaches proposed by [25], an aggregator model is developed based on a dynamic game between a fleet operator and a set of EV owners that behave as a cluster. A DR contract is incorporated through optimization constraints in the problem. In particular, the contract establishes some characteristics of a variable electricity price, i.e. minimum, maximum and average energy value during the day. The EV fleet operator participates in the day-ahead electricity market as a price-taker agent to procure the energy required by the EVs enrolled in the DR program. In this framework, the agent faces uncertainty in the spot prices and also in the energy requirements of the EV fleet derived form their driving patterns. A novel procedure is presented for the determination of the price signal that maximizes the expected value of the objective function of the aggregator and the optimal load pattern for the EV fleet, under the proposed criteria. An MPEC optimization problem is formulated to model the conflict between

the involved agents. At the upper-level, the aggregator maximizes its objective function whereas the lower-level depicts the behaviour of rational EV drivers as a cluster. At the lower level, the new approach employs a virtual battery model to represent the ability of the group of EVs to store energy and offer flexibility in energy demand. This tool allows to describe the aggregated flexibility of a possibly large set of loads with a simple dynamic model, without considering the complexity of each participant behaviour. Uncertainties are represented by assuming a scenario-probability framework. The MPEC formulation is changed into a MILP problem that can be solved in commercial optimization software. Therefore, this model can be employed as a price planner or TOU designer for indirect methods of load management for EV.

The main contributions are summarized as follows:

- A game-theoretic approach is proposed to model the interaction between an aggregator and flexible EV owners to design retail tariffs by facing uncertainties in demand and spot prices.
- The consumer behavior is depicted through an optimization problem rather than using demand elasticities or utility functions for EV applications. This approach avoids the estimation process of consumers' preferences focusing rather on historical driving patterns to capture cluster actions.
- By using an aggregated virtual battery formulation as a state-space model, the dynamics of consumer behaviour is captured in the lower-level of the proposed bi-level game.
- The approach captures the EV owners habits as behaviour clusters. The driving patterns are included in the form of EV groups with similar demand profiles, without requiring detail models or measurements for each EV.

The paper is organized as follows. Section 2 introduces the problem setup. Section 3 describes the EV aggregator model. In Section 4, a case study is presented. Next, Conclusions are drawn in Section 5. Finally, the mathematical details are explained in the Appendix.

2. Problem setup

An EV fleet operator or aggregator is a new agent in the power system operation. It acts as interface between wholesale electricity markets and EV owners. The aggregator is in charge of providing the energy requested by the EV fleet by participating in wholesale electricity markets. At the same time, it is responsible of managing its customers demand to offer new services to the grid, such as balancing or congestion management, while deriving profits from the services.

In this work, it is assumed that charging stations offer unidirectional charging, i.e., the EVs cannot inject power to the grid. The control variable that the

aggregator can manipulate is the price signal, as shown in Fig. 1. Energy is bought at the electricity market (e.g. at the day-ahead stage) and then it is sold to EV owners, whose aim is to minimize the cost of their energy consumption by properly designing when to charge their EVs and at what power level.

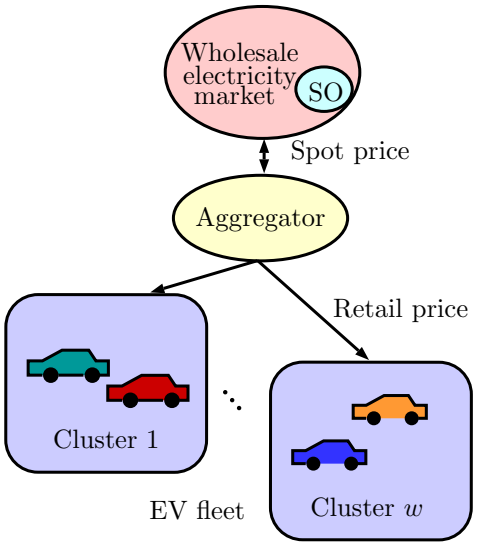


Figure 1: Information flow between aggregator and EV fleet based on price strategy.

The decision-making process has two steps: First, the aggregator designs the price signal offered to the EV owners for the whole day. Then, users decide their energy consumption along the day, on the base of the prices and private requirements (energy required for EV usage). This sequential interaction can be modeled as a dynamic game with Stackelberg structure, whose structure is a bi-level optimization problem where the upper level represents the decision on prices made by the aggregator and the lower one the decision made by the users in front of the given prices. The structure of the problem leads to a Mathematical Program with Equilibrium Constraints (MPEC). An advantage of this approach is that the EV cluster behaviour is integrated in the model as an optimization problem, offering an alternative to standard solutions that require the estimation of demand elasticities [13] or consumer utility functions [26].

