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Energy Price forecasting for optimal managing of Electric Vehicle fleet

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Abstract

Defining tools and algorithms to support the decision-making process for charging electric vehicles is a fundamental theme for the spread of electric vehicles. Utilities can use this approach to incentive or discourage the charge of electric vehicles according to different constraints. In this article we refer the electric vehicle (EV) clusters or fleets, where there is only one energy Buyer for all the cluster. This approach corresponds is an indirect method based on prices to induce behaviours in the management of charging on clusters of electric vehicles. The first actor of the algorithm is an Aggregator of electric vehicle fleet operators acts as a dealer between the electricity market and consumers. A theoretical game model based on Stackelberg's formulation is proposed to capture the interaction between the fleet operator and the owners/drivers of the electric vehicles. A bi-level optimization problem arises to represent the game between the agents involved: At the upper level, the aggregator maximizes its benefits, while the lower level represents the behavior of rational drivers as a fleet. The proposed method is applied to actual data obtained observing the behavior of a car-sharing fleet.

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 scenarios of market prices.

Parameters

η charging efficiency.

δ time-step duration [h].

$\overline{E^S_t}, \underline{E^S_t}$ 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^0_w initial condition of the virtual battery representing the EV aggregation [kWh].

Δ maximum price change by hour.

Random variables

$E^T_{t,w}$ 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.

Optimization variables

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

$P_{t,w}$ charging power of the virtual battery depicting the EV aggregation [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

Today there are a lot of discussion about electric vehicles and their adoption in urban and non-urban contexts. However, there are many reasons that make the adoption process complex and difficult. First of all, it is strongly related to the management of the vehicle and the possibility of recharging it. This is not only a problem of availability of the infrastructure but also of its ability to deliver power without losing its stability and robustness. However, electric vehicles are becoming a reality from the point of view of both commercial fleets and passenger transport. This is because the fleet manager has access to reduced costs due to the quantity purchased: both vehicles and energy. For instance, taxi services and urban car-sharing companies have introduced EVs as a part of their solutions [1, 2, 3, 4, 5]. However, at the electricity distribution level, the additional demand generated by the growing number of electric vehicles could have negative effects on the grid due to undesirable conditions during the charging process. It therefore becomes necessary to organize and plan the recharge in order to overcome these problems [5, 6, 7, 8]. Both from a fleet and a network point of view, it would be useful to have a mechanic able to have an economic advantage to recharge when the network has more availability and to be discouraged when the network has to supply other more critical loads [9, 10, 11, 12, 13]. Then, it becomes necessary to implement a new market agent known as demand aggregator or EV fleet operator. The aggregator has to address two main different problems. First, the price determination must be performed in order to satisfy both consumers and EV fleet operator needs; second, the aggregator has to induce an adequate charging behaviour in the EV user, considering the grid's needs in terms of operational constraints, environmental protection, production cost, and congestion management. A convenient charging schedule planning is required to fulfill the grid objectives.

In general terms, there are two approaches to schedule the charging process: direct control and indirect methods [14]. The first one means that the aggregator directly manages the charging profile of each EV. In this setting, a robust outcome is obtained since, by being a centralized solution, the power system security is guaranteed. However, the fleet operator needs bidirectional communication and smart devices alongside each EV, thus a large investment to deploy a proper infrastructure is required. Furthermore, this paradigm poses some problems of consumer acceptance [15]. On the other hand, indirect methods are based on prices or incentive signals aimed to influence the consumer behaviour (EV owners decisions) [16, 17]. The main advantage of this approach is that the infrastructure costs can be reduced [18], since it is an unidirectional approach. Nevertheless, the solution is not necessarily optimal since it depends on the used algorithm and the quality of the demand model (expected consumers decisions) [19]. In the case of indirect control, electricity prices can be properly formed to diminish load at peak time periods while increasing EV penetration level in the electricity market. A decentralized charging approach based on Time-Of-Use (TOU) tariffs is proposed in [15], where drivers seek to minimize their costs respecting battery capacity, charging power level, energy needs and constraints. Similarly, a decentralized computational algorithm is proposed in [20] by focusing on studying the Nash equilibrium of the charging problems of large populations of EVs. Furthermore, dynamic price signals are proposed to avoid transformer overloads in [21]. In [22], 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 [23], where a social experiment is suggested to estimate the price response of the EV charging process. Additionally, distribution locational marginal pricing is developed to manage network congestion in [24]. Nevertheless, more research in price response model is required to achieve the appropriate performance in the grid, [19]. Note that the previous works rely on consumer models based on demand functions where the elasticity is a key factor. Related to bi-level approaches or Stackelberg structures, some solutions are found in literature on EV charging management. In [25], 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, [26] 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 [27], 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 [28]. 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 cost. Moreover, a profit-maximizing EV aggregator is developed in [29], it participates as a price-taker agent into day-ahead energy and reserve markets, which include compensation for battery degradation. In the previous works, a centralized aggregator with access to the charging infrastructure is assumed.

