Decentralised Coordination of Electric Vehicle Aggregators

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Abstract. Given the rapid rise of electric vehicles (EVs) worldwide, and the ambitious targets set for the near future, the management of large EV fleets must be seen as a priority. Specifically, we study a scenario where EV charging is managed through self-interested EV aggregators who compete in the day-ahead market in order to purchase the electricity needed to meet their clients' requirements. In order to reduce electricity costs and lower the impact on electricity markets, a centralised bidding coordination framework has been proposed in the literature, using a trusted black-box coordinator. In order to improve privacy and limit the need for the coordinator, we propose a reformulation of the coordination framework as a decentralised algorithm, employing the Alternating Direction Method of Multipliers (ADMM). We test the resulting algorithm in a realistic scenario with real market and driver data from Spain. Finally, we discuss the potential of implementing the proposed coordination algorithm in a blockchain, providing transparency and anti-tampering guarantees.

Keywords: Multi Agent Systems · Day-ahead market · Electric vehicle aggregation · Alternating Direction Method of Multipliers · Blockchain.

1 Introduction

To date, there exists a world-wide fleet of more than two million electric vehicles (EVs), combining purely electrical and hybrid [12]. Furthermore, EV sales are growing exponentially in most countries and there are targets to achieve 50 to 200 million of EVs at a global scale in the next decade [11]. These high penetration targets aim to reduce the use of fossil fuels and improve environmental conditions. However, the transition from conventional to electric vehicles is not without challenges [22]. Specifically, compared to traditional fuel powered vehicles, EVs present a novel and heavy strain to existing electricity networks, which will need to accommodate a new type of consumer with high demand.

In order to deal with this challenge, the last decade has seen the introduction of the concept of the EV aggregator [13]: an intermediary between a fleet of EVs and the electricity grid and markets. The aggregator is able to control the charging of its fleet, and this way informed collective decisions can be made. In contrast with individual EV operation, the much higher degree of coordination possible when a fleet is centrally managed by an aggregator offers great benefits. For example, electricity consumption to charge the fleet's batteries can be spread over time, avoiding expensive and polluting demand peaks. In particular, in this work we focus on EV aggregators participating in day-ahead markets, in order to purchase the electricity needed to meet their clients' energy requirements. In more detail, day-ahead markets match electricity supply and demand on an hourly basis (see Section 2), and are the main source of whole-sale electricity. Here, increased electricity demand means increased prices, resulting in the so-called *price impact*, and hence it is in every market participant's interest to avoid unnecessary demand peaks.

In this work we focus on a scenario where different EV aggregators co-exist in the same day-ahead market. These aggregators may vary in nature and size, but it is reasonable to assume that they are self-interested. Indeed, reduced electricity costs translate in more profit for the aggregator and/or more benefits for their EV fleet. In this scenario, reduced overall costs can be achieved by inter-aggregator coordination, producing more informed and optimised bidding. This coordination problem was studied in our previous work [20], where we propose a centralised approach using a coordinator: a trusted entity which collects energy requirement information from the participating EV aggregators and performs a global optimisation problem. Cooperation is encouraged by employing techniques from mechanism design to distribute monetary payments. In a similar vein, we studied the same multi-aggregator scenario from a coalitional perspective [21]. Specifically, given the fact that the coordinator may not be a unique entity, any willing coalition of aggregators can potentially form. By using results from the field of cooperative game theory, we prove that the grand-coalition, where all aggregators cooperate together, provides the most benefits, and propose a payment mechanism which stabilises it.

Against this background, there are several challenges that have not been studied so far:

1. The sharing of information and requirements among aggregators should be minimised, as private entities would be reluctant to sharing these details.
2. Trust-less and transparent operation, removing the need for a trusted coordinator and providing guarantees against malicious tampering.

In order to address these two challenges, we propose a novel decentralised mechanism which allows the coordination of the EV aggregators without the need of a trusted coordinator, and without revealing their private requirement information. Specifically, we reformulate the centralised optimisation algorithm proposed in [20] using the Alternating Direction Method of Multipliers (ADMM), which decomposes optimisation problems into smaller problems coordinated through an aggregation step [5]. ADMM methods have been widely applied in the smart-grid sector, for example in optimal power flow studies [17,26,24,19,23], but have not been applied to a multi-EV aggregator scenario. Moreover, in order to provide full transparency and anti-tampering guarantees, we propose the implementation of this decentralised algorithm in a private blockchain, using smart contracts. Similar blockchain applications in the smart grid sector include smart-grid managing frameworks [18,10,16] and micro-grid operation [17,28,1]. In these works, blockchain technology is found to be an appropriate solution for the decentralised and trust-less operation of their respective models. Hence it seems a good candidate for the similar challenge addressed in this study.