Fig. 2 illustrated the proposed contract between the aggregator and EV owners as a decision sequence diagram. Beforehand, the aggregator and EV fleet are agreed on certain parameters, i.e., contract terms. In this paper, the agreement is subscribed under the following parameters on prices: minimum $\underline{\Gamma}$, maximum $\overline{\Gamma}$ and average energy values $\hat{\Gamma}$ during the day are fixed. The contract sequence is presented below.

- First, the aggregator designs time-variant retail prices by maximizing a

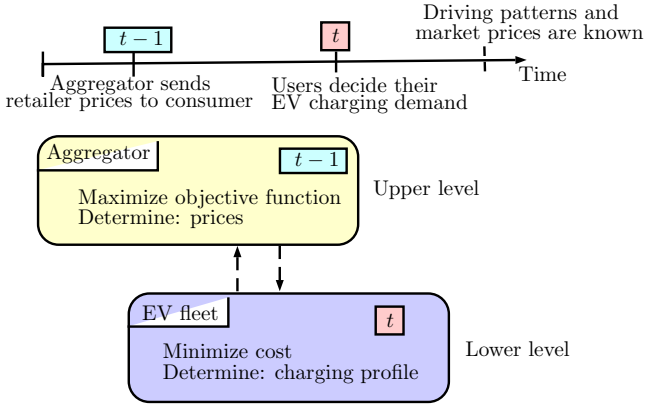


Figure 2: bi-level model.

private objective function, for example its expected profit, assuming uncertainties on demand and market prices.

- Second, the EV cluster decides its consumption patterns during the day, given the prices. It is assumed that EV owners are rational agents that minimize their costs.

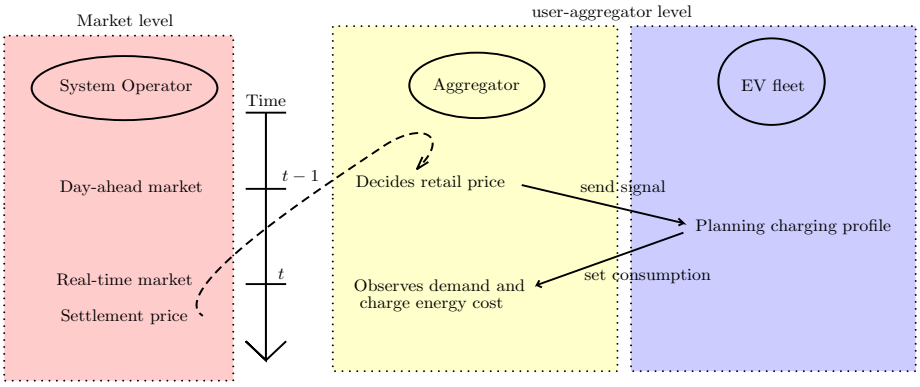


Figure 3: Decision-making process of the market agents.

The whole decision-making problem is illustrated in Fig 3. There are three main agents participating in energy transactions to provide balancing between supply and demand. SO is in charge of clearing the operations between generators and load-serving entities/aggregators. Typically, SO has multiple markets to guarantee a match among producers and consumers. For instance, SO determines the energy price trough day-ahead settlements and real-time (or balancing) markets every day. In this approach, the aggregator buys energy by

bidding in the wholesale electricity market, where prices are formed *ex-post*. Therefore, aggregator faces uncertainty in spot prices when it designs the retail prices for EV owners. Moreover, the EV fleet operator does not know *a-priori* the energy demand of the fleet for the next day. Additionally, it is expected that the aggregator obtains a profit for the services, therefore the average electricity price $\hat{\Gamma}$ charged to EV owners should be greater or equal to the spot price $\Lambda_{t,v}$, for the different curves indicated by the index v. An example of this issue is described in [27]. Then, the aggregator goal is to act as a price planner by sending retail prices in advance in order to induce adequate consumption patterns of EV owners.

