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Optimal scheduling of ancillary services provided by an electric vehicle aggregator

S. de la Torre [a,*], J.A. Aguado [a], E. Sauma [b]

[a] Escuela de Ingenierías Industriales, Universidad de Málaga, Spain
[b] Millennium Institute on Green Ammonia as Energy Vector (MIGA), Engineering School, Pontificia Universidad Católica de Chile, Chile

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ABSTRACT

Massification of Electric vehicles (EVs) is becoming a worldwide reality as a means to combat climate change and local pollution. Considering that most of the time vehicles are in parking places, there is an opportunity for using EVs to provide some valuable services to the power network. In particular, EVs can provide ancillary services in electricity markets through an aggregating agent. To this end, EVs aggregators need to develop decision support tools to optimally allocate energy and regulation resources considering power network constraints. Unlike optimization models for EVs aggregators currently available in the literature, in this paper we propose an optimization approach for EVs aggregators that jointly considers the most important aspects influencing EVs profitability, such as uncertainty, drivers' patterns, capacity constraints, state of charge constraints, regulation demand constraints, regulation offer constraints, regulation bounds constraints, and power-system security constraints. The optimization problem is formulated as a mixed-integer linear programming problem, thus ensuring global optimality. Results are presented in the form of the hourly allocation for charging/discharging power profiles, distinguishing between day-ahead energy and capacity/energy for regulation, and the profit that can be reached, while accounting for network constraints.

The proposed model is illustrated through a case study, which allows us to show that EVs aggregators allow for leading to a more reliable power system operation, avoiding transmission lines congestion, while providing important profits for EV owners who are able to provide regulation services.

1. Introduction

The transportation sector is responsible for more than one fourth of the total greenhouse gas (GHG) emissions worldwide [1]. This fact has motivated the massification of Electric Vehicles (EVs) to combat climate change and local pollution, which entails significant power system investments to support the needed charging infrastructure [1]. However, for most cases, the majority of the time these vehicles are located in parking places. Accordingly, there is an opportunity for using EVs to provide some valuable services to the power network. In particular, with the large penetration of variable renewable energy (mainly wind and solar) present in current power systems, there is a growing need for power flexibility in grids, which can be provided by batteries in EVs. However, to have the significant amount of power flexibility that the power system needs, it is necessary to aggregate many EV batteries. Thus, EVs can provide these flexibility or ancillary services in electricity markets through an aggregating agent.

Roughly speaking, aggregators schedule EV charging at the lowest possible cost while guaranteeing the minimum energy requirement profiles; that is, they have to guarantee that EVs users have enough energy in their batteries to perform their daily journeys. They also have to comply with technical constraints imposed by the system operator, avoiding, whenever possible, line congestion or undesirable voltage level variations. In addition, they can use EVs as energy backup devices, supplying energy to the grid, taking advantage of Vehicle-to-Grid (V2G) technology. In this sense, EVs can obtain additional revenue and can help the electric power system by supporting the integration of renewable energy sources or by providing peak power, frequency regulation and/or spinning reserve [2–13]. All of these ancillary services and other additional services are covered in this work under the general terms "regulation" or "secondary regulation"; distinguishing between the availability to provide a certain service (capacity) and the actual realization of the service (effective energy).

Unidirectional regulation, that is, the provision of regulation services making use of only EV charging capability is studied in [14]. The authors develop a deterministic optimization model aiming at maximizing aggregator profit including the concept of preferred operation point

* Corresponding author.
E-mail address: storre@uma.es (S. de la Torre).

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Acronyms

Electric Vehicle (EV), State of Charge (SOC), Vehicle-to-Grid (V2G).

Notation

Sets

Ω_{eg}	Set of all scenarios considered to account for EVs charging/discharging time uncertainty (EV group scenarios).
Ω_{ep}	Set of all scenarios designed to account for the uncertainty in the prices of energy, regulation capacity, and effective regulation.
Ω_n	Set of nodes in the network.
Ω_t	Set of all periods in the time horizon under study.
Ω_v	Set of all EV groups considered.

Indices

eg	EV group scenarios.
ep	Energy price and regulation capacity scenarios.
n, m	Grid nodes.
t	Time periods.
v	EV groups.

Parameters

AB_v^{eg}	Aggregated value of the EV battery capacities for group v and scenario eg [MWh].
$B^{n,m}$	Susceptance of line $n-m$ [S].
$CC_{v,t}^{eg}$	SOC requirement for EV group v, scenario eg and time period t [MWh].
$EC_{v,t}^{eg}$	Aggregated consumption for EV group v, scenario eg and time period t in journeys [MWh].
$H_{v,t,n}^{eg}$	Binary values parameter that equals 1 when EV group v is connected for scenario eg, time period t and node n and zero in other case.
M_e, M_r, M_b, M_d, M_u	Large enough scalars used in several "Big M" equations through the formulation; in general, these values will be different.
$P_{max}^{n,m}$	Power flow limit for the line that connects nodes n and m [MW].
$P_{t,n}^G, P_{t,n}^D$	Hourly generated power/load in system nodes [MW].
$\overline{P}_v^{eg}, \underline{P}_v^{eg}$	Upper limit for charging/discharging defined for EV group v and scenario eg [MW].
SM_v^{eg}	Minimum SOC for group v and group scenario eg [MWh].
$\lambda_{t,ep}^{EN-D}, \lambda_{t,ep}^{EN-C}$	Energy price for charging/discharging for scenario ep and time period t [€/MWh].
$\lambda_{t,ep}^{RC-D}, \lambda_{t,ep}^{RC-U}$	Price at which the availability for downward/upward regulation is paid for scenario ep and time period t [€/MWh].
$\lambda_{t,ep}^{ER-D}, \lambda_{t,ep}^{ER-U}$	Price at which the effective downward/upward regulation is paid for scenario ep and time period t [€/MWh].
η_C, η_D	EV charging/discharging efficiency.
ω^{eg}	Probability associated to scenario eg in Ω_{eg}.
ω^{ep}	Probability associated to scenario ep in Ω_{ep}.

Variables

$BD_{v,t,n}^{eg,ep}, BU_{v,t,n}^{eg,ep}, BE_{v,t,n}^{eg,ep}$	Auxiliary variables for downward/upward/effective regulation availability/charging and discharging.
$CE_{v,t,n}^{eg,ep}, DE_{v,t,n}^{eg,ep}$	Energy withdrawn/supplied by the EVs from/to the grid for EV group v, time period t, in node n, and scenarios eg and ep [MWh].
$DNREG_{v,t,n}^{eg,ep}, UPREG_{v,t,n}^{eg,ep}$	Downward/upward maximum regulation availability for EV group v, time period t and scenarios eg and ep [MW].
DR_t, UR_t	Downward/upward regulation EV aggregator capacity offered at time period t [MW].
$DRE_{v,t,n}^{eg,ep}, URE_{v,t,n}^{eg,ep}$	Energy from effective downward/upward regulation for group v, time period t, node n and scenarios eg and ep [MWh].
P_{EN}	Profit obtained in the Energy market [€]
P_{ER}	Profit obtained in the Effective Regulation market [€].
P_{RC}	Profit obtained in the Regulation capacity market [€].
$P_{t,n}^{EV}$	EV power contribution at node n and time period t [MW].
$P_t^{n,m}$	Hourly power flow in line $n-m$ [MW].
P_t^S	Hourly power injected in the slack bus [MW].
$SOC_{v,t}^{eg,ep}$	EVs aggregated SOC for EV group v, time period t and scenarios eg and ep [MWh].
$SOCDR_{v,t}^{eg,ep}, SOCUR_{v,t}^{eg,ep}$	EVs aggregated SOC limit for EV group v, time period t and scenarios eg and ep for downward/upward regulation [MWh].
$SOCEE_{v,t}^{eg,ep}$	EVs aggregated SOC for EV group v, time period t and scenarios eg and ep for effective regulation [MWh].
θ_t^n	Phase of the node voltage n at time period t [rad].