In more detail, this paper makes the following contributions to the state of the art:

- We propose the first decentralised optimisation algorithm for the coordination of self-interested EV aggregator participation in day-ahead markets.
- We present a preliminary empirical evaluation that uses real market and driver data to assess the performance of the proposed algorithm.
- We describe a guideline for the blockchain implementation of the proposed decentralised algorithm.

The rest of the paper is structured as follows. Section 2 introduces the considered day-ahead market and the mathematical formalism to quantify price impact. Section 3 details the considered EV aggregators and presents the proposed decentralised optimisation algorithm using ADMM. Next, an empirical evaluation using real market and driver data is detailed in Section 4. The proposed blockchain implementation is discussed in Section 5. Finally, we conclude in Section 6.

2 The Day-Ahead Market

This section details the day-ahead market structure considered in this paper and present in most countries. Moreover, we discuss how to quantify the price impact of buy orders (electricity demand), which is an important aspect of our work. The exposition in this section follows [20,21].

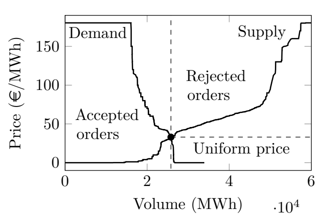

Fig. 1. Aggregated supply and demand curves, and market clearing mechanism. Source: OMIE, 01/11/2016, 11$^{\text{th}}$ hour.

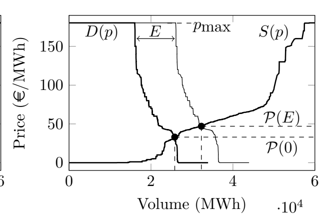

Fig. 2. Price impact of a buy order with volume E and maximum price $p_{\max}$. Source: OMIE, 01/11/2016, 11$^{\text{th}}$ hour.

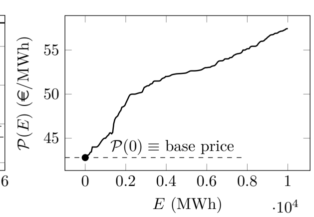

Fig. 3. Final price function $\mathcal{P}(E)$. Source: OMIE, 01/11/2016, 11$^{\text{th}}$ hour.

Day-ahead markets divide each day into 24 hourly slots, each running a separate uniform-priced double-sided auction. Before closure time (usually noon) on day D, bids and offers for each hourly slot of day $D + 1$ must be submitted to the market. Then, a matching algorithm determines the accepted bids and offers, and establishes an hourly uniform price using marginal pricing, this is, the price of the intersection between supply and demand.

Bids (buy orders) and offers (sell orders) for each hourly slot are quantity-price pairs. For bids (offers), the price represents the highest (lowest) price the participant is willing to pay (sell for). As is common in most markets, we define a minimum price $p_{\min} = 0$ and some maximum price, $p_{\max}$. After closure time, the auctioneer aggregates all buy and sell orders, by high-price and low-price priorities, respectively. This generates the aggregated demand and supply curves, and their intersection determines the accepted orders and the resulting uniform price, as depicted in Fig. 1.

Clearly, the arrival of a new buy order pushes the clearing price up if it gets accepted (*i.e.* if it lies towards the left-hand side of the intersection). Fig. 2 illustrates the effect of a new buy order with quantity E placed at price $p_{\max}$. The price increase (price impact) depends on the new order's price and quantity, and on the supply and demand curves. Price impact is an essential market characteristic associated with large market participants, and careful managing is required to avoid pushing prices up unnecessarily. Price impact has been studied in the electricity markets literature by employing residual curves [9,20,21], which are detailed below.

Employing standard notation, for any given hour t, let $D_t(p)$ and $S_t(p)$ be the aggregated demand and supply curves respectively, as a function of price, p. The residual supply curve is defined as $R_t(p) = S_t(p) - D_t(p) = E$, and represents the amount of energy, E, an agent could bid for while maintaining a clearing price p. Conversely, the clearing price when bidding a quantity E is given by $p = R_t^{-1}(E)$. Introducing the notation $\mathcal{P}_t(E) = R_t^{-1}(E)$, the clearing price when the new agent bids an amount E is $p = \mathcal{P}_t(E)$, and the price impact Δp of this order is given by $\Delta p = \mathcal{P}_t(E) - \mathcal{P}_t(0)$, where $\mathcal{P}_t(0)$ represents the *base price* at hour t, i.e. the price without the agent's new bid. This formalism is depicted in Figs. 2 and 3.

We are now ready to introduce the EV aggregator model considered in this paper and the optimal day-ahead bidding algorithm.

3 Optimal Multi-EV Aggregator Participation in the Day-Ahead Market

As discussed in Section 1, an EV aggregator is responsible for the charging of a fleet of EVs and, to this end, purchases the required electricity from the day-ahead market (see Section 2). We will start by describing the considered aggregator structure and operation. Then, we will describe the optimal bidding algorithm proposed in [20,21] and how it can be used to optimise the bidding of a group of EV aggregators with a central coordinator. Finally, we will decompose this centralised algorithm into a decentralised optimisation algorithm by using the Alternating Direction Method of Multipliers (ADMM), as discussed in Section 1.