[30] proposes 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 ev-

ery EV. In [31] 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. [32] remarks 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 [33]. In [34], 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.

This paper develops an aggregator model based on a dynamic game between a fleet operator and EV clusters, under a price-based DR program, with the aim of planning prices. A DR contract is incorporated through optimization constraints in the problem. In particular, it is assumed that the two parties are agreed on certain characteristics of a variable electricity price, i.e. minimum, maximum, average energy value during the day, similar to [35], and maximum price change by hours. In addition, it is considered that the EV fleet operator participates as a price-taker agent in the wholesale electricity market, then it faces stochasticity in spot prices and also in the driving behaviours (energy requirements) of the EV fleet. The proposed approach allows 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 (e.g. profit) whereas the lower-level represents the behaviour of rational EV drivers as a cluster. A virtual battery model is employed 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 first-order model, without considering the complexity of each participant behaviour, see e.g., [36]. Uncertainties are included by considering a scenario-probability framework in the model. The MPEC formulation is transformed 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 in EV. Respect to the previous work [37] the paper introduce some new aspects that can be summarized as follows:

- A new 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 behaviour is depicted through an optimization problem rather than using demand elasticities or utility functions for EV applications.

- 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 and some restriction are introduced on the price ramp.

- 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 structured as follows. Section 2 introduces the problem setup. Section 3 describes the EV aggregator model. In Section 4, a simulation case study is presented. Next, Conclusions are drawn in Section 5.

2 Problem setup

The optimal decision making of a EV fleet operator or aggregator is considered. It is an intermediate agent between wholesale electricity markets and EV owners. The aggregator is responsible of providing charging services to an EV fleet and to manage its customers for other purposes, e.g., ancillary services and balancing operations, while deriving profits from the services. Unidirectional charging is considered, in which price signals are used as the control variables, as shown in Fig. 1. Energy is purchased at the electricity market (e.g. at the day-ahead stage) and then it is sold to EV owners, who face an optimization problem aimed at minimizing the cost of their energy consumption.

From the perspective of the decision-making process, the aggregator has to determine the price signals so that the users then decide their consumption patterns on the base of the energy prices and requirements (energy required for EV usage). This sequential interaction is captured by a dynamic game with Stackelberg structure, which is formulated as a bi-level optimization problem, depicted through an MPEC algorithm. An advantage of this formulation is that the EV fleet behaviour is incorporated in the model as an optimization problem, offering an alternative to standard solutions that require the estimation of demand elasticities [21] or consumer benefit functions [38].

The contract between the aggregator and EV owners is depicted in Fig. 2, which is a decision sequence diagram under the proposed setting. 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 $\overline{\gamma}$, average energy values $\hat{\gamma}$ during the day are fixed. Also the hourly price update is limited to a fixed rate Δ. The contract process is described below.