Binary Variables

$\rho_{v,t,n,1}^{eg,ep}, \rho_{v,t,n,2}^{eg,ep}$	Binary variables for effective regulation charging and discharging and daily market.
$\rho_{v,t,n,3}^{eg,ep}, \rho_{v,t,n,4}^{eg,ep}, \rho_{v,t,n,5}^{eg,ep}$	Binary variables for timely evolution equations of the SOC.

Positive variables

The following variables may only take values equal to or greater than zero.

$BD_{v,t,n}^{eg,ep,+}, BD_{v,t,n}^{eg,ep,-}$	Auxiliary positive variables for downward regulation availability.

and also determining it through optimization and heuristics models and comparing the different approaches. The same authors extend their model [15] considering spinning reserve and unplanned EV departures.

In [16], an optimal strategy for EV aggregators is developed, but only controlling the EV charging scheme to provide regulation. In [17], a linear programming model is proposed in order to maximize the EV

$BE_{v,t,n}^{eg,ep,+}$, $BE_{v,t,n}^{eg,ep,-}$	Auxiliary positive variables for effective regulation charging and discharging.
$BU_{v,t,n}^{eg,ep,+}$, $BU_{v,t,n}^{eg,ep,-}$	Auxiliary positive variables for upward regulation availability.

aggregator revenues obtained from the provision of regulation services, subject to the constraint of achieving a target EV State of Charge (SOC), controlling only the charging sequence. None of these works, however, consider the impacts of network constraints.

A co-optimization approach is presented in [18], which considers, on the one hand, an optimal power flow that avoids line congestion and schedules EV charging giving enough flexibility for regulation and, on the other hand, a decentralized real-time dispatch of the automatic generation control signal. It is proved that an optimal EV SOC can be established to comply with a contracted capacity regulation and that it is possible to achieve high response accuracy to the regulation signal. In [19], the authors determine optimum aggregation areas for a given network configuration that can be used for EV aggregators and system operators to take decisions regarding regulation and line congestion issues. The model features a low computation effort and it is proved in base and future case scenarios illustrating some effectiveness in terms of voltage and load loss control. Although these approaches model network constraints, they do not consider uncertainties.

In [20], a model based on stochastic optimization of EV charging and frequency regulation is proposed considering the uncertainty associated to the hourly energy and regulation prices as well as the regulation signal. Results are compared against deterministic model predictive problems giving a reduction in EV charging costs. Several works have also been presented taking into account the participation of the EV aggregators in electricity markets. In [21], generation, EV charging, reserve and regulation are considered. A market clearing procedure without security constraints is proposed along with a real-time operation to deploy reserves with renewable generation forecasting. A day-ahead optimization model is proposed to determine energy and secondary reserves bids minimizing total costs in [22] considering payments for both capacity and energy from regulation. Other strategies considering bidding EV regulation through optimization have been proposed in [10,11,23,24]. In [12], a two-level optimization algorithm for EVs is proposed to determine optimal operation strategies of EV aggregators and the charging power of each individual EV considering the participation in ancillary service markets. The authors in [13] propose a control strategy to operate at fast time-steps which allows EV aggregators maximize capacity payments from ancillary service markets. In [25], the authors highlight that the size of the EV fleet is also a key factor to assess the profitability of V2G schemes. This is because large fleets of EVs are generally needed to significantly impact the electricity demand curve. Drivers' consumption patterns are not considered in any of those works.

As a summary of the literature review, it is worth mentioning that (i) only the authors in [18] consider the characteristics of the grid and the possibility of line congestion, (ii) only in [22] the effective charging from regulation, including their economic terms in the objective function, is taken into account in contrast to other works like [14,15,21,23,24], (iii) bidirectional regulation (that is, the energy injection from EVs to the grid) is not included in [16,20,22,26], and (iv) none of the cited works jointly consider uncertainty in prices, power system operation impacts, and driving patterns.

In this paper, we propose a detailed model for the problem faced by EV aggregators to assess their participation in electricity markets for regulation services, while jointly considering the most important aspects influencing EVs profitability, such as uncertainty, drivers' patterns, capacity constraints, state of charge constraints, regulation demand constraints, regulation offer constraints, regulation bounds constraints, and power system security constraints. To the best of our knowledge, such a comprehensive model has not been addressed in any similar way in the literature.

Our model presents the following features:

- The aggregator manages a fleet of EVs.
- The aggregator participates in energy markets in order to buy the energy that the EVs need to satisfy their mobility constraints.
- The aggregator may also participate in energy markets in order to sell excess energy, using V2G capabilities.
- The aggregator participates in a secondary regulation market, wherein it receives payments for both capacity offered and effective charging and discharging performed.
- The electric power system is modelled in detail, implementing the power flow equations (a DC-power flow model is used, implementing Kirchhoff's Laws), among other technical constraints.
- The uncertainty associated with day-ahead energy prices is considered via scenarios.

The proposed model is a mixed-integer linear program aiming at maximizing EV aggregator benefit. It allows an EV aggregator to know which are the most suitable time periods to perform regulation and purchase/sell energy from the daily market. In addition, the EV aggregator can foresee which nodes can be problematic from the point of view of system reliability, helping the system operator.

Accordingly, the EV aggregator problem is solved jointly considering the energy market for EV charging/discharging and the regulation market for energy and capacity, in contrast to other approaches that consider either only one of them or both separately. In this sense, it is possible to reach an optimal result that avoids forcing batteries to reach their energy limits. However, this approach requires to predict at the first step all the parameters that include uncertainty, losing some accuracy due to the further time gap for the estimation.

On the other hand, none of the works mentioned in the literature review consider battery ageing effects. This is one of the major challenges to be overcome with respect to the regulation provision, specially when V2G effective discharging is used. Despite the economical barriers related to this issue, it has not been solved yet. The scientific community and practitioners agree that the discharging process significantly affects battery life and performance [27–31]. Although a comprehensive analysis related to battery use is out of the scope of this work, some results are provided to estimate this effect, once the solution is obtained. Our study shows that, as pointed out by some authors [32], it is imperative to overcome the issues related to the battery degradation when full charge/discharge cycles take place.

The main contributions of this paper can be summarized as follows:

- Development of a comprehensive tool, based on stochastic optimization, that may be used by an EV aggregator to jointly schedule energy and capacity/energy for regulation markets taking into account the most relevant power system constraints.
- Development of a tool that also allows EV aggregators to assess their participation in electricity markets through the determination of the most suitable time periods to bid and the prediction of the nodes that can lead to line congestion.
- Development of a simple scenario-based methodology that simultaneously includes the uncertainty associated to energy and regulation prices and driving patterns.