3.1 EV Aggregator Model

In our model, following [4,20,21], EVs arrive and depart dynamically over time. When an EV i arrives to the charging point, it communicates the desired departure time, t_d^i, and desired state of charge at departure, SoC_d^i, to the aggregator. We assume that arrival time and state of charge, t_0^i and SoC_0^i can be automatically inferred by the aggregator. Each EV has a maximum charging speed, $P_{\max}^i$ in kW, which depends on two factors: the available physical infrastructure, and the EV's battery. The charging schedule of the EV is then left at the aggregator's discretion, which can choose when to perform the charging while guaranteeing the desired state of charge by departure time. This flexibility allows charging the battery in an informed way, rather than randomly, or at arrival, providing cheaper electricity costs.

Due to the nature of the day-ahead market, electricity bids need to be placed between 12 and 36 hours before delivery time (assuming market closure at noon, see Section 2). This requires the market participants to forecast their electricity needs and to bid accordingly.

Following [4,20,21], we model the requirements of an EV by employing two vectors with 24 entries each, $\mathbf{r}^{\min,i}$ and $\mathbf{r}^{\max,i}$. Specifically, $r_t^{\min,i}$ is the amount of energy needed at hour t assuming charging has been left for the last possible moment and that the charging requirements need to be fulfilled. Conversely, $r_t^{\max,i}$ is the amount of energy needed at hour t assuming charging starts as soon as possible. For example, consider an EV arriving at 3pm, stating 9pm departure time and 8kWh charging needs with $P_{\max} = 3$kW. Then, $\mathbf{r}^{\min,i}$ would be as specified in Table 1. Specifically, if 6pm is reached with no charging done, at least 2kW of energy needs to be charged between 6-7pm in order to fulfil the EV driver requirements. The same applies with 3kW between 7-8pm and 8-9pm. Similarly, for the same scenario, the requirement vector $\mathbf{r}^{\max,i}$ would be as specified in Table 2.

Then, in order to provide mathematical tractability, two global energy requirement vectors, $\mathbf{R}^{\min}$ and $\mathbf{R}^{\max}$, can be obtained by summing the hourly requirements of all the EVs associated to the particular aggregator, *i.e.* $R_t^{\min} = \sum_{i=1}^{N} r_t^{\min,i}$ and $R_t^{\max} = \sum_{i=1}^{N} r_t^{\max,i}$. Note that these aggregated constraints do not exactly capture the individual requirements of each EV, but have been widely employed in the literature [4,2,3,8,20,21]. The reasons are the fact that considering constraints for each individual EV renders the problem unfeasible with moderate problem sizes, and the fact that bidding uses day-ahead price and energy requirements forecasts, which will not be exact anyway.

We will denote the quantities that need to be forecasted with a hat: hourly energy requirements, $\hat{R}_t^{\min}$ and $\hat{R}_t^{\max}$, hourly number of available EVs, $\hat{N}_t$, and hourly price impact functions, $\hat{\mathcal{P}}_t$.

3.2 Optimal Day-Ahead Bidding Algorithm

Now that the day-ahead and EV aggregator models have been detailed, we are ready to present the optimal day-ahead bidding algorithm. The algorithm is

$r_3^{\min,i}$	$r_4^{\min,i}$	$r_5^{\min,i}$	$r_6^{\min,i}$	$r_7^{\min,i}$	$r_8^{\min,i}$	$r_9^{\min,i}$
0	0	0	2	3	3	0

Table 1. Example of requirement vector $\mathbf{r}^{\min,i}$

$r_3^{\max,i}$	$r_4^{\max,i}$	$r_5^{\max,i}$	$r_6^{\max,i}$	$r_7^{\max,i}$	$r_8^{\max,i}$	$r_9^{\max,i}$
3	3	2	0	0	0	0

Table 2. Example of requirement vector $\mathbf{r}^{\max,i}$

from [20,21] and reproduced here for convenience. The mathematical problem is defined as follows: given an EV aggregator's forecasted requirements and price impact functions, find the optimal distribution of energy quantities to bid across the 24 hourly slots of the next day, $\boldsymbol{E} = (E_0, \ldots, E_{23})$, in order to satisfy its clients' charging needs while minimising the total cost of the purchased energy. We assume that the agent's bids are set at maximum price, $p_{\max}$, in order to guarantee execution. Hence only bidding hours and quantities need to be decided.