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

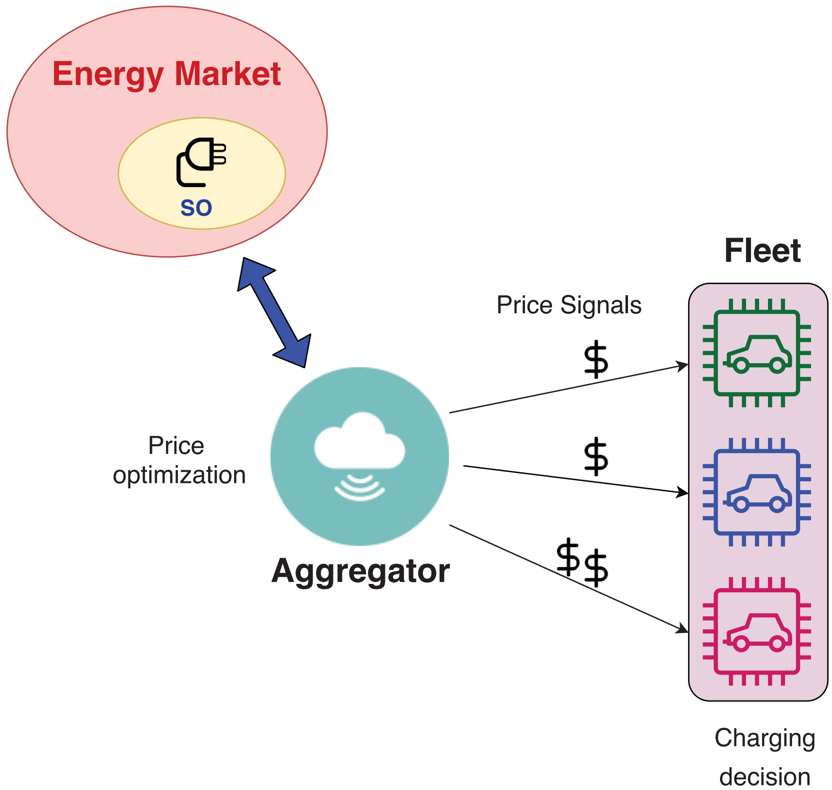

Figure 1: Functional flow description between aggregator and EV fleet based. In the aggregator the price is optimised and signed (also with different values) to the fleet that decide definitively the charging strategy

private objective function, for example its expected profit, considering uncertainties on demand and spot prices.

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

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. Thus, under the terms of the proposed contract, aggregator has to obtain earnings for the provided service, i.e. the average electricity price $\hat{\gamma}$ charged to EV owners should be greater or equal than the stochastic price $\lambda_{t,v}$, which is the spot price at the period time t in the scenario w. An example of this issue is described in [39]. 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 envelope 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 identical EVs from a car-sharing service in Italy, which can be utilized 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. Finally, the best aggregator strategy is captured by means of an optimization problem. 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.

3 Model formulation

This section presents the proposed method for optimization which describes the operation of the EV aggregator. A group of electric vehicles is studied as if it behaved as a single virtual battery within a fleet of electric vehicles. This virtual battery represents the aggregate flexibility of that group of electric vehicles and its charge curve. Flexibility means the availability to be recharged at a certain time and at a certain price. The aggregator has information about the fleet, which can be estimated, for example, through measurements at the charging points, assuming that the technology is available in the system. In addition, the fleet operator participates in the market as a LSE/retailer in a price-taker approach.

This model proposes a solution to the aggregator planning problem by assuming rational behaviour of EV owners grouped as clusters.

In this work, time is discretized into 24 hour periods. Nevertheless, the duration of these time steps may be adjusted to attain a more detailed modelling of the charging process. The proposed formulation 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 following subsections.

3.1 Electric vehicle fleet model

The Aggregator has to anticipate the EV behaviour in order to properly design 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., [27, 40].

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 [41] for thermostatically controlled loads.

The EV fleet model is formulated as follows:

$$E^S_{t,w} = E^S_{t-1,w} - E^T_{t,w} + \eta\delta P_t \ : \ \alpha_{t,w} \quad \forall t \tag{1a}$$

$$E^S_{t,w} \leq \overline{E^S_t} \ : \ \mu^a_{t,w} \quad \forall t \tag{1b}$$

$$\underline{E^S_t} \leq E^S_{t,w} \ : \ \mu^b_{t,w} \quad \forall t \tag{1c}$$

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

$$P_t, E^S_{t,w} \geq 0 \quad \forall t \tag{1e}$$

Eq. (1a) is the energy balance for the virtual battery representing the EV fleet behaviour, where $E^S_{t,w}$ is the energy stored by the cluster (virtual battery), η is the charging efficiency, P_t is the charging power requested by EV fleet, $E^T_{t,w}$ is a random variable that models the energy demand of drivers, at each interval t, for using the EV fleet. w is a sub-index that represents the different scenarios that can be observed. It accounts for the aggregated battery discharge produced by the use of the EVs during each interval of length δ. Eq. (1b), (1c) and (1d) are upper and lower stored energy bound ($\overline{E^S_t}$ and $\underline{E^S_t}$), and upper charging power limit $\overline{P_t}$, respectively. Lastly, eq. (1e) are the declarations of non-negative variables. Notice that $\alpha_{t,w}$, $\mu^a_{t,w}$, $\mu^b_{t,w}$, $\mu^c_{t,w}$ are the corresponding dual variables of constraints (1).