The rest of the paper is organized as follows. Section 2 describes the scenario-based approach employed to model the uncertainty associated to both energy and regulation prices and EV driving patterns and the full optimization model. An illustrative case study is presented in Section 3, whose results are discussed in Section 4. Finally, Section 5 concludes the paper.

2. Optimization problem formulation

In this section, an optimization problem is formulated in order to properly model the rational behaviour of an EV aggregator company facing different markets and operating within an stochastic environment. This optimization problem comprises a detailed objective function and a set of constraints.

2.1. Uncertainty modelling

To model the uncertainty associated to EV driving patterns and market prices, a simple scenario-based approach is considered on this work.

A set of different scenarios, Ω_{ep}, is selected to account for the stochasticity in the price vector. The prices considered are: buy/sell energy, up/down regulation capacity and up/down effective regulation. More specifically, for the purpose of this work, hourly price curves for EV charging and discharging have been used. Prices for capacity regulation have been similarly assumed, although capacity prices for upward and downward regulation have been chosen to be equal, (this condition could easily be relaxed); effective energy regulation prices for up and down regulation are different and also depend on the time of the day.

In this work, vehicles that have similar behaviour are grouped together, hence avoiding the burden of modelling individual EVs; for each case we consider, we have several groups of vehicles that we can track. Naturally, another set of scenarios, Ω_{eg}, is taken into account for the different possible configurations of the EV groups. The EVs considered in this work are all identical, with a battery capacity of 20 kWh and a maximum power for charging/discharging of 3.7 kW. The scenarios used for EV groups take into account the facts that the number of cars in a group may change and also that the paths taken by the vehicles during the day may change, as a consequence, the total energy needs of a group of vehicles are different from scenario to scenario. More details on the selections of scenarios are presented in the case study section of the paper. Note that, for realistic case studies, this information may be obtained from mobility surveys that some authorities carry out, and that include a range of different questions to the users of roads and transportation facilities in general; the questions asked may include origin and destination of their trips, routes selected, time allotted, etc.

The scenarios in Ω_{ep} are chosen to be equiprobable. Analogously, the scenarios in Ω_{eg} are considered equiprobable.

2.2. Objective function

The objective function maximizes the profit earned by the EV aggregator as a result of its participation in all three above mentioned market mechanisms (energy exchange, regulation capacity and effective regulation). The total profit maximization can be formulated as:

$$\text{maximize} \ \ \{P_{EN} + P_{RC} + P_{ER}\} \tag{1}$$

$$P_{EN} = \sum_{(v,t,n)} \sum_{(eg,ep)} \omega^{eg} \cdot \omega^{ep} \cdot (\lambda_{t,ep}^{EN-D} \cdot DE_{v,t,n}^{eg,ep} - \lambda_{t,ep}^{EN-C} \cdot CE_{v,t,n}^{eg,ep}) \tag{2}$$

$$P_{RC} = \sum_{t} \sum_{ep} \omega^{ep} \cdot (\lambda_{t,ep}^{RC-D} \cdot DR_t + \lambda_{t,ep}^{RC-U} \cdot UR_t) \tag{3}$$

$$P_{ER} = \sum_{(v,t,n)} \sum_{(eg,ep)} \omega^{eg} \cdot \omega^{ep} \cdot (\lambda_{t,ep}^{ER-D} \cdot DRE_{v,t,n}^{eg,ep} + \lambda_{t,ep}^{ER-U} \cdot URE_{v,t,n}^{eg,ep}) \tag{4}$$

The objective function presented in (1), comprises three terms, described below:

- In (2), P_{EN} represents the profit obtained from energy exchanges, computed as the difference between the income from EV discharging (V2G) and the costs of EV charging. Note that this is computed taking into account the different prices for the energy exchange; in general, these prices are different for each hour and scenario. Also note that this term may be a positive or a negative amount. DE and CE refer to the traded energy in the hourly spot market.
- In (3), P_{RC} computes the income obtained from EV regulation capacity. The prices offered for both UP and DOWN regulation capacity are included. It is important to highlight that the offers in this market are made for a total amount of energy for each time period, but no specific node or specific vehicle group is declared when presenting the offer. Moreover, the offers are made before having information on which price and EV scenarios will end up taking place, so the offers must be valid for any price or vehicle scenarios (note that variables DR_t and UR_t only have one subindex). This term can only be a positive amount.
- In (4), P_{ER} is the income related to *effective* energy charging/discharging, resulting from the participation in the regulation system. Note that, though the offers to the regulation capacity market discussed in the previous point are aggregated, the effective energy generated or consumed for regulation purposes has to be computed for each node, EV group and scenario. This term can only be a positive amount. DRE and URE refer to the traded energy in the secondary regulation market.

In the equations above, each term is obtained by multiplying the specific price by the corresponding energy or power variable related to charging, discharging or capacity and multiplied also by the weight of the considered scenarios. Also, note that the 6 main variables in the formulation are the ones included in (2)–(4). It is important to notice that the variables in Eqs. (2) and (4) may take a different value for each scenario, whereas the variables in (3) take a single value for each hour; the explanation is that the variables in (3) are offers made to a regulation capacity market and have to be the same regardless of the scenario finally taking place. On the other hand, the rest of the main variables represent that the decisions can adapt to the specific scenario that takes place.

The EV aggregator regulation optimization problem formulation is completed with the constraints introduced in the following subsections.

2.3. State of charge constraints

Firstly, it is important to remark that, in the present formulation, EVs are never considered individually; all the EVs that form an EV group are aggregated together, and all its energy and power exchanges are considered in an aggregated manner. For each aggregated battery in each scenario, its SOC must be computed for each hour: $SOC_{v,t}^{eg,ep}$. The following upper and lower limits must be imposed on the value of SOC variables.

$$SOC_{v,t}^{eg,ep} \le AB_v^{eg} \quad \forall eg, \forall ep, \forall v, \forall t \tag{5}$$

$$SOC_{v,t}^{eg,ep} \ge SM_v^{eg} \quad \forall eg, \forall ep, \forall v, \forall t \tag{6}$$

$$SOC_{v,t}^{eg,ep} \ge CC_{v,t}^{eg} \quad \forall eg, \forall ep, \forall v, \forall t \tag{7}$$

Eqs. (5)–(7) guarantee that SOC lies between its lower and its upper bounds. These bounds are imposed by the battery capacity (AB), (5); the technical operational minimum SOC for the batteries (SM), (6) and the energy requirements of the users (CC), (6). Note that the third of these terms may be different for each hour, reflecting the needs of the users.

The hourly tracking of the SOC takes into account the charging and discharging actions, including their efficiencies and the battery energy consumption in journeys. It is expressed as follows:

$$SOC_{v,t}^{eg,ep} = SOC_{v,t-1}^{eg,ep} + \eta_C \cdot \sum_n CE_{v,t,n}^{eg,ep} - (1/\eta_D) \cdot \sum_n DE_{v,t,n}^{eg,ep} - EC_{v,t}^{eg} \tag{8}$$

$\forall eg, \forall ep, \forall v, \forall t$

Note that a full set of constraints is imposed for each scenario.