As discussed in [20], and in order to avoid a complex minimisation landscape with multiple minima, the forecasted hourly price impact functions $\hat{\mathcal{P}}_t$ (see Sections 2 and 3.1) are approximated by quadratic convex functions. Specifically, they are given by $\hat{\mathcal{P}}_t^{\text{convex}} = a_t E_t^2 + b_t E_t + \hat{\mathcal{P}}_t(0)$, where all the coefficients a_t are restricted to be positive. Formally, the optimisation algorithm is given by Eqs. (1a), (1b), (1c), (1d). In more detail, the objective function (1a) minimizes the total cost of the purchased energy. The constraints guarantee that the amount of purchased energy is enough to satisfy the forecasted demand (1b), that it is not purchased before the forecasted arrival of the EVs (1c) and that the energy purchased at each hour is not greater than the amount that the aggregator is able to charge at the given hour, based on the forecasted number of available vehicles (the aggregator cannot store energy). It is worth noting that the number of constraints is always 72, independent on the fleet size. Also, given the convexity of the problem, there exists a unique global minimum, which we are guaranteed to find.

$$\min_{\{E_t\}} \sum_t \hat{\mathcal{P}}_t(E_t) \cdot E_t \tag{1a}$$

$$\sum_{j=0}^{t} E_j \geq \sum_{j=0}^{t} \hat{R}_j^{\min}, \ \forall t = 0, \ldots, 23 \tag{1b}$$

$$\sum_{j=0}^{t} E_j \leq \sum_{j=0}^{t} \hat{R}_j^{\max}, \ \forall t = 0, \ldots, 23 \tag{1c}$$

$$E_t / \mathit{\Delta} t \leq \hat{N}_t P_{\max}, \ \forall t = 0, \ldots, 23 \tag{1d}$$

3.3 Centralised Joint Bidding

The bidding algorithm detailed in the previous section for a single aggregator can be extended to perform joint bidding, where a coordinator collects the requirements of a number of independent aggregators and applies the optimisation algorithm globally. In more detail, let C be a set of EV aggregators. Then, following [20,21], let $\hat{R}_t^{\min,i}$ and $\hat{R}_t^{\max,i}$ be aggregator i's forecasted energy requirements for hour t , and $\hat{N}_t^i$ the number of available EVs from aggregator i, as specified in Section 3.2. The combined requirements of all the aggregators in C are then:

$$\hat{R}_t^{\min} = \sum_{i \in C} \hat{R}_t^{\min,i} \quad (2) \qquad \hat{R}_t^{\max} = \sum_{i \in C} \hat{R}_t^{\max,i} \quad (3) \qquad \hat{N}_t = \sum_{i \in C} \hat{N}_t^i \quad (4)$$

To find the optimal global energy bids, the bidding optimisation algorithm given by Eqs. (1a), (1b), (1c), (1d) can be applied with constraints given by the combined requirements (2), (3) and (4). This will result in obtaining a global day-ahead energy volume E_t^{global} for each hour t, which can be then distributed among the aggregators in C.

The redistribution mechanism is defined in [20], and allocates an hourly energy schedule to each participating aggregator after obtaining a global energy schedule as detailed above. The redistribution problem is as follows. Letting E_t^i be the amount of energy allocated to EV aggregator i at time t, we need to find E_t^i for $t = 0, \ldots, 23$ and $i = 1, \ldots, n$ satisfying the following constraints:

$$\sum_{j=0}^{t} E_j^i \geq \sum_{j=0}^{t} \hat{R}_j^{\min}, \forall t = 0, \ldots, 23; \forall i = 1, \ldots, n \quad (5a)$$

$$\sum_{j=0}^{t} E_j^i \leq \sum_{j=0}^{t} \hat{R}_j^{\max}, \forall t = 0, \ldots, 23; \forall i = 1, \ldots, n \quad (5b)$$

$$E_t^i / \Delta t \leq \hat{N}_t^i P_{\max}, \ \forall t = 0, \ldots, 23; \forall i = 1, \ldots, n \quad (5c)$$

$$\sum_{i=1}^{n} E_t^i = E_t^{\text{global}}, \ \forall t = 0, \ldots, 23 \quad (5d)$$

In this Constraint Satisfaction Problem (CSP), Eqs. (5a), (5b), (5c) ensure that each EV aggregator has enough energy to satisfy its requirements, no more, no less, for each hour. Eq. (5d) makes sure the sums of the allocated hourly energies add up to the available global energy.

3.4 Decentralised Optimisation Algorithm

We are now ready to introduce the novel decentralised optimisation algorithm based on ADMM [5]. Specifically, our goal is to reformulate the optimisation problems given by Eqs. (1a), (1b), (1c), (5a), (5b), (5c) as an iterative decentralised algorithm, where each EV aggregator solves a local optimisation problem. The solutions to each local problem are coordinated by a global consensus step, and this procedure is iterated. This type of algorithm is appropriate for our problem for several reasons: (i) it converges to the global centralised optimum; (ii) it enables coordination without the aggregators revealing their energy requirements, *i.e.* $\mathbf{R}^{\min}$ and $\mathbf{R}^{\max}$; (iii) it is particularly well suited for blockchain implementation, providing transparency and anti-tampering guarantees (see Section 5 and [17]).

