# Coordination of Electric Vehicle Aggregators: A Coalitional Approach

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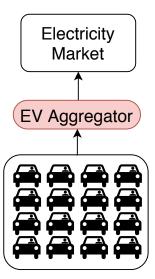
# Electric vehicles (EVs) are a key technology for reducing the environmental impact of transportation



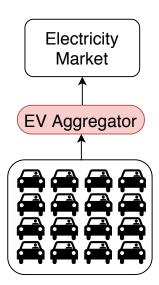
#### But this is not without challenges:

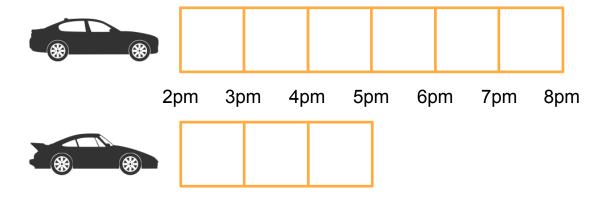
- Large new source of demand
- Increased prices
- Congestion problems

- Intermediary
- Buy electricity
- Control charging
- Smarter decisions

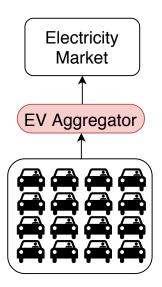


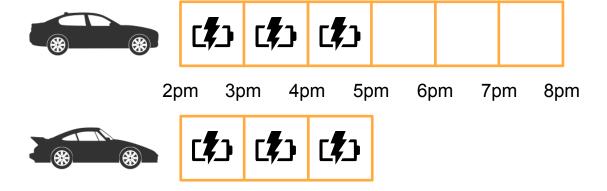
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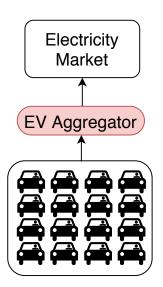


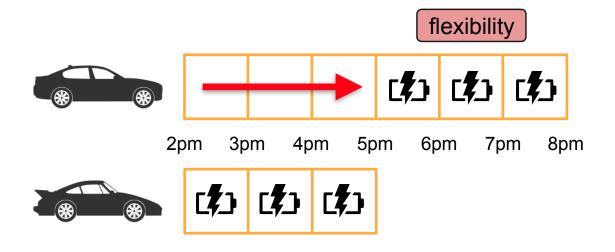
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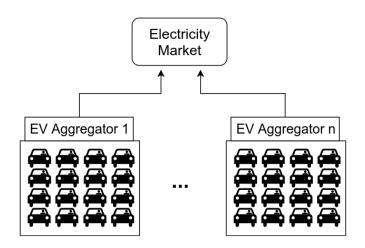
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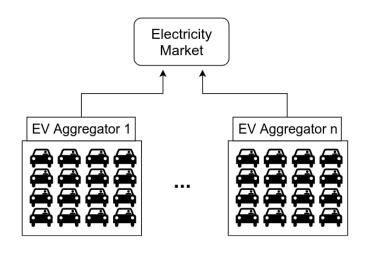
- Reduce demand peaks
- Buy cheap energy
- Reduce costs

### Multiple Aggregators



- Local knowledge: Smart decisions within each aggregator
- No global knowledge

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- No global knowledge

#### Novel work: coalition formation

- Joint bidding
- Reduce electricity costs
- Self-interested and rational
- Buy energy in day-ahead market
   More demand higher prices
- Cooperative game

Previous work: mechanism design (Perez-Diaz et al., 2018)