2.4. Effective regulation constraints

Note that in Eq. (8) only the variables related to the energy market are used (charging and discharging). However, in practice, effective regulation must also be considered; hence an additional set of constraints and variables need to be imposed. Note that the first set of constraints is kept for consistency, as the regulation markets are still uncertain in a real market at the moment of deciding the charging and discharging profile for the day.

Additional variables and constraints needed to implement this model are presented next. Firstly, the actual total energy exchange made by each battery at each node at each time period and for each scenario, $BE_{v,t,n}$, is defined as:

$$BE^{eg,ep}_{v,t,n} = CE^{eg,ep}_{v,t,n} + DRE^{eg,ep}_{v,t,n} - DE^{eg,ep}_{v,t,n} - URE^{eg,ep}_{v,t,n} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{9}$$

Variable $BE^{eg,ep}_{v,t,n}$ computes the net energy exchange seen from the battery, considering both the charging (CE) and discharging (DE) operations and the effective regulation exchange, either up (URE) or down (DRE). Note that this value may be either positive or negative. In our formulation, in order to be able to correctly consider the efficiency of the charging and discharging process, this variable must be decomposed into two positive terms as follows[1]:

$$BE^{eg,ep}_{v,t,n} = BE^{eg,ep,+}_{v,t,n} - BE^{eg,ep,-}_{v,t,n} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{10}$$

As previously mentioned, a new set of constraints must be now imposed regarding the energy exchange variables once effective regulation is included, to that end, a new variable, $SOCEE$, is defined. This variable plays the same role as SOC but including the effective regulation results.

$$SOCEE^{eg,ep}_{v,t} = SOCEE^{eg,ep}_{v,t-1} + \eta_C \cdot \sum_n BE^{eg,ep,+}_{v,t,n} - (1/\eta_D) \cdot \sum_n BE^{eg,ep,-}_{v,t,n} - EC^{eg}_{v,t} \tag{11}$$

$\forall eg, \forall ep, \forall v, \forall t$

Note that new limit constraints have to be imposed:

$$SOCEE^{eg,ep}_{v,t} \le AB^{eg}_{v} \quad \forall eg, \forall ep, \forall v, \forall t \tag{12}$$

$$SOCEE^{eg,ep}_{v,t} \ge SM^{eg}_{v} \quad \forall eg, \forall ep, \forall v, \forall t \tag{13}$$

$$SOCEE^{eg,ep}_{v,t} \ge CC^{eg}_{v,t} \quad \forall eg, \forall ep, \forall v, \forall t \tag{14}$$

2.5. Regulation offers constraints

In a similar fashion, we need to be sure that all the offers presented to the regulation market are feasible and coherent with the schedule proposed for the charging and discharging of the vehicles. However, at the moment of submitting the bids to the regulation markets it is uncertain which ones will be accepted and which ones will not be accepted. Ideally, one would like to have a means of checking all the possible combinations of accepted/not accepted offers to confirm that all combinations result in feasible battery behaviour; this is impossible in our model, as our regulation offers are aggregated through the network and are the same for all the scenarios; but, even if it were possible, the computational burden would be huge, given the combinatorial nature of the problem. So, as an approximation, in our model, we impose constraints related to two opposing worst-case scenario situations, the first one is that we want to make sure that the SOC of the battery is feasible even if only the downward effective regulation variables take effect; the second situation considers that only the upward effective regulation takes place. Note that we use the values of the effective regulation results as a means of checking whether the offers to the regulation market are consistent with the rest of the problem.

Hence, in order to impose limits on the offers to the regulation markets, we must define two new variables:

$$BD^{eg,ep}_{v,t,n} = CE^{eg,ep}_{v,t,n} + DRE^{eg,ep}_{v,t,n} - DE^{eg,ep}_{v,t,n} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{15}$$

$$BU^{eg,ep}_{v,t,n} = CE^{eg,ep}_{v,t,n} - DE^{eg,ep}_{v,t,n} - URE^{eg,ep}_{v,t,n} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{16}$$

Note that this new variables represent, respectively, the energy exchange seen from the battery if all down/up regulation operations are effectively performed, and no up/down regulation takes place.

In our formulation, these variables must also be decomposed into two positive terms as follows:

$$BD^{eg,ep}_{v,t,n} = BD^{eg,ep,+}_{v,t,n} - BD^{eg,ep,-}_{v,t,n} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{17}$$

$$BU^{eg,ep}_{v,t,n} = BU^{eg,ep,+}_{v,t,n} - BU^{eg,ep,-}_{v,t,n} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{18}$$

Using these new variables, new constraints similar to (11) need to be imposed on the auxiliary variables $SOCUR$ and $SOCDR$.

$$SOCDR^{eg,ep}_{v,t} = SOCDR^{eg,ep}_{v,t-1} + \eta_C \cdot \sum_n BD^{eg,ep,+}_{v,t,n} - (1/\eta_D) \cdot \sum_n BD^{eg,ep,-}_{v,t,n} - EC^{eg}_{v,t} \tag{19}$$

$\forall eg, \forall ep, \forall v, \forall t$

$$SOCUR^{eg,ep}_{v,t} = SOCUR^{eg,ep}_{v,t-1} + \eta_C \cdot \sum_n BU^{eg,ep,+}_{v,t,n} - (1/\eta_D) \cdot \sum_n BU^{eg,ep,-}_{v,t,n} - EC^{eg}_{v,t} \tag{20}$$

$\forall eg, \forall ep, \forall v, \forall t$

In this manner, we can assure that the battery state of charge is always within acceptable limits, even without knowing in advance which regulation offers will be accepted. Also, note that, again, new limit constraints have to be imposed:

$$SOCUR^{eg,ep}_{v,t} \le AB^{eg}_{v} \quad \forall eg, \forall ep, \forall v, \forall t \tag{21}$$

$$SOCUR^{eg,ep}_{v,t} \ge SM^{eg}_{v} \quad \forall eg, \forall ep, \forall v, \forall t \tag{22}$$

$$SOCUR^{eg,ep}_{v,t} \ge CC^{eg}_{v,t} \quad \forall eg, \forall ep, \forall v, \forall t \tag{23}$$

$$SOCDR^{eg,ep}_{v,t} \le AB^{eg}_{v} \quad \forall eg, \forall ep, \forall v, \forall t \tag{24}$$

$$SOCDR^{eg,ep}_{v,t} \ge SM^{eg}_{v} \quad \forall eg, \forall ep, \forall v, \forall t \tag{25}$$

$$SOCDR^{eg,ep}_{v,t} \ge CC^{eg}_{v,t} \quad \forall eg, \forall ep, \forall v, \forall t \tag{26}$$

2.6. Integrality constraints

Several constraints relating to integer variables must be imposed in the model. Simultaneous charging and discharging during the same time period, for every EV group, node or scenario, both for energy and regulation is not allowed. These constraints are considered through the corresponding binary variables in Eqs. (27)–(28):

$$0 \le CE^{eg,ep}_{v,t,n} \le \varrho^{eg,ep}_{v,t,n,1} \cdot M_e \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{27}$$

$$0 \le DE^{eg,ep}_{v,t,n} \le (1 - \varrho^{eg,ep}_{v,t,n,1}) \cdot M_e \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{28}$$

Analogous equations must also be stated for the effective regulation energy exchange variables DRE and URE, which must not be different from zero at the same time:

$$0 \le DRE^{eg,ep}_{v,t,n} \le \varrho^{eg,ep}_{v,t,n,2} \cdot M_r \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{29}$$

$$0 \le URE^{eg,ep}_{v,t,n} \le (1 - \varrho^{eg,ep}_{v,t,n,2}) \cdot M_r \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{30}$$

[1] Note that this separation of variables was not needed in Eq. (8), as both CE and DE can never be different from zero at the same time; however, given that we have four terms in (9) it may be possible to have simultaneous values different from zero; for example in CE and URE, and hence, if one were to introduce this terms separately in the $SOCEE$ equation, the amount of "efficiency losses" incurred would be greater than the real values, due to not considering the cancellation effect derived from the real net energy exchange.