In order to find a solution to the problem, the aggregation needs a forecast of EV fleet response to the prices. The proposed model takes into account the EV charging profiles by grouping drivers with similar behaviours in clusters. For instance, Fig. 4 presents a box plot of historical data related to the daily use, in term of energy consumption, for 1000 EVs, from January to April 2018, by cars that are part of a fleet of EVs from a car-sharing service in Italy, which can be applied to estimate driving patterns and define statistical models of energy requirements in urban areas. Note that the energy demand is greater during the night or early morning since the availability of public transport is reduced. Therefore, historical demand patterns can be used to forecast driving behaviours and as a consequence, energy requirements, then this fact provides information on the flexibility of EV demand.

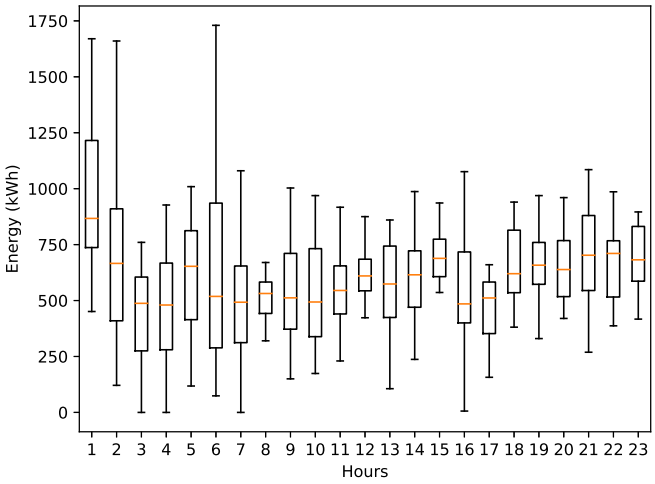


Figure 4: Energy demand for 1000 EV from car-sharing service in Italy.

Finally, the best aggregator strategy is captured by means of an optimization problem, as illustrated in Fig. 5. The aggregator sets an objective function

defining its interests, for example profit maximization, congestion reduction or peak shaving, subject to the contract terms and expected optimal EV fleet behaviour. In this case, the expected EV driving patters are included by adding another level into the problem formulation, in order to depict EV fleet decisions as behaviour clusters.

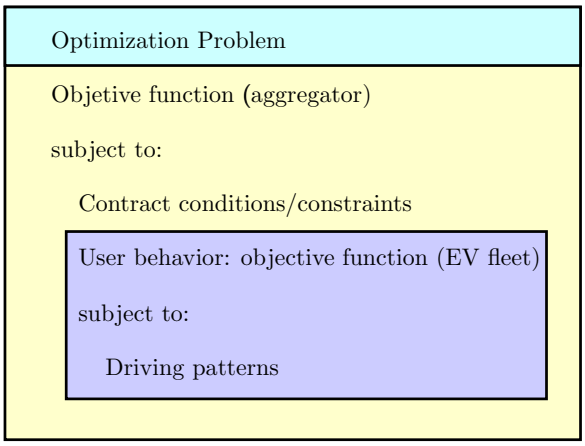


Figure 5: Aggregator problem.

3. Model formulation

In this section, an optimization problem for the EV aggregator is described. The dynamics of a fleet of EVs is modeled as a virtual battery. This virtual battery represents the aggregated energy capacity and flexibility of the group of EVs ad also their charging energy demand. The Aggregator has partial information about the behaviour of the EVs, which can be computed, for instance, through historical data registered at charging points, through appropriate technology.

On the upper side, the fleet operator is modeled as a price-taker retailer in the energy market. While, the EV fleet is represented as a rational agent at the lower side, when formulating the aggregator problem.

The planning horizon is one day, divided in 24 periods. However, the length of the discretized time intervals can be modified to obtain more detailed representations of the EV charging process. The proposed solution is explained in two subsections: EV fleet model, the bi-level problem, and the MILP model. The mathematical details about transforming the resulting MPEC to a MILP problem and relaxing bilinear term in the objective function are explained in the Appendix.

3.1. Electric vehicle fleet model

The Aggregator requires a model of the EVs behaviour to predict the response of the fleet in front of a given price signal, and then design adequate retail prices γ_t. In this sense, Aggregator assumes a model of the EV fleet with uncertainty in its energy consumption, using a predicted energy demand by the cluster for the next day, see e.g., [17, 28].

The EV aggregation is performed as a virtual battery, where the dynamics of the fleet are modeled as a single variable that represents the behaviour of the energy of the group of EVs, using the same principle proposed in [29] for thermostatically controlled loads.