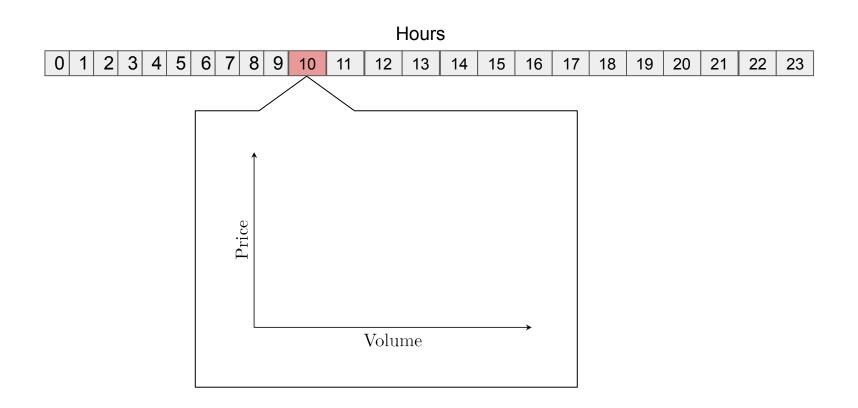
#### Outline

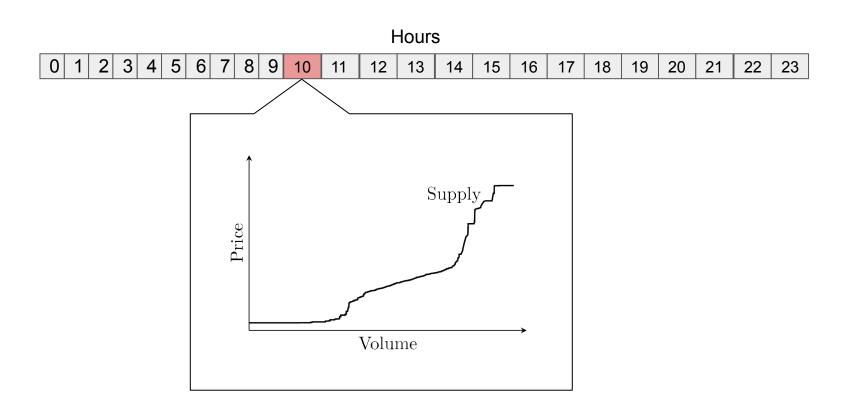
- Day-ahead market
- Optimal bidding
- Coalition formation
- Evaluation
- Conclusions and future work

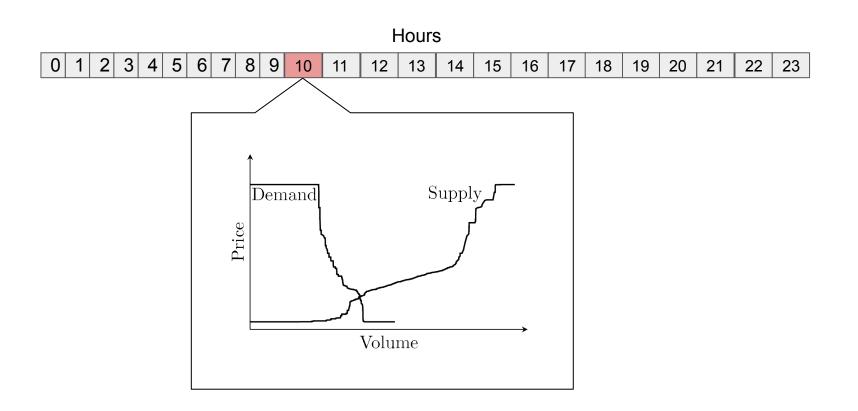
#### Hours

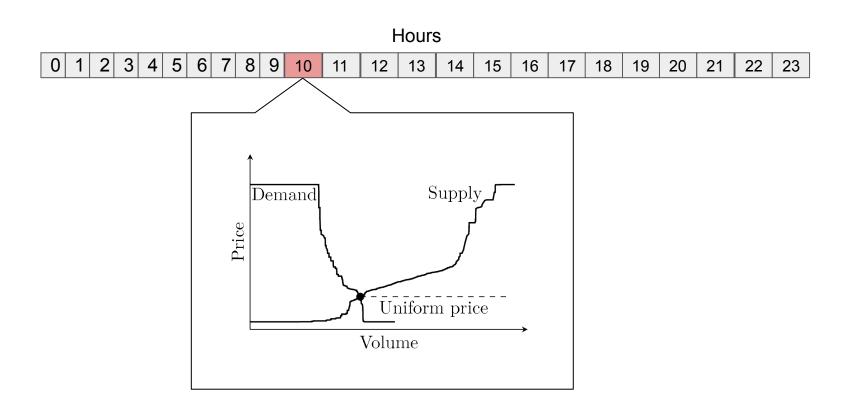


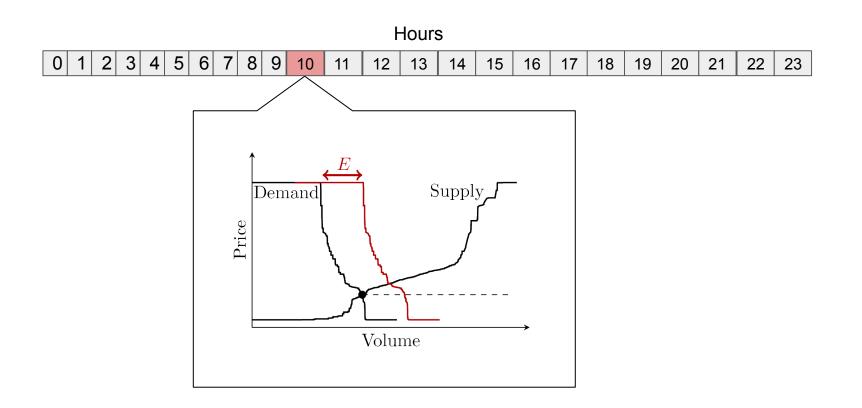
- Run every day of the year
- Separate auction for each hour
- Futures market: one day in advance