Specifically, following the notation introduced in Section 3.3, let $\boldsymbol{E^i} = \left(E_0^i, \ldots, E_{23}^i\right)$ be the energy schedule for aggregator i. Moreover, let $\boldsymbol{E} = \left(\boldsymbol{E}^1, \ldots, \boldsymbol{E}^n\right)$ be the joint vector encapsulating each individual energy schedule, and $\boldsymbol{E}^{\mathrm{glob}} = \left(E_1^{\mathrm{glob}}, \ldots, E_{23}^{\mathrm{glob}}\right)$ be such that $E_t^{\mathrm{glob}} = \sum_{i=1}^n E_t^i$. We are now able to rewrite Eq. (1a) as:

$$
\begin{aligned}
\min_{\boldsymbol{E}^{\mathrm{glob}}} \sum_{t=0}^{23} \hat{\mathcal{P}}_t(E_t^{\mathrm{glob}}) \cdot E_t^{\mathrm{glob}} &= \min_{\boldsymbol{E}} \sum_{t=0}^{23} \left[\hat{\mathcal{P}}_t \left(\sum_{i=1}^n E_t^i \right) \cdot \sum_{i=1}^n E_t^i \right] = \\
&= \min_{\boldsymbol{E}} \sum_{i=1}^n \left[\sum_{t=0}^{23} \left(E_t^i \cdot \hat{\mathcal{P}}_t \left(\sum_{j=1}^n E_t^j \right) \right) \right] \qquad (6)
\end{aligned}
$$

This way the objective function is expressed as a sum of n terms, as required by the ADMM formulation [5]. Note that, given that the price impact of each aggregator affects everybody else, we cannot fully separate Eq. (6) in the variable i. This type of problem is suited to be formulated as a *global variable consensus problem* [5], which works as follows. Consider a minimisation problem in the following form:

$$
\min_{\boldsymbol{x}} \sum_{i=1}^n f_i(\boldsymbol{x})
$$

where the goal is that each term in the sum can be handled independently. In the cases where the variable $\boldsymbol{x}$ is not separable in i, *local* variables $\boldsymbol{x}^i$ and a *global* variable $\boldsymbol{z}$ can be introduced, rewriting the problem as:

$$
\begin{aligned}
&\min_{\{\boldsymbol{x}^i\}} \sum_{i=1}^n f_i(\boldsymbol{x}^i) \\
&\text{subject to: } \boldsymbol{x}^i - \boldsymbol{z} = 0, \forall = 1, \ldots, n
\end{aligned}
$$

The name global consensus problem arises from the constraint that all the local variables should agree. Also, note that any individual constraints can be embedded into each f_i.

In a similar vein and focusing on our scenario, let $\boldsymbol{E}$ and $\boldsymbol{E}^{(i)}$ be the global and local variables respectively, all vectors with dimension $24n$. In more detail, $\boldsymbol{E}^{(i)} = \left(\boldsymbol{E}^{(i),1}, \ldots, \boldsymbol{E}^{(i),n}\right)$ and $\boldsymbol{E}^{(i),j} = \left(E_0^{(i),j}, \ldots, E_{23}^{(i),j}\right)$. Following Eq. (6), the functions f_i are given by:

$$
f_i\left(\boldsymbol{E}^{(i)}\right) = \begin{cases} \sum_{t=0}^{23} \left[E_t^{(i),i} \cdot \hat{\mathcal{P}}_t \left(\sum_{j=1}^n E_t^{(i),j} \right) \right], & \text{if constraints (1b), (1c), (1d) are met by } \boldsymbol{E}^{(i),i} \\ \infty & \text{, otherwise} \end{cases}
$$

The resulting ADMM algorithm is given by the following iterative equations:

$$\boldsymbol{E}^{(i)}_{[k+1]} = \arg\min_{\boldsymbol{E'}} \left(f_i(\boldsymbol{E'}) + \boldsymbol{\xi}^{(i)}_{[k]}{}^T \left(\boldsymbol{E'} - \boldsymbol{E}_{[k]}\right) + \frac{\rho}{2}\|\boldsymbol{E'} - \boldsymbol{E}_{[k]}\|_2^2 \right) \tag{7a}$$

$$\boldsymbol{E}_{[k+1]} = \frac{1}{n}\sum_{i=1}^{n} \left(\boldsymbol{E}^{(i)}_{[k+1]} + \frac{1}{\rho}\boldsymbol{\xi}^{(i)}_{[k]} \right) \tag{7b}$$

$$\boldsymbol{\xi}^{(i)}_{[k+1]} = \boldsymbol{\xi}^{(i)}_{[k]} + \rho \left(\boldsymbol{E}^{(i)}_{[k+1]} - \boldsymbol{E}_{[k+1]} \right) \tag{7c}$$

where the subscript $[k]$ denotes iteration number, and $\boldsymbol{\xi}$ and ρ are the dual variable and the augmented Lagrangian parameter, respectively [5]. The iterative algorithm works as follows: first, each EV aggregator solves their local problem, Eq. (7a), and update their local copy of the energy schedule, $\boldsymbol{E^{(i)}}$. Then, an aggregation step, Eq. (7b), collects all the local solutions proposed by each aggregator and updates the global energy schedule, $\boldsymbol{E}$, reporting this vector back to all the aggregators. Lastly, each aggregator updates their local copy of the dual variable, $\boldsymbol{\xi}^{(i)}$, as per Eq. (7c) and proceeds to the new iteration.

