

Collaborative Vehicle-to-grid Operations in Frequency Regulation Markets

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Table of Contents

1 Introduction

2 Literature

3 Model

4 Solution approach

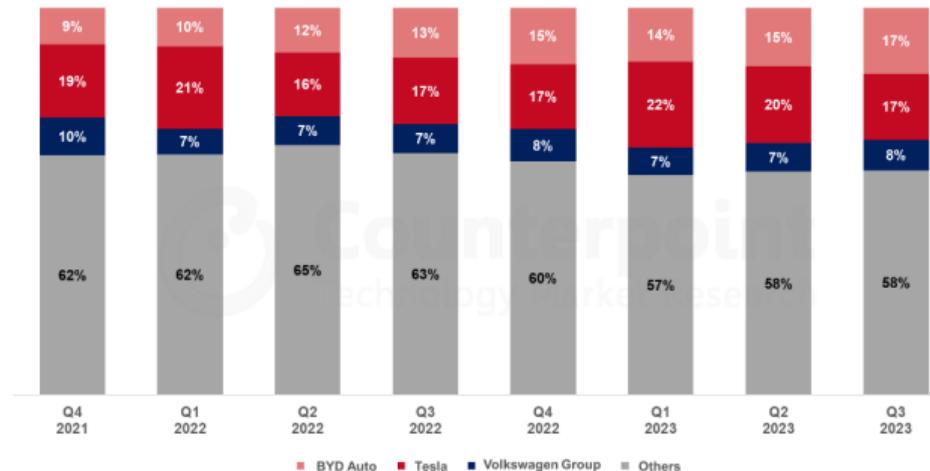
5 Case study

6 Conclusion

Electric Vehicle Market

- Global passenger electric vehicle (EV) sales grew 23% YoY(year over year) in Q3 2023
- China ranked first, with 58% share of total sales, followed by the US and Germany.

Global Passenger Electric Vehicle Market Share, Q4 2021 – Q3 2023



<https://www.counterpointresearch.com/global-electric-vehicle-market-share/>

Electric Vehicle Market

EV trends



7kW家充电桩 2.0

体积小功能强，首桩权益随车附赠

宽高深218x345x153mm，无论挂壁，还是立柱安装都更加灵活。采用分体式设计，在收线时能更方便缠绕在插枪件上，减少发生缠线问题。

电量从10%充电至100%*所需时间

20kW家用快充桩

5 小时

7kW家充电桩 2.0



20kW家用快充桩

三倍充电速度，在家就能极速快充

宽高深395x760x205mm，IP65的防护等级，远超IP54行业标准。暴雨和沙暴天气仍可安心使用，连粉尘都难以进入桩体。开启后声音可小于50分贝，“静”享快速充电。

长续航电池包 (100kWh)

标准续航电池包 (75kWh)

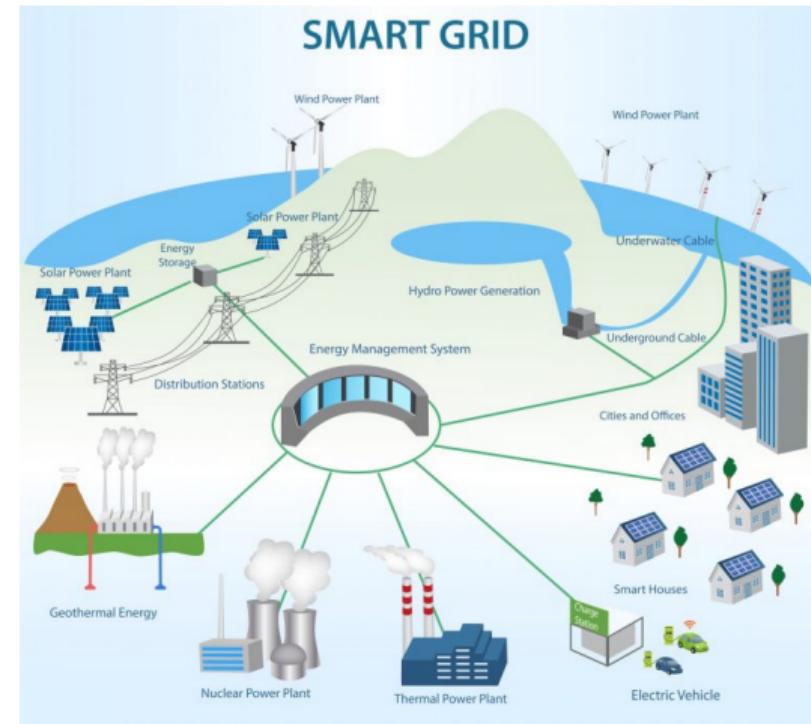
Electric Vehicle Market

Grid side:

- imbalance electricity usage
- instability because of new energy

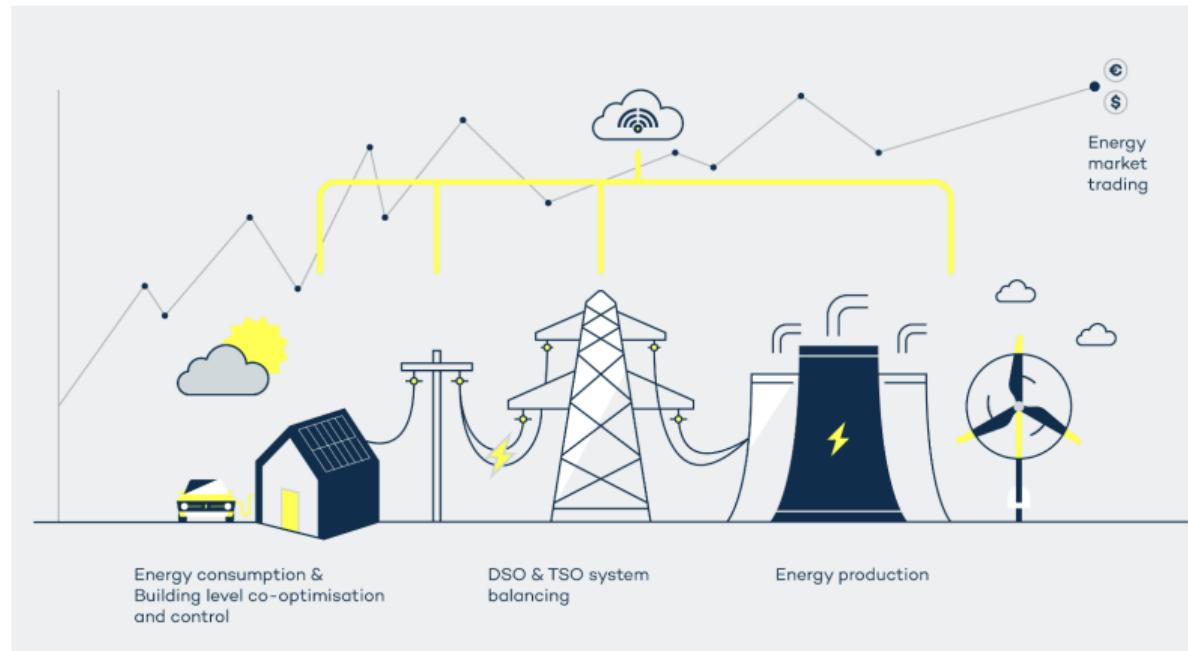
EV side:

- Battery size
- Range
- Charging rate
- Sizable batteries
- Idle 90% of time

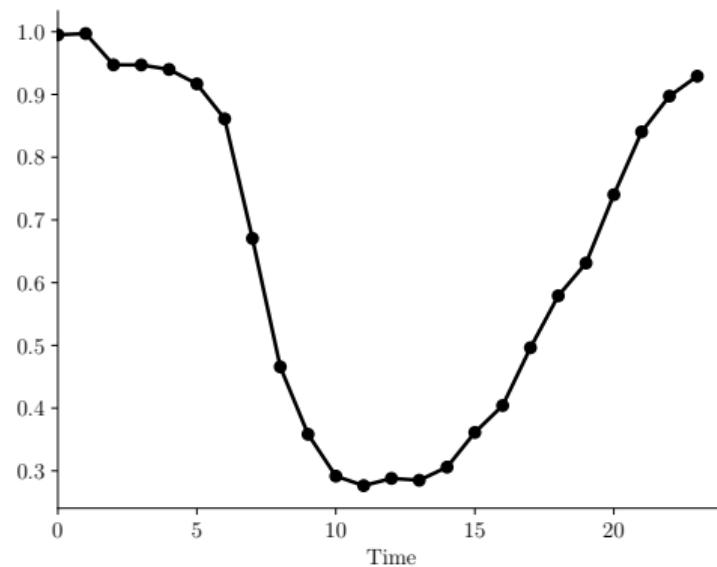


V2G

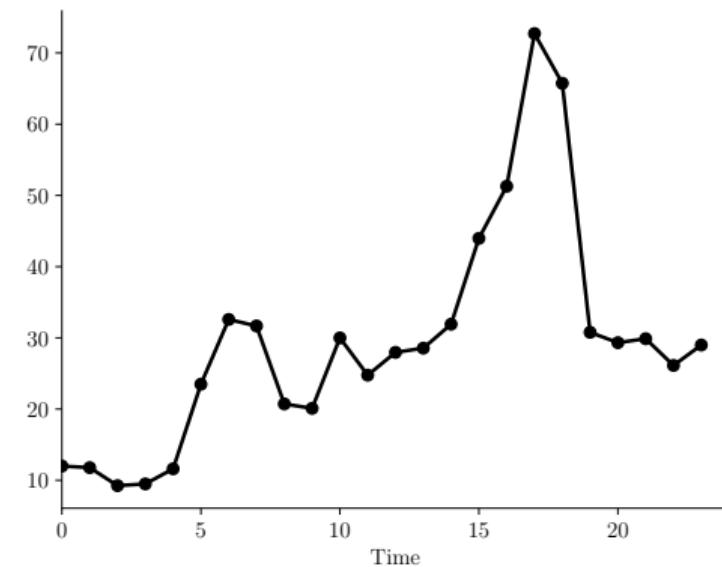
Vehicle-to-grid (V2G): technology that enables energy to be pushed back to the power grid from the battery of an electric car.



Look at the data



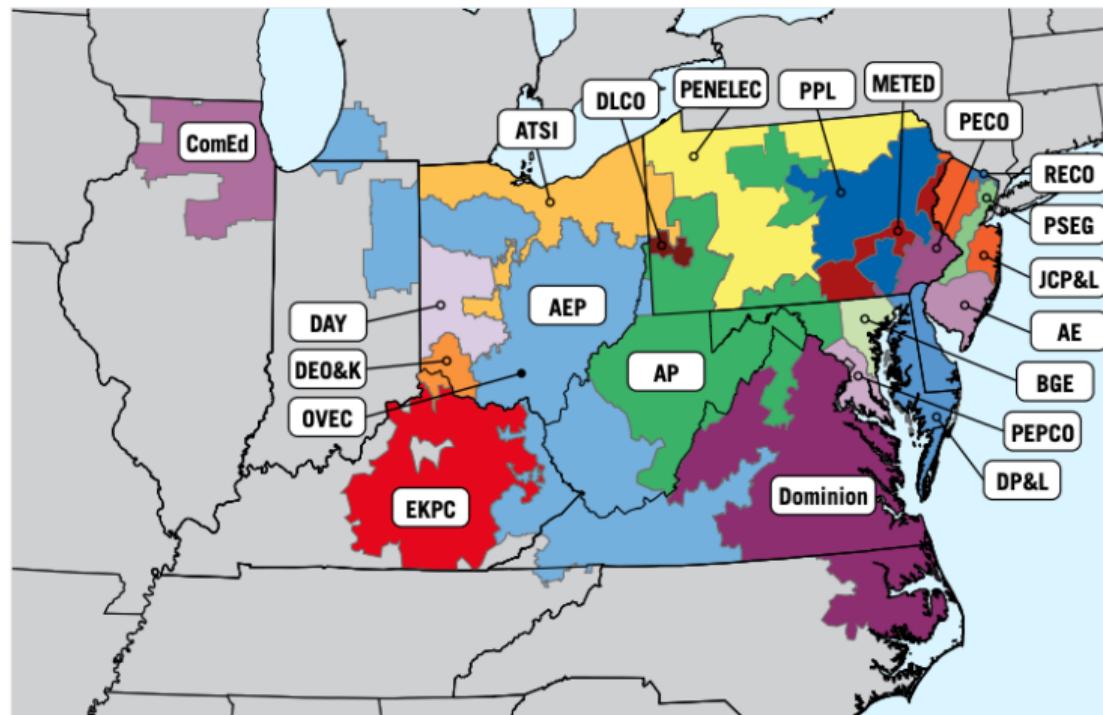
Proportion of cars parked at home
(CHTS)



Market clearing prices for capacity
(PJM)

Power Markets

PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia.