The following set of equations describe the dynamic model of the EV fleet:

$$e^s_{t,w} = e^s_{t-1,w} - E^T_{t,w} + H\Delta p_{t,w} \ : \ \alpha_{t,w} \quad \forall t > 1 \tag{1a}$$

$$e^s_{1,w} = E^0_w - E^T_{1,w} + H\Delta p_{1,w} \ : \ \alpha_{1,w} \tag{1b}$$

$$e^s_{t,w} \leq \overline{E^s_t} \ : \ \mu^a_{t,w} \quad \forall t \tag{1c}$$

$$\underline{E^s_t} \leq e^s_{t,w} \ : \ \mu^b_{t,w} \quad \forall t \tag{1d}$$

$$p_{t,w} \leq \overline{P_t} \ : \ \mu^c_{t,w} \quad \forall t \tag{1e}$$

$$p_{t,w}, e^s_{t,w} \geq 0 \quad \forall t \tag{1f}$$

Eq. (1a) is the balance condition for the virtual battery depicting the EV driver behaviour, where $e^s_{t,w}$ is the energy stored by the cluster (virtual battery), H is the charging efficiency, $p_{t,w}$ is the charging power required by EV fleet, $E^T_{t,w}$ is a random parameter of energy requirements of drivers, at each interval t, to use the EV fleet and w is a sub-index that represents the different curves that can be observed. Each realization of $E^T_{t,w}$ represents the aggregated energy consumed by the fleet during the interval t of length Δ for the index w. Eq. (1b) is the initial value condition for Eq. (1a). The maximum and minimum capacities of the virtual battery are defined in Eq. (1c) and (1d), while Eq. (1e) defines the maximum power level that can be absorbed by the virtual battery. Eq. (1f) establishes that the stored energy and charging power are non-negative variables. $\alpha_{t,w}$, $\mu^a_{t,w}$, $\mu^b_{t,w}$, $\mu^c_{t,w}$ are defined as the dual variables of constraints (1).

When setting up the problem, adequate power and energy limits must be provided. These can be estimated from historical data of driving patterns and energy demand, combined with the technical constraints of the EVs and charging stations. Also, the future energy requirements can be derived from past data of the fleet behaviour, see Fig. 4. The estimation problem of parameters and stochastic parameters is out of the scope of this work. However, note that this input data is important to attain a proper result in real scenarios of the proposed formulation.

Notice that consumers choose their charging profile $p_{t,w}$ already knowing in advance the retail price γ_t and their energy requirements for the day $E^T_{t,w}$ (see

the decision sequence in Fig. 3). Finally, users face the following problem:

$$\begin{aligned} \mathbf{p}_{t,w} \in \quad & \arg\min \quad \sum_t \gamma_t p_{t,w} \\ & \text{subject to} \quad \text{constraints (1)} \end{aligned} \tag{2}$$

Note that the decision problem faced by the EV owners is a deterministic optimization problem parametrized by their energy requirements given the index w and technical constraints. Contrarily, the aggregator faces uncertainty in the power demand when designing prices beforehand. The bi-level optimization problem explained in the following subsection deals with this situation.

3.2. Time-of-use model: bi-level approach

The contract establishes that the aggregator must send the price signal for the 24 hours to the EV fleet at the beginning of the day. Prices must respect the contract conditions: maximum and minimum limits $\overline{\Gamma}$ and $\underline{\Gamma}$ and daily average $\hat{\Gamma}$. The aggregator must also send its bidding strategy to the SO the day before, according to the market structure. The system operator clears the market with the information of all the market participants and only then, the aggregator learns the energy price. Note that in this scheme, the fleet operator must deal with uncertainty in energy prices because it must purchase energy and design retail prices in advance.

The decision problem faced by the aggregator is formulated as a bi-level problem, modeling the interaction between aggregator and EV fleet (see Fig. 5). At the upper-level, the aggregator is taken as a strategic agent, whose aim is to minimize the expected value of its cost function $f(\cdot)$, by designing the price signal γ_t. At the lower-level, the EV fleet decisions are imposed as constraints for the upper problem, where, for each demand scenario, the EV fleet decides its charging schedule in order to minimize the battery charging costs while guaranteeing adequate energy levels in the battery.