Additionally, note that more equations analogous to (27)–(28) must be imposed on $BE\pm$:

$$0 \le BE_{v,t,n}^{eg,ep,+} \le \varrho_{v,t,n,3}^{eg,ep} \cdot M_b \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{31}$$

$$0 \le BE_{v,t,n}^{eg,ep,-} \le (1 - \varrho_{v,t,n,3}^{eg,ep}) \cdot M_b \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{32}$$

Lastly, two more sets of similar equations must be imposed for auxiliary variables $BD+$ and $BD-$, $BU+$ and $BU-$, introduced above.

$$0 \le BD_{v,t,n}^{eg,ep,+} \le \varrho_{v,t,n,4}^{eg,ep} \cdot M_d \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{33}$$

$$0 \le BD_{v,t,n}^{eg,ep,-} \le (1 - \varrho_{v,t,n,4}^{eg,ep}) \cdot M_d \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{34}$$

$$0 \le BU_{v,t,n}^{eg,ep,+} \le \varrho_{v,t,n,5}^{eg,ep} \cdot M_u \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{35}$$

$$0 \le BU_{v,t,n}^{eg,ep,-} \le (1 - \varrho_{v,t,n,5}^{eg,ep}) \cdot M_u \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{36}$$

Note that each of these pairs have their corresponding binary variables $\varrho_{v,t,n,*}^{eg,ep}$ as shown in the notation section.

2.7. Regulation bounds

The capacity that is available for regulation is determined with Eqs. (37)–(40), below.

$$CE_{v,t,n}^{eg,ep} \le H_{v,t,n}^{eg} \cdot \overline{P}_v^{eg} \qquad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{37}$$

$$DE_{v,t,n}^{eg,ep} \le H_{v,t,n}^{eg} \cdot \underline{P}_v^{eg} \qquad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{38}$$

$$CE_{v,t,n}^{eg,ep} - DE_{v,t,n}^{eg,ep} + DNREG_{v,t,n}^{eg,ep} = H_{v,t,n}^{eg} \cdot \overline{P}_v^{eg} \tag{39}$$
$$\forall eg, \forall ep, \forall v, \forall t, \forall n$$

$$DE_{v,t,n}^{eg,ep} - CE_{v,t,n}^{eg,ep} + UPREG_{v,t,n}^{eg,ep} = H_{v,t,n}^{eg} \cdot \underline{P}_v^{eg} \tag{40}$$
$$\forall eg, \forall ep, \forall v, \forall t, \forall n$$

Using these equations the values of the maximum available margin for up/down regulation, $UPREG$ and $DNREG$, are fixed.

Eqs. (37) and (38) state the limits for charging (CE) and discharging (DE) depend on the EV availability H, and the maximum power of the connection point to the grid, $\overline{P}$ and $\underline{P}$. Similarly, Eqs. (39) and (40) compute the upward and downward regulation capacities, as the difference between the real exchange and the respective limits of the exchange.

2.8. Regulation capacity offered

Note that the $UPREG$ and $DNREG$ variables are computed for each vehicle group, for each hour, for each node, for each scenario. However, in our model, offers presented to the regulation capacity market must be aggregated in the form of hourly bids; these bids cover all the network and must be applicable for any scenario that may take place. The values of $UPREG$ and $DNREG$ obtained through the previous equations are used next in order to obtain the bids that can be offered in the regulation capacity market. Considering all the above, a new group of equations must be written:

$$\sum_{(v,n)} DRE_{v,t,n}^{eg,ep} \le DR_t \quad \forall eg, \forall ep, \forall t \tag{41}$$

$$\sum_{(v,n)} URE_{v,t,n}^{eg,ep} \le UR_t \quad \forall eg, \forall ep, \forall t \tag{42}$$

$$DR_t \le \sum_{(v,n)} DNREG_{v,t,n}^{eg,ep} \qquad \forall eg, \forall ep, \forall t, \forall n \tag{43}$$

$$UR_t \le \sum_{(v,n)} UPREG_{v,t,n}^{eg,ep} \qquad \forall eg, \forall ep, \forall t, \forall n \tag{44}$$

Eqs. (41)–(42), state that the effective energy charging and discharging from regulation must be less than the amount offered in the market. Finally, (43)–(44) state that the total energy offered in the regulation market must be less than or equal to the total available regulation capacity.

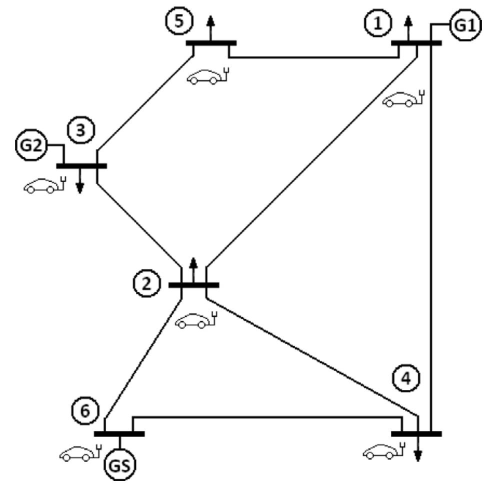

Fig. 1. Garver six-bus system.

Finally, note that a constraint is needed imposing that the amounts of energy accepted in the effective regulation market must always be within the limits previously computed.

$$DRE_{v,t,n}^{eg,ep} \le DNREG_{v,t,n}^{eg,ep} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{45}$$

$$URE_{v,t,n}^{eg,ep} \le UPREG_{v,t,n}^{eg,ep} \quad \forall eg, \forall ep, \forall v, \forall t, \forall n \tag{46}$$

2.9. Power-system security equations

The power flow equations, power-system balance and line technical limits are considered in (47)–(50):

$$P_{t,n}^{EV} = \sum_{v} \sum_{(eg,ep)} \omega^{eg} \cdot \omega^{ep} \cdot (DE_{v,t,n}^{eg,ep} - CE_{v,t,n}^{eg,ep} \tag{47}$$
$$+ URE_{v,t,n}^{eg,ep} - DRE_{v,t,n}^{eg,ep}) \qquad \forall t, \forall n$$

$$P_t^S + \sum_G P_{t,n}^G - \sum_D P_{t,n}^D + P_{t,n}^{EV} + \sum_{n \propto m} P_t^{m,n} = 0 \qquad \forall t, \forall n \tag{48}$$

$$P_t^{n,m} = B^{n,m} \cdot (\theta_t^n - \theta_t^m) \qquad \forall t, n \propto m \tag{49}$$

$$-P_{max}^{n,m} \le P_t^{n,m} \le P_{max}^{n,m} \qquad \forall t, n \propto m \tag{50}$$

Eq. (47) gives the weighted EV power nodal contribution. Eq. (48) assures the system power balance between load and generation. The DC power flow equations are defined in (49). Finally, the line technical limits are expressed in (50).