It is important to recall that the power and energy limits can be obtained by analyzing the driving patterns of EV users, added to the physical characteristics of the EV fleet and the charging stations. Then, this information can be acquired using historical data to predict the future energy requirements (see Fig. 4). This estimation process of parameters and stochastic variables is out of the scope of this work. However, note that this input data is vital to obtain a suitable result in real applications of the proposed model.

Notice that users decide their charging profile $P_{t,w}$ already knowing the retail price γ_t and their energy requirements for the day $E^T_{t,w}$, see the decision sequence in Fig. 3. Finally, consumers face the following problem:

$$P_{t,w} = \begin{array}{ll} \arg\min & \sum_t \gamma_t P_t \\ \text{subject to} & \text{constraints (1)} \end{array} \tag{2}$$

Therefore, EV owners solve a deterministic optimization problem that is associated with their energy requirements for each scenario w and technical constraints. However, when designing the prices, Aggregator faces uncertainty in the demand. This situation is captured through a bi-level optimization problem which is explained in the following subsection.

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

According to the contract, aggregator sends regulated prices to consumers in advance. These are comprised between $\overline{\gamma}$ and $\underline{\gamma}$, their daily average is $\hat{\gamma}$ and the maximum price change by hour is Δ. Furthermore, the fleet operator has to inform its bidding strategy in advance to the SO. With that information of all market participants, SO clears the market and then communicates to aggregator the market results. Given that the EV fleet operator has to purchase energy and design retail prices in advance, it faces uncertainty in spot prices and EV driving patterns.

A bi-level problem is posed to model the interaction between aggregator and EV fleet . In the upper-level, an strategic aggregator is considered to determine the prices γ_t. The lower-level is formulated as a constraint of the main problem, where, for each demand scenario, the EV fleet minimizes the charging costs. The stochastic optimization problem is proposed below,

$$\begin{array}{ll} \underset{\Phi^U}{\text{minimize}} & \mathbf{E}_v \left[f\left(\gamma_t, \lambda_{t,v}, \mathcal{P}_t\right)\right] \\ & \text{subject to} \\ & -\gamma_t \text{ satisfies contract terms} \\ & -P_{t,w} \text{ is the optimal power request} \\ & \text{of the fleet in front of price } \gamma_t \text{ and} \\ & \text{scenario } w \end{array} \tag{3}$$

$f\left(\gamma_t, \lambda_{t,v}, \mathcal{P}_t\right)$ 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, peak demand reduction or congestion control.

If the objective function of the aggregator is profit maximization,

$$f\left(\gamma_t, \lambda_{t,v}, \mathcal{P}_t\right) = \sum_t (\gamma_t - \lambda_{t,v})\delta\mathcal{P}_t, \tag{4}$$

Then, the problem faced by the aggregator becomes,

$$
\begin{aligned}
\underset{\Phi^U}{\text{minimize}} \quad & \mathbf{E}_v\left[f\left(\gamma_t, \lambda_{t,v}, \mathcal{P}_t\right)\right] \\
\text{subject to} \quad & \underline{\gamma} \leq \gamma_t \leq \overline{\gamma} \quad \forall t \\
& \frac{1}{nt}\sum_t \gamma_t = \hat{\gamma} \\
& |\gamma_t - \gamma_{t-1}| \leq \Delta \\
& \mathcal{P}_t = \mathbf{E}_w[P_{t,w}] \\
& \quad P_{t,w} = \arg\min_{\Phi^L_w} \quad \sum_t \gamma_t P_{t,w} \quad \forall w \\
& \qquad\qquad \text{subject to} \quad \text{constraints (1)}
\end{aligned}
\tag{5}
$$

where $\Phi^U = \{\gamma_t\}$ and $\Phi^L_w = \left\{E^S_{t,w}, P_{t,w}\right\}$. Constraints of the upper-level ensure that the demand price is enclosed between $\underline{\gamma}$ and $\overline{\gamma}$, and also they enforce 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 (5) has two random variables 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 [42].