The usual stopping criterion involves the primal and dual residuals, stopping the iterative process when certain user-specified tolerances, ϵ_{pri} and ϵ_{dual} have been reached [5,17]. Specifically, the primal residual is denoted by $\boldsymbol{r}_{[k]} = \left(\boldsymbol{r}^1_{[k]}, \ldots, \boldsymbol{r}^n_{[k]}\right)$, where $\boldsymbol{r}^i_{[k]} = \boldsymbol{E}^{(i)}_{[k]} - \boldsymbol{E}_{[k]}$. Similarly, the dual residual is given by $\boldsymbol{s}_{[k]} = \boldsymbol{E}_{[k]} - \boldsymbol{E}_{[k-1]}$. The stopping criterion then takes the form:

$$\|\boldsymbol{r}_{[k]}\|_2^2 \le \epsilon_{\text{pri}} \tag{8a}$$

$$\|\boldsymbol{s}_{[k]}\|_2^2 \le \epsilon_{\text{dual}} \tag{8b}$$

3.5 Payment Mechanism

So far we have focused on solving the multi-EV aggregator scheduling problem, in order to find the optimal schedule for each participant that minimises energy expenditure and grid impact. An essential component of this coordination mechanism is the determination of the payment for each aggregator. An adequate payment mechanism prevents strategic manipulation and incentivises cooperation. Discussion about payment mechanisms is outside of the scope of this paper, and we refer to our previous work [20,21].

4 Empirical Evaluation

In this section we present a preliminary analysis of the performance of the decentralised algorithm proposed in Section 3.4. This empirical evaluation employs real market and driver data from Spain. The main purpose of this study is to analyse the convergence of the decentralised algorithm to the optimal solution (found using the centralised algorithm from Section 3.2). We will start by detailing the real data employing in the simulations, and then describe the empirical results.

4.1 Experimental Setup

The experiment setup described in this section closely follows the case studies presented in [20,21]. We consider a night-time residential scenario in which EVs arrive in the evening and need to be charged by the next morning. The EVs are assumed to be medium-sized with 24kWh battery capacity and maximum charging speed $P_{\max} = 3.7$kW. Moreover, charging efficiency is set to 90%.

Real market data from the Spanish day-ahead market OMIE[3] is employed in the simulations, as described in [20]. Specifically, for this paper we focus on a single trading day, 1/11/2016. Similarly, real driver data from a Spanish survey is used to determine probabilistic EV driving patterns, as detailed in [20]. In more detail, we employ the distribution of times for the first and last trip from and to home, as shown in Table 3.

t_0	Time	19h	20h	21h	22h	23h
	Probability	0.16	0.25	0.32	0.12	0.15

t_d	Time	6h	7h	8h	9h	10h
	Probability	0.04	0.02	0.34	0.5	0.1

Table 3. Possible arrival (t_0) and departure (t_d) times rounded to the nearest hour, with their respective probabilities.

Regarding energy requirements, the desired state of charge of an EV at arrival and departure times are drawn from uniform distributions as follows: $\mathrm{SoC}_0 \in [\mathrm{SoC}_{\mathrm{total}}/4, \mathrm{SoC}_{\mathrm{total}}/2]$ and $\mathrm{SoC}_f \in [2 \cdot \mathrm{SoC}_{\mathrm{total}}/3, \mathrm{SoC}_{\mathrm{total}}]$. Consequently, the EV charging requirements range between a large percentage of the battery (up to 75%), to a small percentage (down to 16%), accounting for long and short trips home.

4.2 Experimental Results

The main focus of our study is the convergence of the decentralised algorithm to the optimal solution. A key determinant of convergence is the augmented Lagrangian parameter ρ (see Eqs. (7a), (7b), (7c)). Intuitively, it controls the *weight* that the similarity of local and global solutions has in the local minimisation algorithms (see Eq. 7a). If it is set too large or too small, the algorithm will not converge. For every problem, there is a range of values providing convergence, but again, for some values it can be very slow. Thus, a suitable value for ρ needs to be found in order to make the algorithm applicable and quick. Also, in a different vein, the number of participating aggregators affects the convergence of the algorithm: the higher the number of participants, the more fragmented the optimisation problem is, so more iterations may be required.