2.10. Optimization problem formulation

Finally, considering the objective function and all the constraints presented, the full optimization problem is cast as a mixed-integer stochastic programming problem that maximizes EV aggregator profit. This problem comprises Eqs. (1)–(50).

3. Illustrative case study: Problem parameters and input data

In this section, the main input data of the case study are presented. First, the electric power system characteristics are described and, then, the parameters regarding the optimization problem are given.

The system considered in this study is based on the data given in [33]. It is composed of six buses with a configuration of loads and generators given in Fig. 1. The slack bus is assumed to be bus 6. Line parameters and power flow limits are shown in Table 1, considering a 100 MVA base. All lines have 100 MW of active power limit. We assume there are EVs in every bus; these EVs travel from a starting bus to which they come back after travelling thorough some other nodes.

Table 1
Line characteristics.

Line	$R[pu]$ (Ω)	$X[pu]$ (Ω)
1–2	0.10	0.40
1–4	0.15	0.60
1–5	0.05	0.20
2–3	0.05	0.20
2–4	0.10	0.40
2–6	0.08	0.30
3–5	0.05	0.20
4–6	0.08	0.30

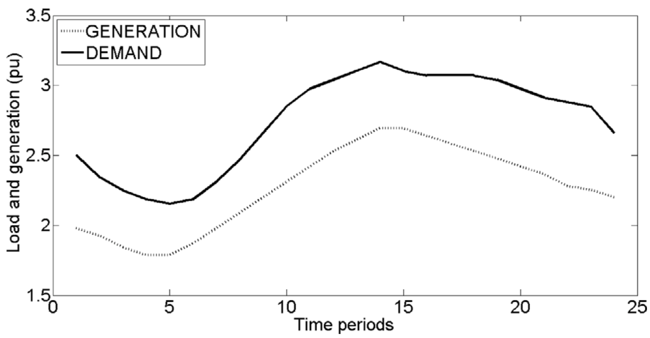

Fig. 2. Aggregated system load and generation.

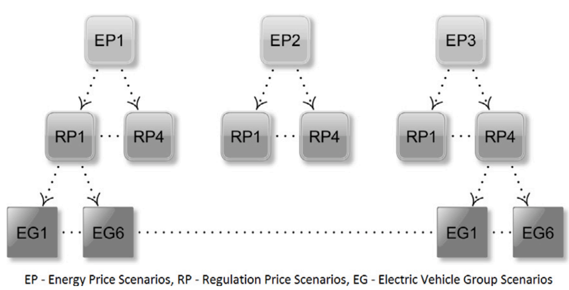

Fig. 3. Scenarios considered in this work.

The network represented in Fig. 1 is a power transmission (high-voltage line) network. The rationale for using a power transmission network is that, although most EV operations occur at the power distribution network level, ancillary services are provided in the wholesale electricity market by aggregators. Thus, since the focus of this work is on studying the potential contribution of EVs to the provision of ancillary services in the wholesale electricity market, a power transmission network is needed to illustrate the potential contribution of EVs to the power flexibility needed by the entire power system. Accordingly, the power transmission network in Fig. 1 aggregates a large amount of EVs in each bus (or node) of the network.

The hourly aggregated loads and power supplied by generators are shown in Fig. 2. The remaining power generation is supplied either by the slack bus or by V2G operations from the EVs.

As mentioned before, an approach based on scenarios is taken into consideration to model the uncertainty associated to EV driving patterns and market prices. Specifically, three scenarios for energy prices (EP1–EP2–EP3), four for energy/capacity regulation prices (RP1–RP2–RP3–RP4) and six for EV groups are considered (EG1...EG6). These scenarios are combined to give a total number of $3 \cdot 4 \cdot 6 = 72$ scenarios (see Fig. 3). For simplicity, we assume the scenarios are equiprobable.

Hourly price curves for EV charging and discharging have been assumed for the purpose of this work; we assume a real-data hourly price for our base scenario and the remaining scenarios are obtained through a process of scaling up and down $\pm 20\%$; thus, scenarios (EP1–EP2–EP3) are obtained. Prices for regulation have been similarly assumed,

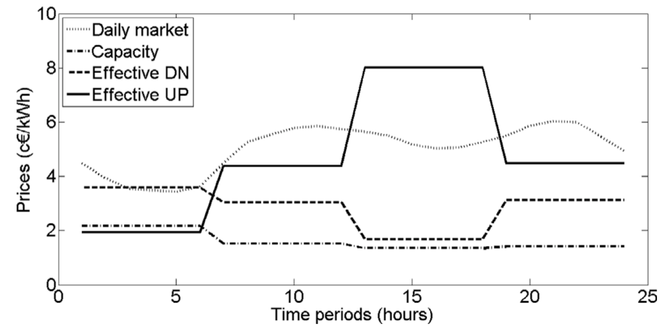

Fig. 4. Hourly prices.

Table 2
EV group scenarios.

	EVs 1	EVs 2	EVs 3	Pattern 1	Pattern 2
v_1	200	300	500	$n_1 \to n_2 \to n_1$ (t_7, t_{19})	$n_1 \to n_2 \to n_3 \to n_1$ (t_7, t_{14}, t_{20})
v_2	300	400	600	$n_2 \to n_3 \to n_2$ (t_8, t_{20})	$n_2 \to n_3 \to n_4 \to n_2$ (t_8, t_{15}, t_{18})
v_3	400	500	700	$n_3 \to n_4 \to n_3$ (t_6, t_{13})	$n_3 \to n_4 \to n_3$ (t_{10}, t_{19})
v_4	500	600	800	$n_4 \to n_5 \to n_4$ (t_9, t_{21})	$n_4 \to n_5 \to n_6 \to n_4$ (t_7, t_{13}, t_{19})
v_5	600	700	900	$n_5 \to n_6 \to n_5$ (t_8, t_{19})	$n_5 \to n_6 \to n_1 \to n_5$ (t_9, t_{12}, t_{20})

with capacity prices for upward and downward regulation being equal, but effective energy prices for regulation up and down different. We generate four different scenarios for regulation prices; for each of these scenarios we set the hourly prices for regulation capacity, effective regulation up and effective regulation down, this process generates scenarios (RP1–RP2–RP3–RP4). Fig. 4 shows all the hourly prices for one specific scenario.