The problem faced by the aggregator in eq. (5) is a non-linear stochastic bi-level optimization problem that cannot be solved efficiently by computational algorithms. The equivalent single-level MILP formulation of the nonlinear MPEC problem is the following:

$$
\begin{aligned}
\underset{\Phi^{DP}}{\text{maximize}} \quad & \sum_v \sum_w \pi(w,v)[\sum_t (\alpha_{t,w} E^t_{t,w} - \mu^a_{t,w}\overline{E^S_t} + \mu^b_{t,w}\underline{E^S_t} \\
& - \mu^c_{t,w}\overline{P_t} - \lambda_{t,v} P_{t,w}) - \alpha_{1,w} E^0_w] \\
\text{subject to} \quad & \underline{\gamma} \leq \gamma_t \leq \overline{\gamma} \quad \forall t \\
& \frac{1}{nt}\sum_t \gamma_t = \hat{\gamma} \\
& |\gamma_t - \gamma_{t-1}| \leq \Delta \\
& \text{constraints (1)},\ (7a) - (7d),\ \text{and (8)}.
\end{aligned}
\tag{6}
$$

being
$\Phi^{DP} = \{E^S_{t,w}, P_{t,w}, \gamma_t, \alpha_{t,w}, \mu^a_{t,w}, \mu^b_{t,w}, \mu^c_{t,w}, z^a_{t,w},\ z^b_{t,w}, z^c_{t,w}, X_{t,w}\}$. In addition, the expected value in (5) is changed by the summation on $\pi(w,v)$, which means the probability of occurrence of each demand scenario w and each spot price scenario v. A scenario tree can be used to capture the uncertainties in the model.

3.3 MILP problem formulatin

The lower-level optimization problem in (5), i.e. consumer decisions, are changed by their Karush–Kuhn–Tucker optimality conditions, [43, 35]. 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,

$$\gamma_t - \eta\delta\alpha_{t,w} + \mu^c_{t,w} = 0 \quad \forall t, w \tag{7a}$$

$$\alpha_{t,w} - \alpha_{t+1,w} + \mu^a_{t,w} - \mu^b_{t,w} = 0 \quad \forall t < nt, w \tag{7b}$$

$$\alpha_{t,w} + \mu^a_{t,w} - \mu^b_{t,w} = 0 \quad \forall t = nt, w \tag{7c}$$

$$\mu^a_{t,w},\ \mu^b_{t,w},\ \mu^c_{t,w} \geq 0 \quad \forall t, w \tag{7d}$$

$$(E^S_{t,w} - \overline{E^S_t})\mu^a_{t,w} = 0 \quad \forall t, w \tag{7e}$$

$$(\underline{E^S_t} - E^S_{t,w})\mu^b_{t,w} = 0 \quad \forall t, w \tag{7f}$$

$$(P_{t,w} - \overline{P_t})\mu^c_{t,w} = 0 \quad \forall t, w \tag{7g}$$

Products of Lagrange multipliers and constrained continuous functions in the complementary slackness conditions, i.e, expressions (7e)-(7g), are equivalently replaced by linear equations through Fortuny-Amat transformation [44], similar to [35]. Then, (7e)-(7g) can be substituted by the following constraints.

$$\begin{aligned}
-(E^S_{t,w} - \overline{E^S_t}) &\leq M(1 - z^a_{t,w}) \quad \forall t, w \\
\mu^a_{t,w} &\leq M z^a_{t,w} \quad \forall t, w \\
-(\underline{E^S_t} - E^S_{t,w}) &\leq M(1 - z^b_{t,w}) \quad \forall t, w \\
\mu^b_{t,w} &\leq M z^b_{t,w} \quad \forall t, w \\
-(P_{t,w} - \overline{P_t}) &\leq M(1 - z^c_{t,w}) \quad \forall t, w \\
\mu^c_{t,w} &\leq M z^c_{t,w} \quad \forall t, w \\
z^a_{t,w}, z^b_{t,w}, z^a_{t,w} &\in \{0, 1\}
\end{aligned} \tag{8}$$

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

$$\begin{aligned}
\sum_t \gamma_t P_{t,w} = \sum_t [\alpha_{t,w} E^t_{t,w} - \mu^a_{t,w}\overline{E^S_t} + \mu^b_{t,w}\underline{E^S_t} - \mu^c_{t,w}\overline{P_t}] \\
- \alpha_{1,w} E^0_w
\end{aligned} \tag{9}$$

where E^0_w is the initial condition of stored energy in the EV fleet. Expression (9) can be replaced in the objective function of problem (5). Finally, the resulting optimization problem is stated in (6).