We study the convergence of the decentralised algorithm with different values of ρ, for a given number of aggregators. In this preliminary evaluation we will focus on three scenarios, with two, three and five EV aggregators respectively. Results are shown in Figs. 4, 5 and 6. In the top plots we can see the total amount of daily energy selected by the decentralised optimisation algorithm at each iteration, compared to the optimal solution. The bottom plots show how

[3] `http://www.omie.es/en/inicio`

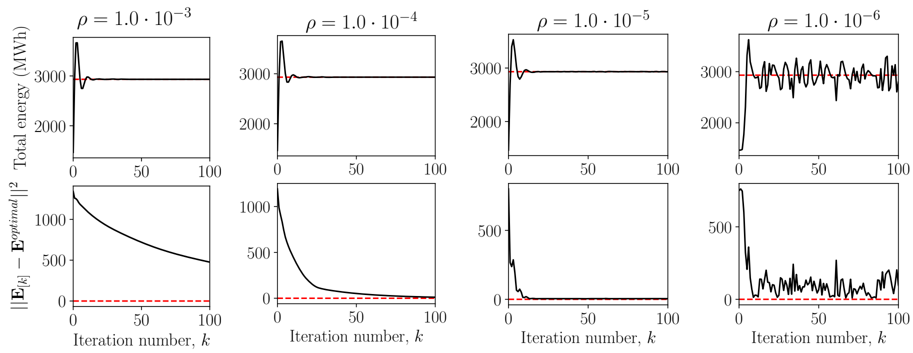

Fig. 4. Convergence of the ADMM decentralised algorithm to the optimal centralised solution, for different values of ρ. Simulations with two EV aggregators, each with 150 000 EVs. Market data from 1/11/2016.

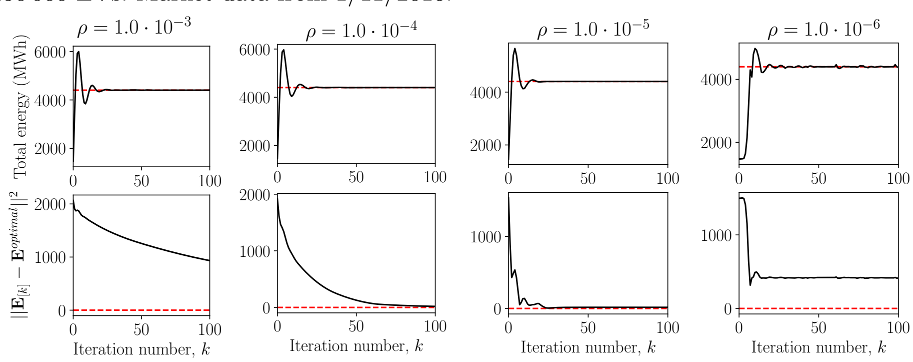

Fig. 5. Convergence of the ADMM decentralised algorithm to the optimal centralised solution, for different values of ρ. Simulations with three EV aggregators, each with 150 000 EVs. Market data from 1/11/2016.

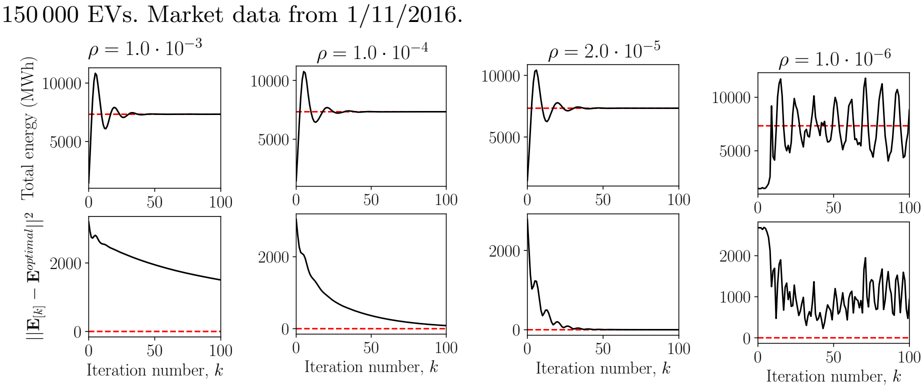

Fig. 6. Convergence of the ADMM decentralised algorithm to the optimal centralised solution, for different values of ρ. Simulations with five EV aggregators, each with 150 000 EVs. Market data from 1/11/2016.

far the decentralised solution is from the optimal solution. We can see similar convergence behaviour for the three scenarios, although the case with two EV aggregators is slightly faster and more uniform. These preliminary results show evidence of good computational scaling with the number of EV aggregators, something key for tackling larger problem sizes. Moreover, for both scenarios, convergence starts slow for a value of $\rho = 10^{-3}$, becoming fastest for a value $\rho \sim 10^{-5}$, and diverging for larger values. This suggest a value about $\rho = 10^{-5}$ presents the best convergence for these scenarios, although larger problem sizes need to be tested.