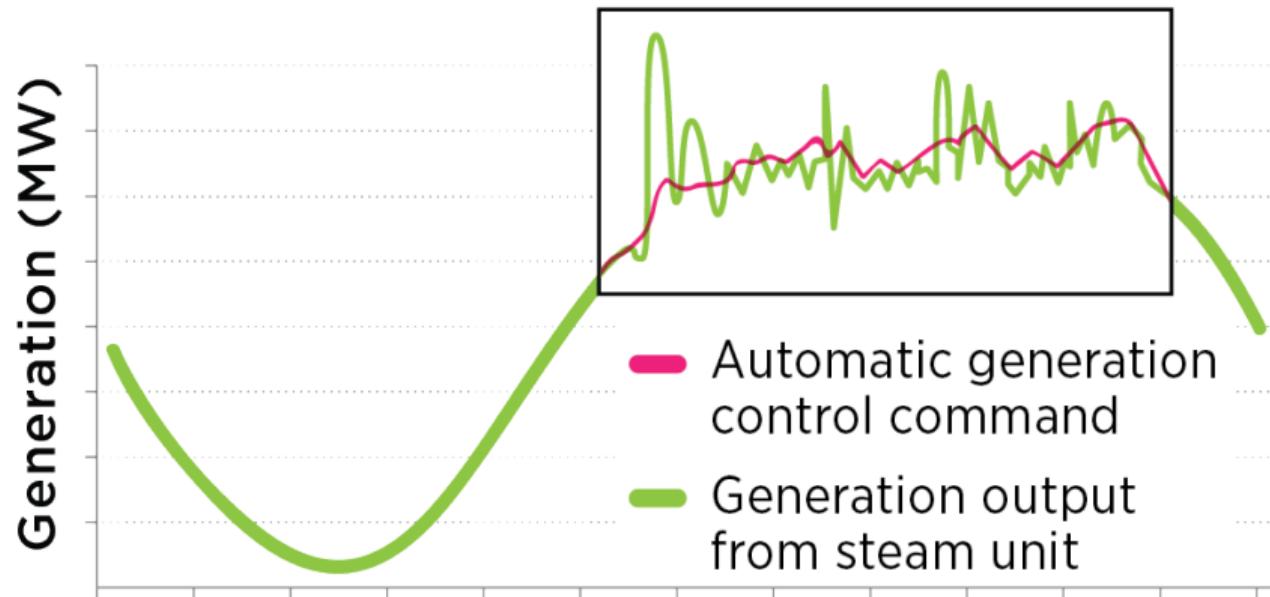
Power Markets

The PJM power market is divided into three main segments:¹

- Energy Market
- Capacity Market
- Ancillary services: help balance the transmission system – matching supply and demand while maintaining a system frequency of 60 Hertz.
 - ▶ Regulation: control small mismatches between load and generation
 - ▶ Reserves: help to recover system balance by making up for generation deficiencies if there is loss of a large generator.

¹<https://learn.pjm.com/three-priorities/buying-and-selling-energy>

Frequency Regulation Markets



China practise

中华人民共和国中央人民政府 [www.gov.cn](#)

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国家发展改革委 国家能源局关于加快建设全国统一电力市场体系的指导意见

发改体改〔2022〕118号

(三)持续完善电力辅助服务市场。推动电力辅助服务市场更好体现灵活调节性资源的市场价值,建立健全调频、备用等辅助服务市场,探索用户可调节负荷参与辅助服务交易,推动源网荷储一体化建设和多能互补协调运营,完善成本分摊和收益共享机制。统筹推进电力中长期、现货、辅助服务市场建设,加强市场间有序协调,在交易时序、市场准入、价格形成机制等方面做好衔接。

V2G platform

Research Question:

For a V2G platform:

- How to bid in the day-ahead regulation market?
- How to incentivize (by rebates) the EV drivers?

