Two Alternative Approaches for Modelling a Portfolio of Electric Vehicles

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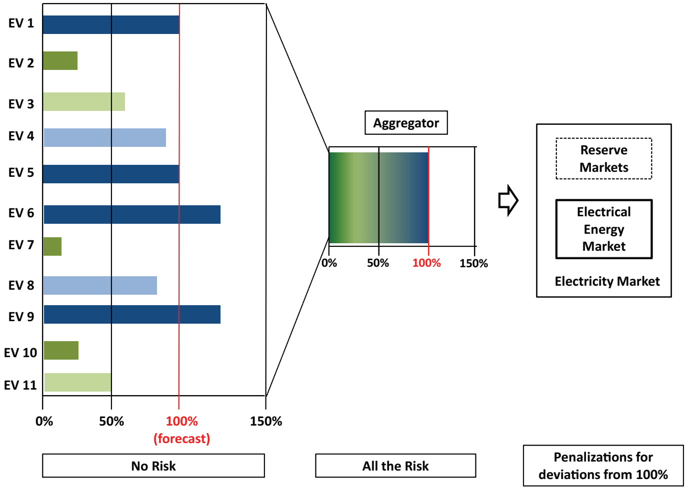
EV Aggregation Agent

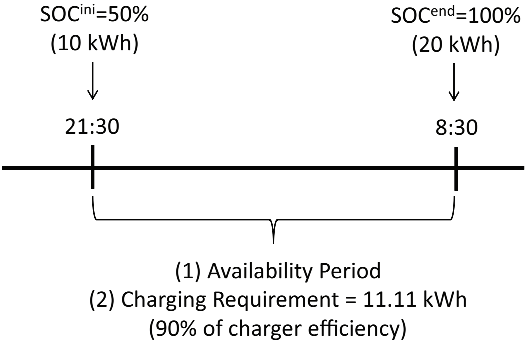
Current rules do not allow the individual participation of small loads (minimum bid is 5 MW)



Bussines Model of an EV Aggregator

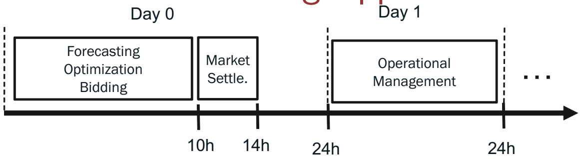
- Controls the charging process for decreasing the wholesale costs
- Two types of clients are envisioned:
  - **flexible**: direct control of the charging process → cheap retailing tariffs
  - **inflexible**: no direct control
- The fundamental goal is to keep the driver's autonomy
  - direct control only when the EV is plugged-in and available for charging
  - use the minimum information about the driver (driver's routes are not needed)
  - the EV is completely free to arrive for charging and depart before charging completion
  - the aggregator supports all the financial costs of the deviations from market bids

Modeling the EV with Two Variables



- These two variables are forecasted using historical data
- The driver when arrives for charging defines the target SOC and charging completion hour
- EV availability is a binary time series, and the charging requirement is an irregular time series

The Two Alternative Modelling Approaches



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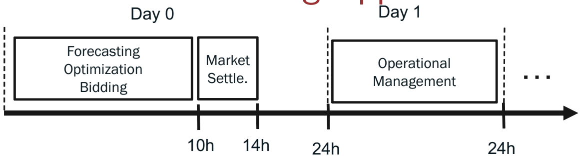
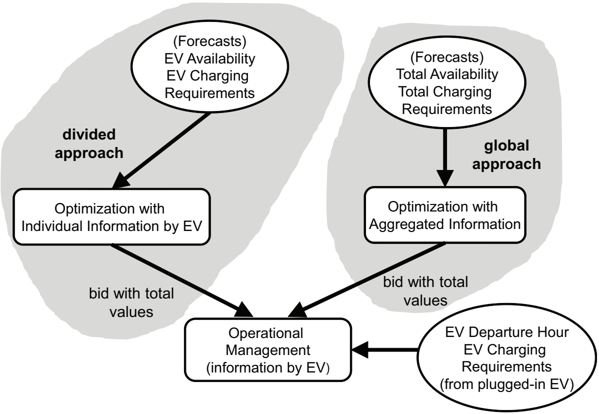




Advantages and Disadvantages

- Global approach:
  - **Advantage:** aggregated values present less variability and a more pronounced periodic behavior
  - **Disadvantage:** does not fully capture the impact of the charging process in the total maximum power for charging

		H1	H2	H3	H4	H5	H6
Information used in the **Global Approach**	Total Max Charging Power [kW]	9	9	9	9	9	9
Individual Information from each EV		Individual Charging [kWh]					
	EV 1 (charging req. = 18 kWh)	3	3	3	3	3	3
	EV 2 (charging req. = 5 kWh)	3	0	2	0	0	0
	EV 3 (charging req. = 7 kWh)	3	0	3	1	0	0
	Total Adjusted Max Charging Power [kW]	9	8	8	4	3	3