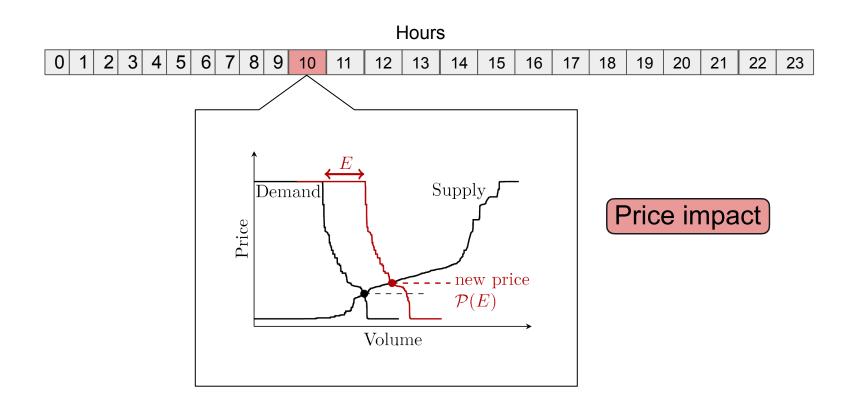


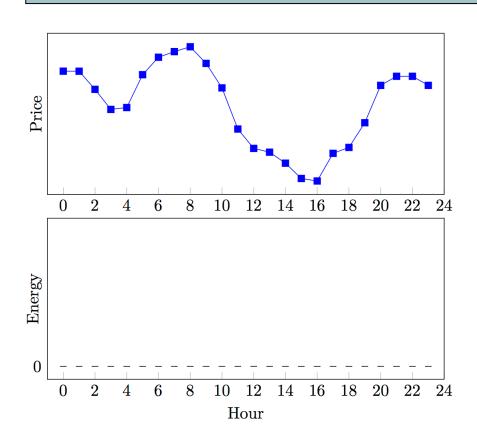


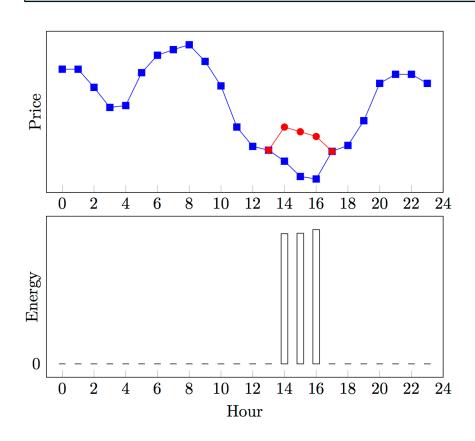


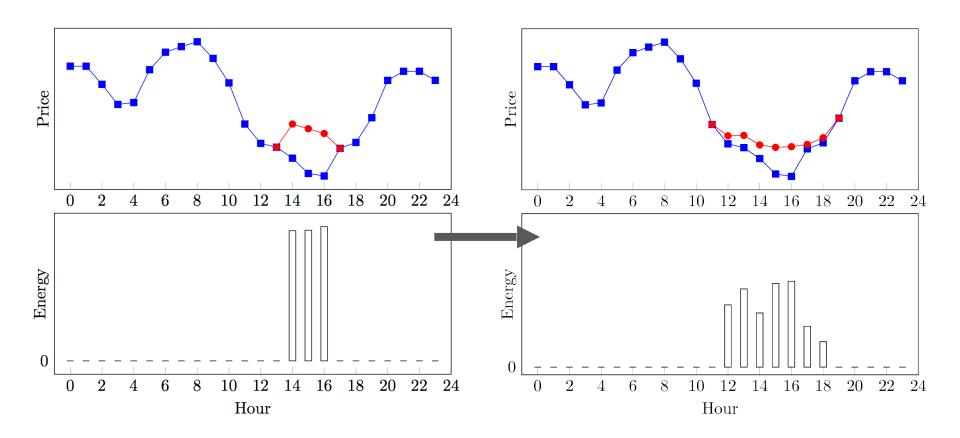












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### **Optimal Bidding**

Perez-Diaz et al., Applied Energy (2018)