The EVs considered in this work are all identical, with a battery capacity equal to 20 kWh, and for every EV the minimum SOC is fixed at 20% of the battery capacity; also, note that the maximum charging and discharging power considered is 3.7 kW. To model different EV behaviours, five EV groups are considered. For the reference scenario, each group has 200, 300, 400, 500 and 600 EVs, respectively. To generate two additional scenarios, these numbers are increased by an amount of 100 and 300 EVs in each group, respectively; see columns EVs 1, EVs 2 and EVs 3 in Table 2. For each EV group, two different driving patterns are considered, as seen also in Table 2; the nodes and time periods given in the table describe the journey performed; e.g.: the first EV group performs 2 trips under the $Pattern\,1$ condition: the first trip at 7 a.m. brings the EVs from $node_1$ to $node_2$; the return trip a 7 p.m. brings the EVs back from $node_2$ to $node_1$. In all, 6 different scenarios are considered to model each group, as each group can have 3 possible values for the number of vehicles and 2 possible itineraries during the day. Note also that, in the proposed data, all vehicles end their day in the same node as they began, reflecting the fact that many EVs belong to private owners or companies that park the vehicles for the night in a specific location; furthermore, note that nodes 4 and 5 are home to many more EVs than nodes 1 and 6, indicating that the former are residential areas and the latter are probably industrial or commercial areas.

Regarding the SOC requirements, it is assumed that the SOC has to reach a minimum of 25% of the battery capacity before the first journey of the day and also that the SOC has to be equal to or greater than the initial SOC at the end of the day. The parameter $H^{eg}_{v,t,n}$ can be determined according to the data presented so far and taking into account the transition nodes shown in Table 2. To calculate the battery consumption, a 30 km average trip and 0.20 kWh/km are assumed. Charging and discharging efficiencies are 0.90 and 0.95, respectively.

Table 3
Characteristics of the study cases.

Experiment	EV charging	EV discharging	Regulation	Other
1	✓	✗	✗	✗
2	✓	✓	✗	✗
3	✓	✓	Only ↓	✗
4	✓	✓	↓ and ↑	✗
5	✓	✓	↓ and ↑	Congestion
6	✓	✓	↓ and ↑	Number of EVs x3

4. Case study: Results and discussion

In this section, the results obtained from solving the optimization problem described in previous sections are presented. The main variables included in this analysis are the following: the hourly values of the $SOCs$ and capacity limits, the amount of power dedicated to regulation up and down, power flow in system lines and the profit obtained by the EV aggregator.

The study is centred on six experiments, see Table 3. The first and second experiments do not include the regulation service, $Exp1$ considers only EV charging and $Exp2$ considers both EV charging and discharging (V2G). These first two cases are specially interesting as basic benchmarks for the remaining experiments studied. The next two experiments include charging, discharging and regulation. In $Exp3$, only downwards regulation is featured, while full regulation capabilities are included in $Exp4$. No line congestion appears in any of these two experiments. $Exp5$ is similar to $Exp4$, but considering line congestion, which is forced in line 3–5 by means of a reduction in its technical thermal limit. Finally, $Exp6$ describes a particular additional scenario in which a three-fold increase in the number of EVs is assumed. Table 3 summarizes the characteristics of the experiments described above. Henceforth, results regarding $Exp4$, are considered as a reference, and the results from all other experiments are presented as compared against it.

In order to model battery degradation and loss of capacity, we have used data provided by manufacturers that takes into account both the DoD and the number of cycles. In this context, the degradation costs in the battery are significant, compared to the revenue obtained by the aggregator.

Figs. 5 and 6 show the hourly SOC values for EV group 2 and the power assigned for charging, discharging and regulation; for the remaining groups the configuration is quite similar considering that driving patterns are not very different among the scenarios and only the number of EVs is modified. $SOCUR$ and $SOCDR$ represent those SOCs that bound upward and downward regulation capacity, while $SOCEE$ is the SOC that includes energy from regulation and SOC only considers EV charging and discharging. It can be noticed that, due to regulation prices, both the capacity and effective energy for upward regulation are placed in the intermediate time periods between 15 h and 18 h. In the same way, downward regulation is scheduled at the beginning and at the end of the day also because of the constraints related to both the SOC before the first journey and the final energy requirements. In Fig. 7, which gives the hourly allocation for regulation, the aspects mentioned above can also be clearly noticed. It is important to bear in mind that the SOC curve gives the hourly values of the energy contained in EV batteries when the aggregator is only offering capacity and $SOCEE$ is the optimal track of the SOC when energy payments coming from regulation up and down are also considered. In this sense, the vertical amount for each time period from the SOC curve to $SOCUR$ and $SOCDR$ curves gives the power available for regulation and any SOC between these values is feasible, with the computed optimal defined by $SOCEE$.

In Fig. 8, the highest hourly system line power flows are given. It can be appreciated that, for the initial test parameters, there is no line congestion, but lines 2–3 and 3–5 are heavily loaded.

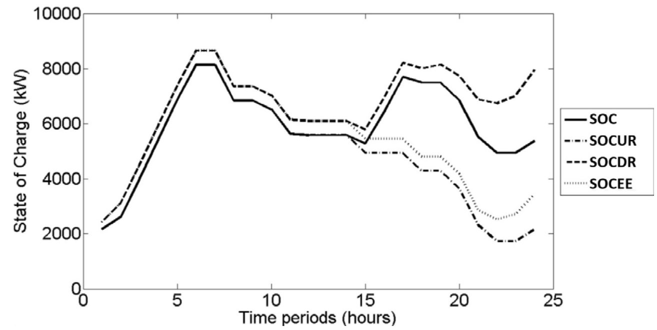

Fig. 5. Experiment 4 — SOC for EV group 2.

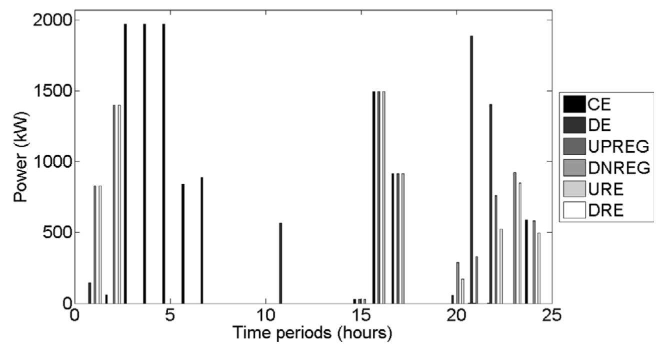

Fig. 6. Experiment 4 — Regulation Power for EV group 2.

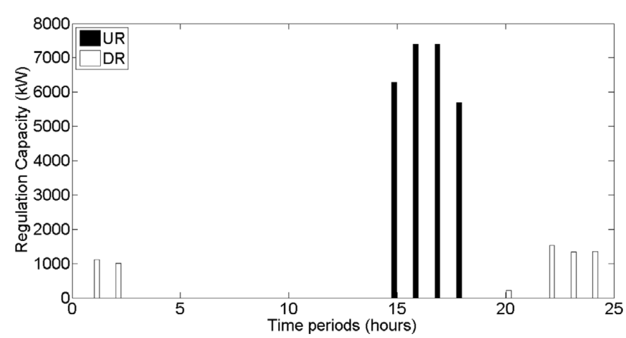

Fig. 7. Experiment 4 — Hourly regulation capacity.

The benefit obtained by the aggregator can be calculated dividing the value of the objective function by the average number of EVs. If the capacity of power transmission lines is decreased, the benefit of the aggregator is decreased because it must adapt its strategy to avoid line congestion. However, the room for manoeuvre is narrow due to the SOC constraints, the available capacity based on the number of EVs and the fixed system loads that lead to overloaded lines with small line technical limit reductions.