4 Simulated Case Study

In this section, a simulated case study is presented to illustrate the proposed model to control an EV fleet energy demand by means of 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 performed for a planning horizon of 24 h divided into hourly time steps.

Number of EVs	1000
Capacity of each EV	12 kWh
Maximum charging power of each EV	3 kW
Charging efficiency	90%
Initial condition of EV fleet	2000 kWh

Table 1: Data of EV.

For car-sharing activities, it is expected that the most frequent trips are relatively short ones and the main activity is during the night or weekend, when the availability of public transport is reduced. During workdays, the number of trips is shortened due to the fact that most people are at work. In practice, hourly energy consumption is below 1 kWh for each vehicle. Fig 4 presents the statistics of energy spent by the EV fleet in a day with the previous characteristics, corresponding to the the first semester of 2018. 20 scenarios with the same probability of occurrence are considered to evaluate the proposed model. The scenarios have been selected randomly from the data set.

Concerning the uncertainty faced by the aggregator when buying energy in the spot market, 3 different spot prices 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 [35]. The price signals $\lambda_{t,v}$ are shown in Fig. 5 and vary from €0.1/kWh to €0.39/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.

For this simulation, 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 $\underline{\gamma} = \hat{\gamma} - \hat{\gamma}(0.3)$. the maximum hourly price change is limited to $\Delta = 0.2(\overline{\gamma} - \underline{\gamma})$. From the above, the aggregator problem is how to define 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 (6) that results from the bi-level program (5) is solved using *FICO Xpress-Optimizer v29.01.10* under *Julia 0.6.4* on a Windows-based personal computer. 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 5 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 €0.057/kWh, Then, between hours 11 to 12 the price lowers to €0.051/kWh, later at hours 13 to 21 the price is €0.045/kWh and finally, a price of €0.039/kWh is fixed for hours 22 to 24.

Fig. 6 shows a envelope plot of the charging power for the considered scenarios, given the price policy. Note that the fleet is incentivized to charge during the first (early) hours, between hours 13 and 14 and after hour 21, when the spot price is low. Fig. 7 shows a envelope plot of the energy stored by the fleet. It can be seen that after the first 6 hours, when the fleet acquires energy to respect the lower SoC limit, the stored energy oscillates, rising when the price is low.

The expected profit for each pricing program is summarized in Table 2. Results with uncertainty in the spot prices and also assuming known day-ahead prices are evaluated. The aggregator attains greater profit by employing the proposed TOU contract than using a fixed price for all the scenarios. For this simulation, the proposed model represents a profit improvement of 15.6%. Nevertheless, this result can be improved by modifying the agreed parameters (Δ,$\hat{\gamma}$, $\overline{\gamma}$ 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.

Program	Fixed price (€)	Dynamic pricing (€)
Expected profit	160.51	185.56
spot1	345.31	375.22
spot2	275.77	299
spot3	283.13	318.75

Table 2: Expected profit.

5 Conclusions

This article proposed an algorithm for optimal pricing decisions through a gamification strategy. This algorithm is suitable for fleet managers of electric vehicles in order to obtain optimal prices that maximize their profit, while at the same time inducing behaviour on drivers, in order to reduce the impact on distribution networks. The problem has been addressed using an MPEC programming algorithm, since the relationship between agents has a hierarchical structure that belongs to the so-called Stackelberg (or leader-follower) games. The formulation allows to link the decisions of the electric vehicle fleet, modeled as a cluster (a virtual battery), and the objectives of the aggregator to determine the optimal price signals and load patterns. As a result, in the case of TOUs, the EV fleet operator, while By maximising its profits, it gives owners of electric vehicles a price incentive to shift their demand for electric charging to periods when the aggregator can obtain better benefits than under a fixed price contract.

The proposed model does not require the derivation of utility functions or price elasticity parameters from electric vehicle owners. On the contrary, the behaviour of the electric vehicle fleet is represented as a dynamic model of a virtual battery with a stochastic energy demand, characterised by a series of energy consumption scenarios that can be estimated from electric vehicle usage data not linked to the owner's economic decisions.

Future extensions of this research may move in different directions. The formulation may include other applications such as support for auxiliary services or balancing markets. In addition, the model can be extended by adding network constraints to model the demand for electric vehicle charging stations.