The following set of equations define the stochastic optimization problem:$\hat{\eta s}_t$

$$\begin{aligned} \underset{\Phi^U}{\text{minimize}} \quad & \mathbf{E}_v \left[f\left(\gamma_t, \Lambda_{t,v}, \mathbf{p}_t\right) \right] \\ \text{subject to} \quad & \underline{\Gamma} \leq \gamma_t \leq \overline{\Gamma} \quad \forall t \\ & \frac{1}{nt} \sum_t \gamma_t = \hat{\Gamma} \\ & \mathbf{p}_t = \mathbf{E}_w[\mathbf{p}_{t,w}] \\ & \mathbf{p}_{t,w} = \underset{\Phi_w^L}{\arg\min} \quad \sum_t \gamma_t p_{t,w} \quad \forall w \\ & \qquad\qquad \text{subject to} \quad \text{constraints (1)} \end{aligned} \tag{3}$$

where $\Phi^U = \{\gamma_t\}$ and $\Phi_w^L = \left\{e_{t,w}^s, p_{t,w}\right\}$. Constraints at the upper-level ensure that the demand price is bounded between $\underline{\Gamma}$ and $\overline{\Gamma}$, and also they impose by contract that the dynamic price has a fixed daily average. Furthermore, $\Lambda_{t,v}$

is the energy price resulting form the market clearing and nt is total number of periods. Note that the Problem (3) has two random parameters which are $\Lambda_{t,v}$ and $E^T_{t,w}$, the last one appearing in the lower level problem, eq. (1a). Scenarios for the prices can be obtained using the method proposed in [30].

$f(\gamma_t, \Lambda_{t,v}, \mathbf{p}_t)$ is the objective function to be minimized by the fleet operator. The aggregator sets the objective according to its targets. For instance, f can be focused on profit maximization ($\sum_t(\gamma_t - \Lambda_{t,v})\Delta\mathbf{p}_t$), peak demand reduction ($\max_t \mathbf{p}_t$) or congestion control.

The problem faced by the aggregator in eq. (3) is a non-linear stochastic bi-level optimization problem that cannot be solved efficiently by computational algorithms. If the objective function of the aggregator is profit maximization,

$$f(\gamma_t, \Lambda_{t,v}, \mathbf{p}_t) = \sum_t (\gamma_t - \Lambda_{t,v})\Delta\mathbf{p}_t, \tag{4}$$

the equivalent single-level MILP formulation of the nonlinear MPEC problem is the following:

$$\begin{aligned}
\underset{\Phi^{DP}}{\text{maximize}} \quad & \sum_v \sum_w \pi(w,v)[\sum_t(\alpha_{t,w}E^t_{t,w} - \mu^a_{t,w}\overline{E^s_t} + \mu^b_{t,w}\underline{E^s_t} \\
& - \mu^c_{t,w}\overline{P_t} - \Lambda_{t,v}p_{t,w}) - \alpha_{1,w}E^0_w]\Delta \\
\text{subject to} \quad & \underline{\Gamma} \le \gamma_t \le \overline{\Gamma} \quad \forall t \\
& \frac{1}{nt}\sum_t \gamma_t = \hat{\Gamma} \\
& \text{constraints (1), } (A.1a) - (A.1d), \text{ and } (A.2).
\end{aligned} \tag{5}$$

being $\Phi^{DP} = \{e^s_{t,w}, p_{t,w}, \gamma_t, \alpha_{t,w}, \mu^a_{t,w}, \mu^b_{t,w}, \mu^c_{t,w}, z^a_{t,w}, z^b_{t,w}, z^c_{t,w}\}$. In addition, the expected value in (3) is changed by the summation on $\pi(w,v)$, which means the probability of occurrence of each demand w and each spot price v. A scenario tree can be used to capture the uncertainties in the model. The Appendix describes in detail the transformation from the bi-level problem to the MILP formulation.

4. Simulated Case Study

In this section, a simulated case study is presented to illustrate the proposed solution to manage an EV fleet energy demand through the price signal. Scenarios of energy consumption are built from historical data of vehicles from a car-sharing service collected during the Italian project Teinvein, corresponding to a fleet of small electric cars. The main characteristics of the EV fleet are provide in Table 1. The simulation is executed for a planning horizon of 24 h divided into hourly time steps.

The energy demand of the EV fleet has been extracted from the historical data of the car-sharing service during the last semester of 2017. Fig 4 shows a box-plot of hourly energy consumption for a day. Considering that the EVs

Fleet size	1000
Battery capacity per EV	12 kWh
Upper limit on charging power per EV	3 kW
Charging efficiency	90%
Starting stored energy level	2000 kWh

Table 1: characteristics of the EV fleet.

are used for car-sharing activities it is observed that most of the trips are short ones, EV usage is higher during the night and weekends, While there is a lower activity during workdays. It is observed that hourly energy consumption is below 1 kWh for each vehicle. 20 scenarios have been selected randomly from the data set and it is assumed that they have the same probability of occurrence.