As previously mentioned, the results presented here correspond to Experiment 4, our reference case, with both types of regulation and with no line congestion. In Experiment 5, congestion in line 3–5 is forced through the reduction in its technical limit. The technical limit was chosen subtracting small quantities from the hourly maximum power flow values in the reference experiment until further reductions lead to infeasible results. Finally, for experiment 6, the number of EVs were made three times larger than the initial number.

Table 4 shows the total daily aggregator income and costs in € and the average income/costs values, based on the number of the EVs for the different simulated experiments. In this Table, CH is the cost associated with buying energy to charge; DH is the income associated

Table 4
Daily aggregator income and costs, for all experiments performed.

Income/Cost	1	2	3	4	5	6
CH (€)	739.24	1822.99	1775.95	3061.68	3269.22	9185.05
DH (€)	0.00	1425.05	1363.95	1253.79	1436.07	3761.42
RUP (€)	0.00	0.00	0.00	438.58	438.58	1315.75
RDN (€)	0.00	0.00	551.75	132.19	132.19	396.57
ERUP (€)	0.00	0.00	0.00	2613.68	2613.68	7841.05
ERDN (€)	0.00	0.00	1337.03	261.53	261.53	784.59
Total profit (€)	−739.24	−397.94	1476.78	1638.09	1612.83	4914.33
EV profit (€/EV)	−0.2772	−0.1492	0.5538	0.6143	0.6048	0.6143

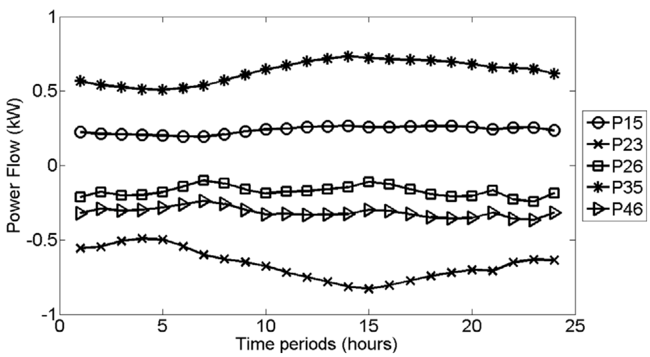

Fig. 8. Line power flows.

with selling energy to the network (V2G operations); RUP and RDN are the incomes associated with up and down regulation capacity; finally, ERUP and ERDN are incomes associated with effective up and down regulation, respectively.

It can be noticed from Table 4 that, when only charging and discharging are allowed, the difference between income and costs is negative; that is, the aggregator has to pay for the energy stored in EV batteries to fulfil the driving requirements. The battery discharging leads to a decrease in costs, but it is not enough to obtain a positive profit. However, when regulation is considered, this difference becomes positive; that is, the income exceeds the operation costs, and some profit can be obtained. Note that the highest profit is obtained in $Exp4$, when both types of regulation are allowed and no line congestion takes place. Also note that when congestion appears, profits are reduced. For $Exp6$, the number of EVs is increased, and the total aggregator benefit is also increased; however, the profit per EV is not modified due to the linear nature of the problem.

The results presented in Table 4 show that, in this case, the aggregator has to carefully watch those EVs that charge/discharge in nodes 2, 3 and 5 because they can have an important effect on the closest lines that are heavily loaded. This effect depends on the assumed parameters of the problem and the system characteristics and particularly on the distribution factors.

Battery degradation estimation

In addition, an ex-post estimation of the global degradation battery costs is presented. Taking the information from [27,34,35], and based on the final SOCs curve, the battery degradation costs in € per day is given in Table 5 for Experiments 3, 4 and 5 previously presented; e.g. in the case of Experiment 3, the battery may perform its daily duties with an average of 1.5 cycles per day and a maximum depth of discharge of 30%; this will add a cost of approximately 0.9 € per day to the cost previously obtained. These figures are based on a battery investment of 200 €/kWh and assuming that the battery has to be replaced when the capacity loss reaches 70% for the corresponding DoD and cycle regime. From Table 5, it is clear that aspects regarding battery costs and performance must be improved; that is, battery investment has to be reduced and battery technology advancement must decrease battery degradation to make the regulation service profitable. Recent developments in battery technology point clearly in that direction, hence we conclude that these applications will be profitable very soon.

Table 5
Estimated battery degradation costs.

Experiment	DoD (%)	cycles/day	Costs (€/EV day)
3	30	1.5	0.9112
4	80	1	1.6162
5	50	2	2.0253

Finally, additional simulation experiments have been performed considering, first, a reduction in regulation prices and, second, splitting the main problem into two sequential stages. Results show that energy payments from regulation for the first case can be decreased more than 60% with respect to the reference experiment maintaining a positive aggregator profit, but without considering battery degradation. Therefore, it is proved that capacity payments are very important for the aggregator operation. In the second case, if the complete problem is divided into two problems, the first stage that considers only energy charging/discharging from daily market prevents the aggregator to obtain additional regulation income due to the lack of flexibility derived from the SOC that is fixed and taken as data for the second stage. Due to this, it is verified that joint optimization of both energy and regulation leads to optimal aggregator benefit compared to the approach based on the consideration of two independent stages. In addition, it is worth mentioning that the aggregator in our model acts as the link between the main grid and EV private owners, collaborating with the system operator, but not governed by it. In this sense, different results may be achieved considering EV fleet management or changing the interaction among the different stakeholders.

5. Conclusions

An optimization approach for daily energy and regulation management for EV aggregators has been proposed. The optimization problem is formulated as a mixed-integer linear programming problem aimed at maximizing EV aggregator profit, while jointly considering the most important aspects influencing EVs profitability, such as uncertainty in prices and drivers' patterns, capacity constraints, state of charge constraints, regulation demand constraints, regulation offer constraints, regulation bounds constraints, and power-system security constraints.

The results have demonstrated that EVs have potential to provide significant economic benefits to EV aggregators. In particular, in the case studies presented here, EV aggregator's profit becomes positive when up and down regulation is considered. Additionally, we showed that line congestion may significantly impact on aggregators' benefit and their EV operations. Accordingly, an interesting extension of this work in the future is the analysis of the relationship between the long-term investment decisions in the transmission system (i.e., transmission expansion planning) and the EV aggregators' operation decisions, exploring potential co-benefits for EV aggregators of relieving congestion in the power network.

It has been also shown that capacity payments play an important role for the EV aggregator operation to be economically feasible, even potentially more important than those payments from frequency regulation.

From the modelling viewpoint, the energy and regulation co-optimization problem turns out to be the optimal approach compared to the classical two stage approach that breaks down the aggregator problem into daily energy and regulation problems.

Finally, it is worth mentioning that, if battery degradation is taken into account, regulation may not be profitable under the assumptions made in this work and some kind of compensation might be needed through, for instance, EV subsidies or higher prices for both energy and capacity for regulation in order to ensure EV aggregators' positive profit.

CRediT authorship contribution statement

S. de la Torre: Conceptualization, Methodology, Software, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition. **J.A. Aguado:** Conceptualization, Methodology, Investigation, Validation, Writing – review & editing, Project administration, Funding acquisition. **E. Sauma:** Methodology, Validation, Investigation, Visualization, Writing – review & editing, Funding acquisition.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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