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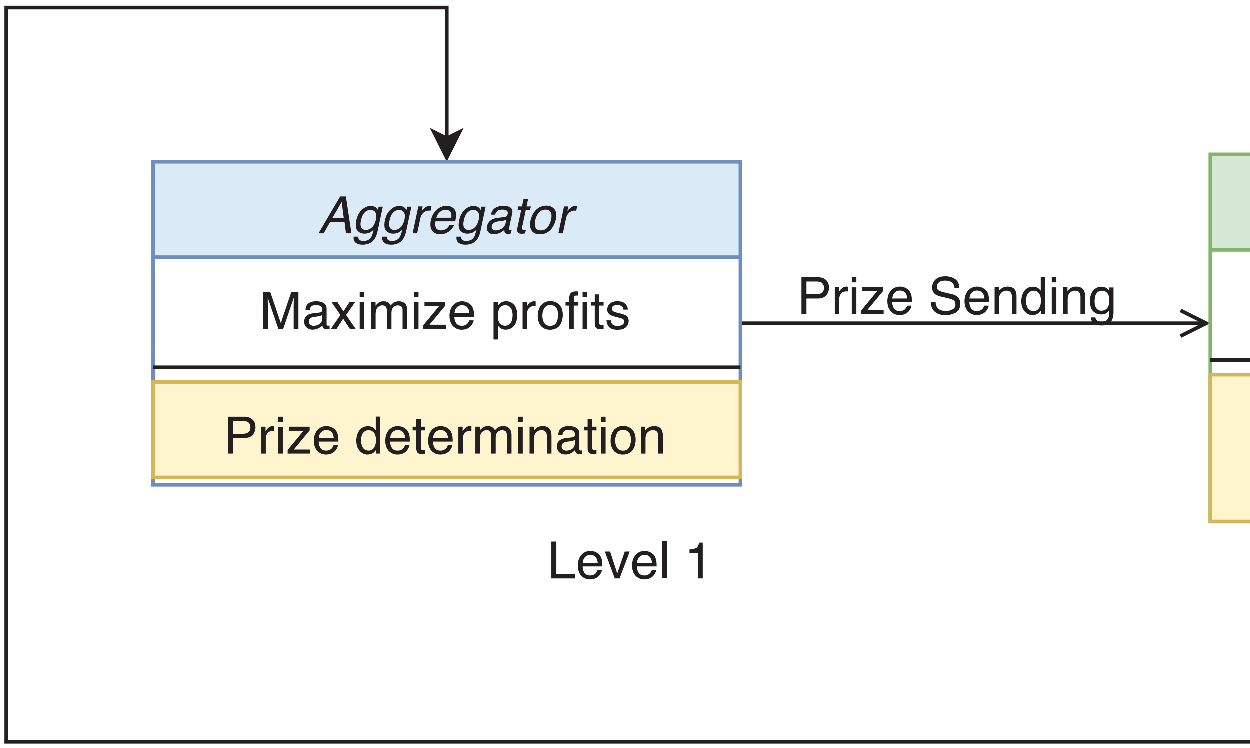

Figure 2: Main features of the proposed bi-level model.

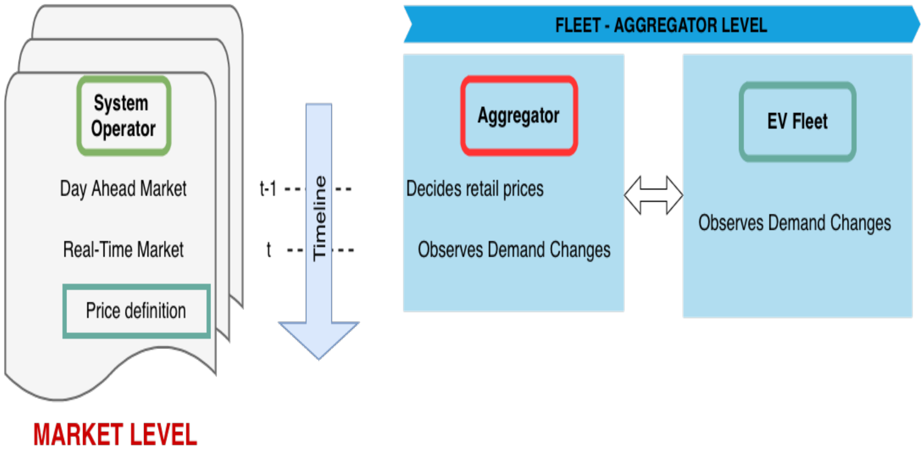

Figure 3: Decision-making process of the market agents.