Concerning the uncertainty faced by the aggregator when buying energy in the spot market, 3 different spot prices with equal probability are considered. These are denoted as *Spot1*, *Spot2* and *Spot3* and correspond to actual energy prices in the Italian day-ahead market during January 2020, note that these price signals follow a duck curve, [25]. The price signals $\Lambda_{t,v}$ are shown in Fig. 6 and vary from €0.032/kWh to €0.065/kWh.

For the simulation, power bounds of the virtual battery are kept constant along the day to ease the analysis, but they can be modified according to EV fleet conditions, e.g., number of EVs connected to the grid. Energy bounds were taken as the aggregated state-of-charge of the fleet. However, those limits should be the results of studying the EV fleet behaviour as a previous step when using the proposed model.

The following contract conditions are defined: Aggregator sells energy to consumers at an average price 20% more expensive than the purchase price, i.e., $((1/nt)\sum_t \Lambda_{t,v})1.2 = \hat{\Gamma}$. Furthermore, the maximum and minimum energy retail prices are established as $\overline{\Gamma} = \hat{\Gamma} + \hat{\Gamma}(0.3)$ and $\underline{\Gamma} = \hat{\Gamma} - \hat{\Gamma}(0.3)$. From the above, the aggregator problem is how to define hourly retail prices, given the uncertainties on wholesale energy prices and driving patterns of the EV aggregation, in order to maximize its profit.

The single-level mixed-integer linear programming problem (5) that results from the bi-level program (3) is solved using the NEOS server services [31], employing the *FICO Xpress-Optimizer v29.01.10* under *Julia 0.6.4* environment. The resulting MILP problem with 20 energy consumption scenarios and three possible spot price sequences has 1440 free variables and requires less than 3 minutes to be solved.

Additionally, in order to evaluate the proposed model, the optimal fleet behaviour when faced to constant energy prices is considered, i.e, using the formulation (2) by replacing the time-variant price Γ_t by the fixed price $\hat{\Gamma}$,

which is the average price agreed between the parties.

Fig 6 presents the resulting optimal price signal for the proposed model. The *fixed* price charged to consumers is €0.051/kWh. The *Dynamic* price Γ_t is most expensive during the first hours, between hours 1 to 10, with a value of €0.065/kWh. Then, between hours 11 to 20 the price lowers to €0.04/kWh and finally, a price of €0.035/kWh is fixed for hours 21 to 24.

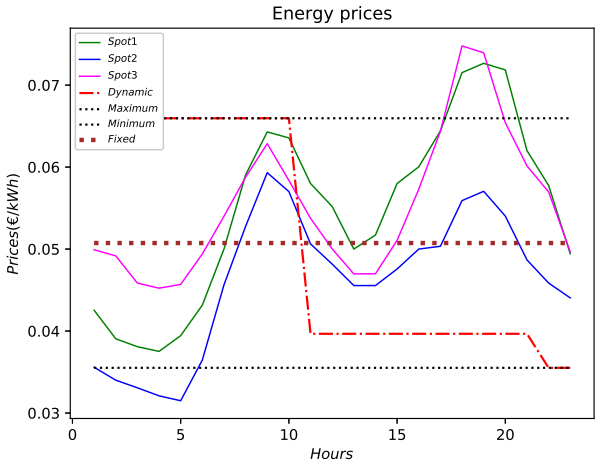


Figure 6: Considered energy prices.

Fig. 7 shows a box plot of the resulting charging power for the 20 considered scenarios, given the price policy. Five different periods can be identified. First, The fleet buys energy despite the high price in order to rise the SoC from the initial $2000kW$ to a fully charged condition after 6-5 hours. Then, the EVs slowly discharge their batteries to satisfy energy demand until prices reduce and stored energy achieves its lower bound. Between hours 13 and 15, EVs buy power at a mid-low price, rising the SoC again. From hour 16 until hour 20, there is not consumption and demand is supplied from the stored energy, lowering the SoC. Finally, between hours 21 until the end of the day, when price is low, the fleet consumes enough energy to complete the daily service with an adequate SoC, see Fig. 8.