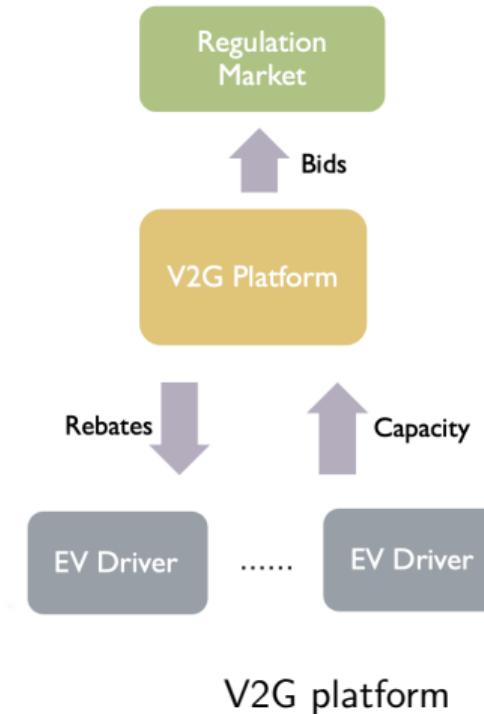


Table of Contents

1 Introduction

2 Literature

3 Model

4 Solution approach

5 Case study

6 Conclusion

Literature review

In the literature,

- V2G operations
 - ▶ Smart charging operations: Widrick et al. (2018), Wu et al. (2020), Chen et al. (2023)
 - ▶ Economic value of V2G: Broneske and Wozabal (2017), Zhang et al. (2021)
- EV operations
 - ▶ Location and network design: Mak et al (2013), He et al. (2021), Qi et al. (2023)
 - ▶ EV adoption: Avci et al. (2015), Lim et al. (2015)

In comparison, in our work,

- incorporate drivers' **endogenous travel schedules** as well as the **platform rebates**.
- coordinate a **pool of individual EV drivers**.

Table of Contents

1 Introduction

2 Literature

3 Model

4 Solution approach

5 Case study

6 Conclusion

Model overview

Develop tractable optimization model for V2G platform

	<p>EV driver side</p> 	<p>Power market side</p> 
Decisions	<p>Rebates for plugging in</p>	<p>Capacity bids in reg market</p>
Operations Features	<p>Self-scheduling behavior Heterogeneity in utility</p>	<p>Time-varying prices Stochastic generation signal Mileage requirement</p>

Model overview

Develop tractable optimization model for V2G platform

EV driver side



Power market side



Decisions

Rebates for plugging in

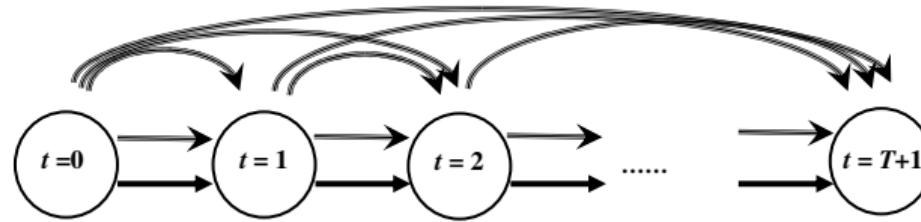
Operations
Features

Self-scheduling behavior
Heterogeneity in utility

Capacity bids in reg market

Time-varying prices
Stochastic generation signal
Mileage requirement

Driver side



→ Activity arc $a \in A$

→ Charging arc $a \in A'$

Longest path problem (on an acyclic graph):

$$\Pi(v) = \max_{\mathbf{x} \in \Lambda} \sum_{a \in A \cup A'} v_a x_a, \quad \text{where } \Lambda \equiv \left\{ \mathbf{x} \in \{0,1\}^{|A \cup A'|} : \sum_{a \in A \cup A'} b_{na} x_a = f_n, \quad \text{for } n \in N \right\}.$$