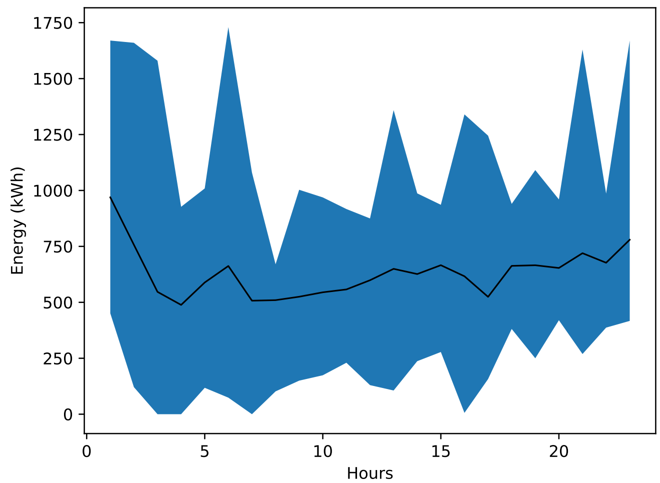

Figure 4: Energy demand for 1000 EV from car-sharing service in Italy.

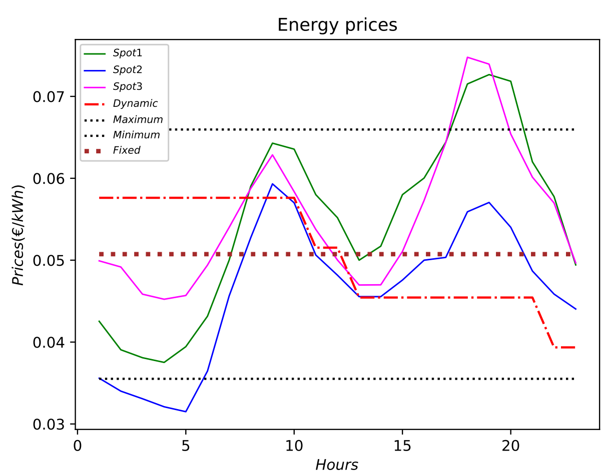

Figure 5: Considered energy prices.

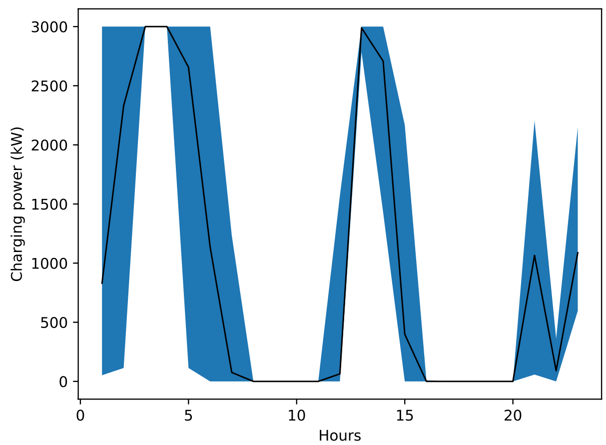

Figure 6: A envelope plot of EV Charging power considering all scenarios.

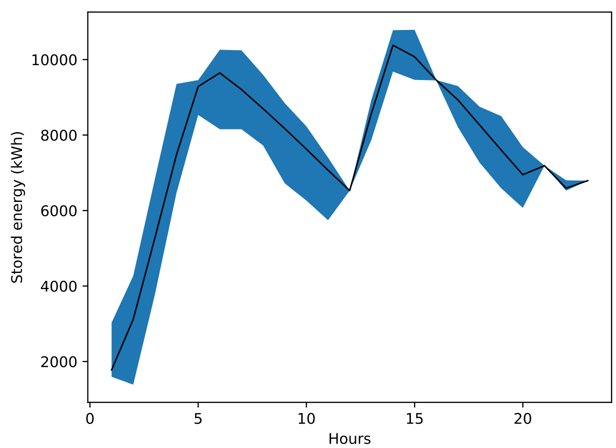

Figure 7: A envelope plot of EV stored energy considering all scenarios.