Note that demand shows low variance among the 20 considered scenarios. Large variations can be observed at hours 2, 6 and 21, been maximum at hour 6, when power varies between 0 and $\overline{P}$, meaning that for some scenarios the fleet charges at maximum power while for others there is not consumption at all. Fig. 1 shows that at this hour energy demand has a high variance between scenarios, while Fig. 8 illustrates that the stored energy is close to the maximum at this hour for all scenarios. Then, the large variations can be explained by

the fact that at hours 5-6 the fleet changes behaviour from full charge to no charging and the switching moment varies between hour 5 and 6, depending on the uncertain demand.

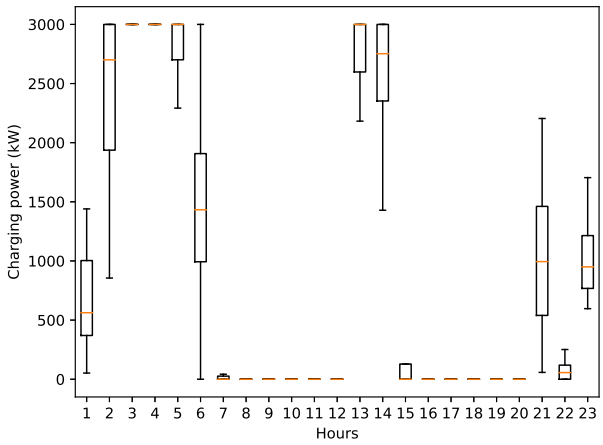


Figure 7: A box-plot of EV Charging power considering all scenarios.

In order to assess the effect of uncertainty in the performance of the price planning strategy, the expected profit of the aggregator is evaluated under constant and dynamic prices for different spot price assumptions. Problem (5) is solved considering no uncertainty in spot prices for each price sequence shown in Fig. 6. The expected profit for each condition is summarized in Table 2. It can be seen that, for any price assumption, the aggregator attains greater profit by employing the proposed TOU contract than using a fixed price. Note also, that the uncertainty in spot prices considerably reduces the profit, as the aggregator must design a single price sequence for all the possible spot price realizations. In this case study, the proposed model represents a profit improvement of 27.4%. Nevertheless, this result can be improved by modifying the agreed parameters ($\hat{\Gamma}$, $\overline{\Gamma}$ and $\underline{\Gamma}$) in the contract. Hence, this method can be a useful tool to design prices for TOU programs, allowing EV fleet operators to encourage a change in the energy consumption patterns of driver-owners by modifying retail prices.

5. Conclusions

In this paper we have proposed a contract between an aggregator and a fleet of electric vehicles, allowing to design prices that induce users to modify their energy consumption in demand response programs. The objective of the fleet operator is to minimize a private cost function (for example operation costs) while driver-owners are represented as rational agents that minimize the cost

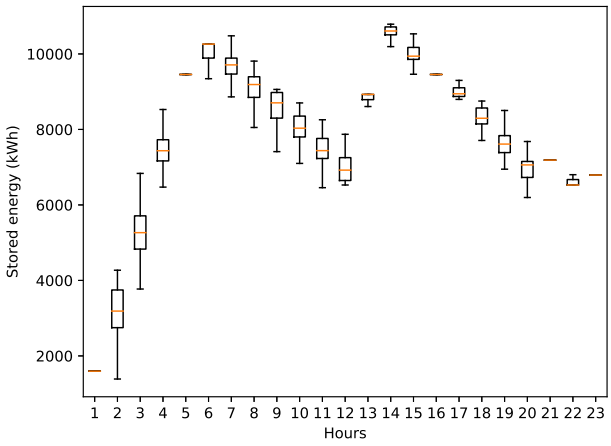


Figure 8: A box-plot of EV stored energy considering all scenarios.

Program	Fixed price (€)	Dynamic pricing (€)
Expected profit	160.51	221.10
spot1	345.31	417.23
spot2	275.77	336.36
spot3	278.94	351.51

Table 2: Expected profit.

of procuring the energy required to satisfy their driving profiles. A stochastic bi-level optimization problem was formulated, using a virtual battery model of the EV fleet. The resulting problem is an MPEC, considering the hierarchical structure of the relation between agents as a Stackelberg game.

The formulation allows to link the EV fleet decisions, modelled as a cluster, and the aggregator objectives to determine optimal price signals and load patterns. As results, in the TOU case, the EV fleet operator, while maximizing its profits, sends EV owners a price-incentive to shift their electric charging demand to periods where the aggregator can obtain better benefits than with a fixed price contract.