• Aggregator needs to decide energy allocation:  $\mathbf{E} = (E_0, \dots, E_{23})$  aim: minimise energy costs

# **Optimal Bidding**

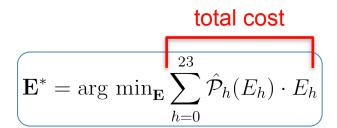
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- Forecast:
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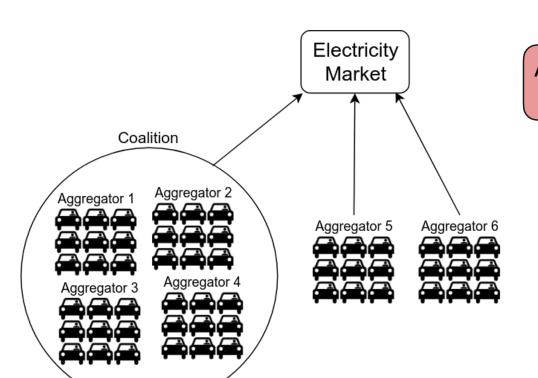
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- Aggregator needs to decide energy allocation:  $\mathbf{E} = (E_0, \dots, E_{23})$  aim: minimise energy costs
- Forecast:
  - Prices
  - Energy requirements
- Find optimal allocation:



... while satisfying its energy requirement constraints: make sure energy is not bought too early or too late

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Aggregators can form coalitions in order to coordinate bidding

- 1. Share energy requirements
- 2. Optimise joint bidding
- 3. Redistribute energy
- 4. Redistribute energy costs

- ullet Consider a set of EV aggregators:  $N=\{1,\ldots,n\}$
- ullet A coalition is a subset of aggregators:  $C\subseteq N$
- Value function:  $v(C) = -\cos (\mathbf{p}(C), \mathbf{E}(C))$

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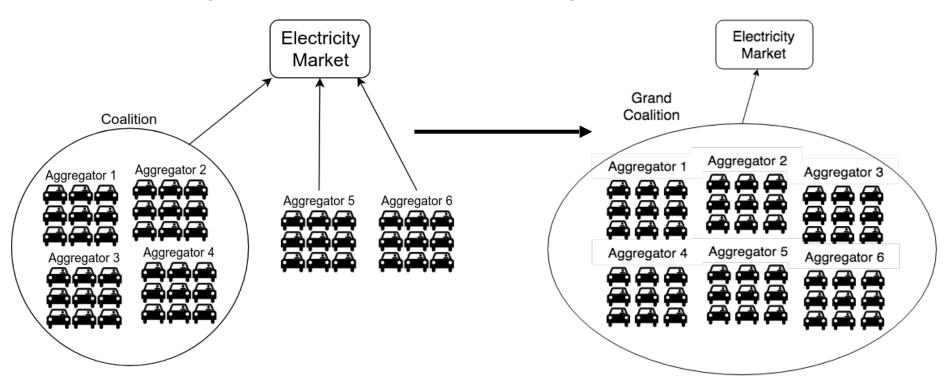
#### externalities

v(C, CS)

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common when shared resources (Funaki *et al.*, 1999)

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- The game is balanced non-empty core by the Bondareva-Shapley Theorem
- The game is **not convex** the Shapley Value is not guaranteed to be in the core

Find an alternative payment allocation lying in the core

Use the least-core: minimise worst case excess for all possible coalitions

$$e(\mathbf{x}, C) = v(C) - \sum_{i \in C} x_i$$

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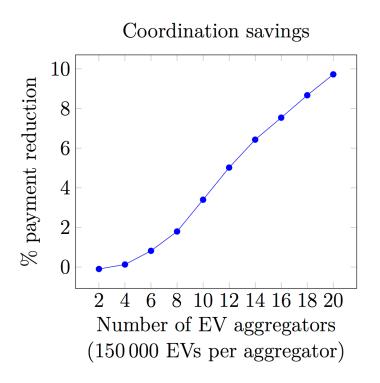
#### Empirical evaluation

- Real market data from Spanish day-ahead market (OMIE)
- Real driver behaviour from Spanish driver survey (MOBILIA)
- Two payment mechanisms: least-core and Shapley Value