5 Proposed Blockchain Implementation

So far, we have motivated and formulated a decentralised algorithm addressing the coordination of multi-EV aggregator bidding in day-ahead markets. Specifically, the proposed algorithm addresses the first challenge presented in Section 1, *i.e.* reducing the amount of private information shared by the aggregators. In more detail, when using a centralised algorithm, each aggregator needs to report sensitive information to the central coordinator [20,21]. Differently, with the proposed decentralised approach, each aggregator solves a private local problem concerning their own private requirements, so no explicit sharing of these is needed. However, the second challenge, *i.e.* trust-less and transparent operation, has not been addressed so far. In order to do so, as introduced in Section 1, we propose employing a blockchain to implement the aggregation step of the proposed decentralised algorithm, similarly to [17]. In more detail, this aggregation step requires communication between each aggregator and the coordinator, hence is susceptible to tampering. Also, if the coordinator remains a black-box, *i.e.* an entity that receives messages from the aggregators and responds with some other message without its internal workings being transparent, the aggregators cannot be sure that they are billed and allocated a fair electricity schedule.

As a brief introduction, a blockchain is a decentralised ledger and computation environment, protected by cryptographic techniques, which allows the participants to agree on the state of the system at all times. The name comes from its architecture, where transactions and information are recorded in *blocks*, each block referencing all the previous blocks in the chain, hence *blockchain*. For a more detailed introduction to blockchain technology, see [7,17]. Moreover, apart from monetary transactions, blockchains can be seen as a general computing system, by using *smart contracts*. A smart contract is simply a piece of code hosted publicly and immutably in the blockchain, which can receive messages from other blockchain users and send its own following its internal logic.

Also, if desired, the proposed coordination mechanism can be fully implemented in the blockchain by using cryptocurrencies. This way, no centralised entity is needed, and all the bidding and coordination process can run transparently on the blockchain. Moreover, it is worth noting that the operation of the coalition of EV aggregators can be easily externally audited, maybe by the government or the electricity market operator.

Lastly, Algorithm 1 describes the proposed implementation of the decentralised algorithm on the blockchain, closely following [17]. In more detail, the local optimisation problems $\mathbf{P}_i$ are executed locally by each aggregator, sending the results to the smart contract $\mathbf{S}_1$, who does the aggregation step. This process is iterated until the algorithm has converged.

```
Data: initialise E_[0], E_[0]^(i), ξ_[0]^(i), ε_pri, ε_dual
while ||r_[k]||_2^2 ≤ ε_pri and ||s_[k]||_2^2 ≤ ε_dual do
    begin P_i: private optimisation problem, compute locally
        Update ξ_[k]^(i), Eq. (7c)
        Update E_[k]^(i), Eq. (7a), and send to smart contract S_1
    end
    begin S_1: ADMM aggregation, smart contract
        Update E_[k], Eq. (7b)
        if ||r_[k]||_2^2 ≤ ε_pri and ||s_[k]||_2^2 ≤ ε_dual then
            ADMM algorithm finished
            Compute payments for each aggregator
            Send schedule and allocated payments to S_2
        end
    end
end
```

Algorithm 1: Decentralised optimal multi-EV aggregator day-ahead bidding algorithm implemented in a blockchain.

6 Conclusion

We have presented a decentralised coordination mechanism for multi-EV aggregator bidding in the day-ahead market, employing an Alternating Direction Method of Multipliers algorithm. This proposed algorithm extends our previous work, which addresses the same scenario, but with a centralised framework. Specifically, the proposed decentralised framework removes the need of the aggregators communicating private requirement information to the coordinator, as each aggregator solves its own local private optimisation problem with their own requirements. In order to study the appropriateness of the proposed algorithm, we present an empirical evaluation using real market and driver data from Spain, showing the convergence of the decentralised method to the optimal solution for two different scenarios, with two and three cooperating EV aggregators respectively. Finally, we also propose a guideline for implementing this decentralised algorithm on a blockchain, providing a trust-less execution environment with greatly increased transparency and anti-tampering guarantees.

Several aspects are left for future work. Firstly, in order to better assess the performance decentralised algorithm, a more exhaustive empirical study needs to be conducted, addressing larger problem sizes and spanning longer periods of time. Secondly, the strategic manipulation opportunities of the proposed algorithm need to be studied. In more detail, as we assume that the participating EV aggregators are self-interested, they could *cheat* the coordination mechanism if a greater personal benefit is perceived. In our previous work, employing centralised algorithm, we address this issue by carefully designing suitable payment mechanisms. However, when the bidding algorithm is decentralised, there is new room for manipulation, as misreporting the solutions of the local problem *may* affect the global solution. Thirdly, the blockchain aspect of our work needs to be fully implemented in a test blockchain. Specifically, good scaling to large problem sizes is key to ensure the practical applicability of the proposed coordination mechanism.

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