The proposed model does not require the derivation of utility functions or price elasticity parameters of the EV owners-drivers. On the contrary, the EV fleet behaviour is represented as a dynamic model of a virtual battery with an stochastic energy demand, characterized by a set of energy consumption scenarios that can be estimated from EV usage data not related to economic decisions of the owner.

A case study, based on actual energy demand data from an EV fleet deployed

in Italy, illustrates the ability of the the model to optimize price planning in order to maximize the benefits of the aggregator. Numerical results, considering 20 demand scenarios and three market price realizations, show that the expected profit is increased by more than 27% for all the spot prices considered, by properly inducing the fleet to modify the energy demand profile.

Future extensions of this research can move in several directions. The formulation can include other applications like support to ancillary services or balancing markets. Furthermore, the model can be extended adding network constraints to model the EV demand for charging stations.

Appendix A. Transforming into an MILP problem

The lower-level optimization problem in (3), i.e. consumer decisions, are changed by their Karush–Kuhn–Tucker optimality conditions, [32, 25]. KKT formulation applies here since the lower-level problems are convex in the continuous variables $e^s_{t,w}$ and $p_{t,w}$, and since the upper-level variable, γ_t, can be considered as a parameter by the lower-level aggregation.

In addition to the primal feasibility restrictions (1), the KKT necessary optimality conditions of the lower-level problem imply that,

$$\gamma_t - H\Delta\alpha_{t,w} + \mu^c_{t,w} = 0 \quad \forall t, w \tag{A.1a}$$
$$\alpha_{t,w} - \alpha_{t+1,w} + \mu^a_{t,w} - \mu^b_{t,w} = 0 \quad \forall t < nt, w \tag{A.1b}$$
$$\alpha_{t,w} + \mu^a_{t,w} - \mu^b_{t,w} = 0 \quad \forall t = nt, w \tag{A.1c}$$
$$\mu^a_{t,w},\ \mu^b_{t,w},\ \mu^c_{t,w} \geq 0 \quad \forall t, w \tag{A.1d}$$
$$(e^s_{t,w} - \overline{e^s_t})\mu^a_{t,w} = 0 \quad \forall t, w \tag{A.1e}$$
$$(\underline{E^s_t} - e^s_{t,w})\mu^b_{t,w} = 0 \quad \forall t, w \tag{A.1f}$$
$$(p_{t,w} - \overline{P_t})\mu^c_{t,w} = 0 \quad \forall t, w \tag{A.1g}$$

Products of Lagrange multipliers and constrained continuous functions in the complementary slackness conditions, i.e, expressions (A.1e)-(A.1g), are equivalently replaced by linear equations through Fortuny-Amat transformation [33], similar to [25]. Then, (A.1e)-(A.1g) can be substituted by the following constraints.

$$\begin{aligned}
-(e^s_{t,w} - \overline{e^s_t}) &\leq M(1 - z^a_{t,w}) \quad \forall t, w \\
\mu^a_{t,w} &\leq M z^a_{t,w} \quad \forall t, w \\
-(\underline{E^s_t} - e^s_{t,w}) &\leq M(1 - z^b_{t,w}) \quad \forall t, w \\
\mu^b_{t,w} &\leq M z^b_{t,w} \quad \forall t, w \\
-(p_{t,w} - \overline{P_t}) &\leq M(1 - z^c_{t,w}) \quad \forall t, w \\
\mu^c_{t,w} &\leq M z^c_{t,w} \quad \forall t, w \\
z^a_{t,w}, z^b_{t,w}, z^a_{t,w} &\in \{0, 1\}
\end{aligned} \tag{A.2}$$

where M is a sufficiently large constant. This formulation introduces additional complexities by using binary variables $z^a_{t,w}$, $z^b_{t,w}$ y $z^c_{t,w}$, nevertheless, now all the restrictions are linear.

The term $\gamma_t p_{t,w}$ is non-linear, then the strong duality theorem on the lower-level is employed in order to transform it into a linear expression. Therefore, the bilinear term can be stated as

$$\sum_t \gamma_t p_{t,w} = \sum_t [\alpha_{t,w} E^t_{t,w} - \mu^a_{t,w} \overline{E^s_t} + \mu^b_{t,w} \underline{E^s_t} - \mu^c_{t,w} \overline{P_t}] - \alpha_{1,w} E^0_w \tag{A.3}$$

where E^0_w is the initial condition of stored energy in the EV fleet. Expression (A.3) can be replaced in the objective function of problem (3). Finally, the resulting optimization problem is stated in (5).

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