#### Goals:

- 1. Evaluate the benefits of joint bidding
- 2. Compare the payment mechanisms

#### Benefits of joint bidding



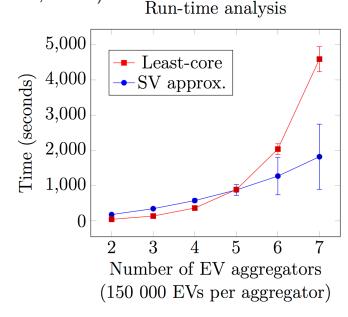
- Individual bidding vs. grand-coalition
- Savings grow with number of EVs: price impact is more important
- Up to 10% savings for 8% of EVs in the UK

## Compare payments

- Least-core and approx. Shapley Value (Maleki, 2013)
- Two different scenarios (November 2016)
  - 1. Different size
  - 2. Different flexibility



- Good agreement:
  - Within 1% for the first
  - Within 3% for the second



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- First coalitional model of self-interested EV aggregators
- Externalities: introduce  $\gamma$ -conjecture
- Properties: super-additive, balanced, not convex
- Least-core payment is in the core
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- Vehicle-to-grid (V2G)
- Incorporate physical network constraints

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Thanks!

#### Related work

- Hierarchical charging: (Qi et al., 2013), (Shao et al., 2016)
  - High level coordinator
  - Aggregators comply
- Game theoretic: (Wu et al., 2016)
  - Minimise risk
  - Nash equilibrium (does not need to exist)
  - 3 Aggregators, 1000EV each
- Mechanism design: (Perez-Diaz et al., 2018)
  - Similar scenario to this work
  - Derive optimisation, redistribution and VGC payments
  - No theoretical truthfulness
  - Very large numbers of aggregators and EVs

## **Optimisation Algorithm**

Perez-Diaz et al., Coordination and payment mechanisms for electric vehicle aggregators (2018)

$$\min_{\{E_t\}} \sum_{t} \hat{\mathcal{P}}_t^{\text{convex}}(E_t) \cdot E_t$$

$$\sum_{j=0}^{t} E_j \ge \sum_{j=0}^{t} \hat{R}_j^{\text{late}}, \ \forall t = 0, \dots, 23$$

$$\sum_{j=0}^{t} E_j \le \sum_{j=0}^{t} \hat{R}_j^{\text{early}}, \ \forall t = 0, \dots, 23$$

$$E_t/\Delta t \le \hat{N}_t P_{\text{max}}, \ \forall t = 0, \dots, 23$$

# **Shapley Value Approximation**

Maleki et al., Bounding the Estimation Error of Sampling-based Shapley Value Approximation (2013)

$$SV_i = \sum_{C \subseteq N \setminus \{i\}} \frac{|C|!(n - |C| - 1)!}{n!} (v(C \cup \{i\} - v(C)))$$

$$\mathbb{P}(|\hat{\text{SV}} - \text{SV}| \ge \varepsilon) \le \delta \qquad \begin{array}{c} \delta = 0.05 \\ \varepsilon = 0.05 \cdot \text{MC}(a, N \setminus \{a\}) \end{array}$$

Necessary number of samples is: 
$$m \geq \frac{\log(2/\delta)r^2}{2\varepsilon^2}$$

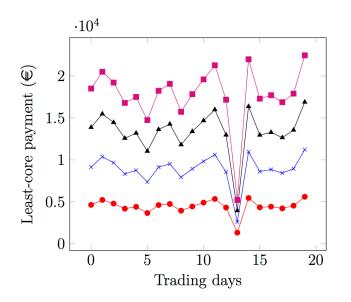
where 
$$r = \mathrm{MC}(a, N \setminus \{a\}) - \mathrm{MC}(a, \emptyset)$$

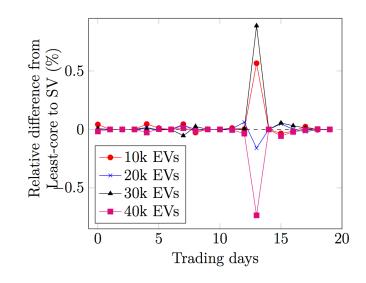
## **Least-Core Payment**

$$e^*, \mathbf{x}^* = \arg \min_{\mathbf{x} \in \mathbb{R}^n, e \in \mathbb{R}} e, \text{ s.t.}$$
$$v(C) - \sum_{i \in C} x_i - e \le 0, \forall C \subset N$$
$$v(N) - \sum_{i \in N} x_i = 0$$

### Aggregators with different sizes

- Different sizes: 10k, 20k, 30k, 40k
- Random EV arrival (evening) and departure times (morning)





### Aggregators with different flexibilities

Common size: 150k EVs each

• Different flexibilities: ----