- Divided approach:
  - **Advantage:** uses individual information from each EV, which prevents the problem with the maximum available power
  - **Disadvantage:** high variability of the individual time series

Global Approach - Formulation

Minimize the cost of purchasing electrical energy in the day-ahead energy market

$$\min \sum_{t \in H} \left(\hat{p}_t \cdot E_t\right)$$

Constraints

- max available power for charging as a function of the % of satisfied charging requirements; $\hat{P}_t^{\max}$ (max. charg. power), $\hat{R}_j$ (charging req.)

$$E_t/\Delta t \leq \hat{P}_t^{\max} \cdot (1 - \alpha_t)\,,\ \forall t \in H$$
$$\alpha_t = \beta \cdot \left(\sum_{j=1}^{t-1} \left(E_t - \hat{R}_j\right) \Big/ \hat{R}_t^D\right),\ \forall t \in H$$

- guarantee that the charging requirement is only allocated when there is sufficient EV for consuming the bid quantity
- assures that the total charging requirement is satisfied with the energy purchased in the market

$$\sum_{j=1}^{t} (E_j) \geq \sum_{j=1}^{t} \left(\hat{R}_j\right),\ \forall t \in H$$

Divided Approach - Formulation

Minimize the cost of purchasing electrical energy in the day-ahead energy market

$$\min \sum_{t \in H} \left(\hat{p}_t \cdot \sum_{j=1}^{M_t} (E_{t,j}) \right)$$

Constraints

- Electrical energy purchased for the j-th EV is limited by the maximum available power for charging

$$E_{t,j}/\Delta t \leq P_j^{\max}, \forall t \in H, \forall j \in \{1, \cdots, M_t\}$$

- The energy purchased for each plug-in period H_j^{plug} must match the charging requirement

$$\sum_{t \in \hat{H}_j^{plug}} (E_{t,j}) = \hat{R}_j, \forall j \in \{1, \cdots, M_t\}$$

Forecasting

Synthetic time series for EV are used (work from F.J. Soares)

- Model for the global approach
  - charging requirement and maximum available power

$$y_t = \phi_0 + \phi_1 \cdot y_{t-1} + \phi_2 \cdot y_{t-2} + \cdots + \phi_l \cdot y_{t-l} + H_t + D_t + \varepsilon_t$$

  - Model fitting with generalized least squares
- Model for the divided approach
  - EV availability: Generalized Linear Model (logit link function)

$$p\left(y = 1|.\right) = 1/(1 + \exp\left(-\left(\phi_0 + \phi_1 \cdot y_{t-1} + \cdots + \phi_l \cdot y_{t-l}\right)\right))$$

  - The charging requirement is estimated with bootstrapping
- Day-ahead electrical energy price
  - Linear additive model with cubic splines

$$p_t = \phi_0 + \phi_1 \cdot p_{t-1} + \phi_2 \cdot p_{t-2} + \cdots + \phi_l \cdot p_{t-l} + f\left(\hat{w}_t\right) + H_t + D_t + \varepsilon_t$$

Operational Management Algorithm - Formulation

Min. of the total deviation costs (π_t^+ penalization for energy surplus, π_t^- penalization for energy shortage)

$$\min \sum_{t=1}^{T} \left(\varphi \left(E_t - \sum_{j=1}^{M_t} \left(E_{t,j}^* \right) \right) \right)$$

$$\varphi(u) = \begin{cases} u \cdot \hat{\pi}_t^+, u \geq 0 \\ u \cdot \hat{\pi}_t^-, u < 0 \end{cases}$$

$$\Leftrightarrow \min \sum_{t=1}^{T} \left(\max \left(-u \cdot \hat{\pi}_t^-, -u \cdot \hat{\pi}_t^+ \right) \right)$$

The convex function is transformed into a LP problem by expressing the formulation in its epigraph form

$$\min \sum_{k=t_0}^{T} (v_k)$$

$$\left(E_k - \sum_{j=1}^{M_t} \left(E_{k,j}^* \right) \right) \cdot \hat{\pi}_k^+ \leq v_k, \forall k \in \{t_0, \cdots, T\}$$

$$-\left(E_k - \sum_{j=1}^{M_t} \left(E_{k,j}^* \right) \right) \cdot \hat{\pi}_k^- \leq v_k, \forall k \in \{t_0, \cdots, T\}$$

$$E_{k,j}^* / \Delta t \leq P_k^{\max}, \forall j \in \{1, \cdots, M_t\}, \forall k \in H_j^{plug}$$

$$\sum_{k \in H_j^{plug}} \left(E_{k,j}^* \right) = R_{t_0,j}, \forall j \in \{1, \cdots, M_t\}$$

$$v_k \geq 0$$

Steps of the Operational Algorithm

The optimization problem is solved with a sequential process:

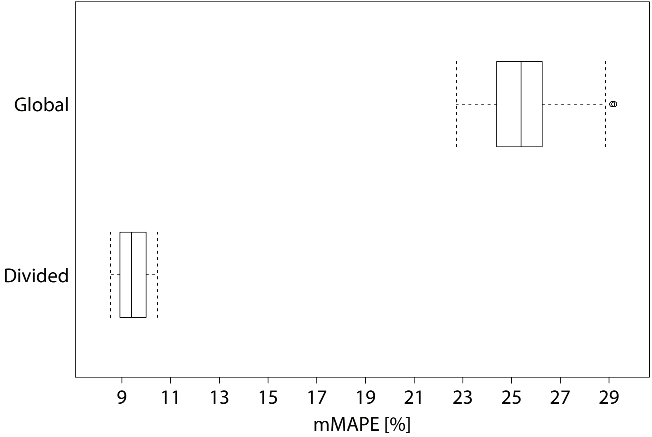
1. in the beginning of time interval t_0, new information (expected end of charge hour and charging requirement) from the recently plugged EV is available
2. the LP problem is solved with this new information for a period between t_0 and the hour of the last EV to depart
3. set points corresponding to the optimal charging levels for time interval t_0 are communicated to the plugged-in EV; only the dispatch for time interval t_0 remains unchanged, the charging levels for the subsequent time intervals can be modified in the next time interval
4. the charging requirement $R_{t_0,j}$ is updated for the next period, $R_{t_0+1,j} = R_{t_0,j} - E_{t_0,j}$
5. this optimization process is repeated for the next time interval, t_{t_0+1} (go to step 1).

Case-Study

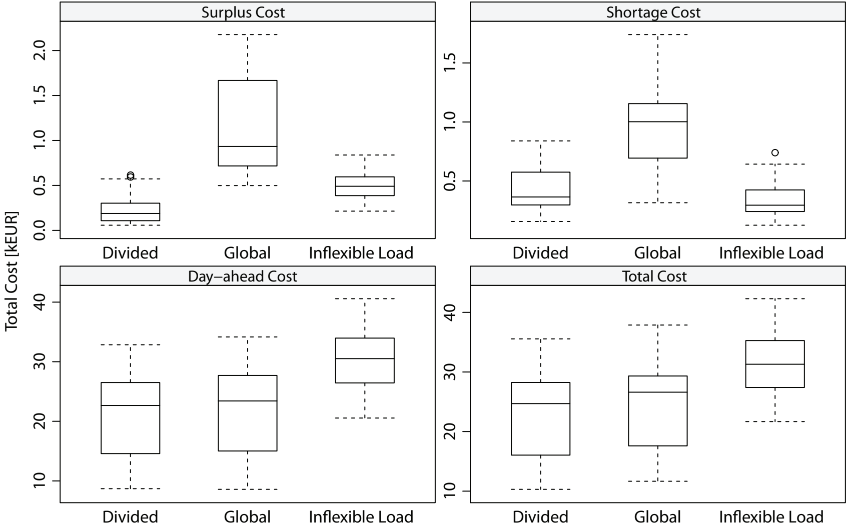
- Participation in the energy market of the Iberian Market
- Fleet with 1500 EV
- Sampling process [based on Torgo (2010)] with 100 samples from a 3 years period (2009-2011)
- The total cost is computed with the following components
  - cost of purchasing electrical energy in the day-ahead market
  - **surplus deviation:** sell this energy surplus at a regulation price below the day-ahead energy price
  - **shortage deviation:** for this energy shortage it has to pay a regulation price above the day-ahead energy price

Total Deviations

$$mMAPE = \frac{\sum_{j=1}^{N} (|y_j - \hat{y}_j|)}{\sum_{j=1}^{N} (y_j)} \cdot 100$$



Total Cost


Total Cost [kEUR]
Surplus Cost
2.0
1.5
1.0
0.5
0.0
Divided
Global
Inflexible Load
Shortage Cost
1.5
1.0
0.5
Divided
Global
Inflexible Load
Day−ahead Cost
40
30
20
10
Divided
Global
Inflexible Load
Total Cost
40
30
20
10
Divided
Global
Inflexible Load

Conclusions

- The mMAPE in the divided approach is within 8.5-12%, while in the global approach is within 18-30% $\rightarrow$ higher deviation cost
- The divided approach reduces the total cost around 11%, compared to the global approach
- The divided approach is more robust to different spot price patterns
- *Inflexible load* approach also benefits from aggregating EV, which results in low deviations costs,
  - but, the total cost is high because EV are charged during high price periods
- The EV forecasting algorithms showed acceptable quality for a practical application
- The algorithms can be applied without any change to case-studies with real EV data