Driver side

- Each driver's utility vector as a realization of r.v. \tilde{v}
- Aggregate behavior reflected by:
 - ▶ $E[\Pi(\tilde{v})]$
 - ▶ $P(x_a(\tilde{v}) = 1) = y_a$
- Difficult problem!
 - ▶ If components of \tilde{v} follow independent two-point distributions, computing $E[\Pi(\tilde{v})]$ is #P-complete [Hagstrom 1988]
- Alternative approach: distributionally-robust optimization
- Tight upper bound on $E[\Pi(\tilde{v})]$, given moments of \tilde{v}

Driver side

Persistency model

For a discrete optimization problem

$$Z^* = \max E_\theta(\max\{\tilde{\mathbf{c}}\mathbf{x} : \mathbf{x} \in \mathcal{X}\})$$

If \mathbf{x} is 0-1 decision variables, given mean and variance information, the problem can be computed by the following concave maximization problem:

$$Z^* = \max \left\{ \sum_i (\mu_i y_i + \sigma \sqrt{y_i(1-y_i)}) \right\}$$

y_i : persistency value

Natarajan K, Song M, Teo CP (2009) Persistency model and its applications in choice modeling.
Management Science 55(3):453-469.

Driver side

Persistency model

Suppose \tilde{v}_a has mean μ_a and standard deviation σ_a .

$$\sup_{\tilde{v}_a} E(\Pi(\tilde{v})) = \max_{y \in \text{conv}(\Lambda)} \sum_{a \in A} (\mu_a y_a + \sigma_a \sqrt{y_a(1 - y_a)})$$

- (Linear) reward longest-path problem \rightarrow (Concave) reward network flow problem on same graph
- SOCP formulation

Driver side

Parameter Calibration

How to obtain μ_i and σ_i ?

- μ_i : expected utility of activity i
- σ_i : variance of utility of activity i

Inverse optimization:

$$\min_{(\mu, \sigma, \epsilon, \rho, \lambda)} \epsilon$$

$$\text{s.t. } \sum_{a \in A \cup A'} \left(\mu_a \hat{y}_a + \sigma_a \sqrt{\hat{y}_a(1 - \hat{y}_a)} \right) + \epsilon \geq \frac{1}{2} \sum_{a \in A \cup A'} \left(\lambda_a + \sqrt{\lambda_a^2 + \sigma_a^2} \right) + \sum_{n \in N} f_n \rho_n$$

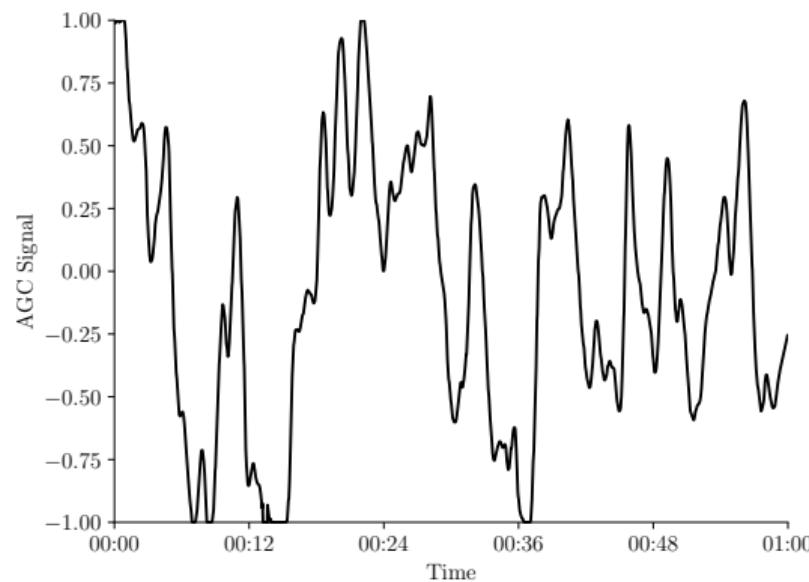
$$\lambda_a = \mu_a - \sum_{n \in N} b_{na} \rho_n \text{ for } a \in A \cup A'.$$

Model overview

Develop tractable optimization model for V2G platform

	EV driver side	Power market side
Decisions	Rebates for plugging in	Capacity bids in reg market
Operations Features	Self-scheduling behavior Heterogeneity in utility	Time-varying prices Stochastic generation signal Mileage requirement

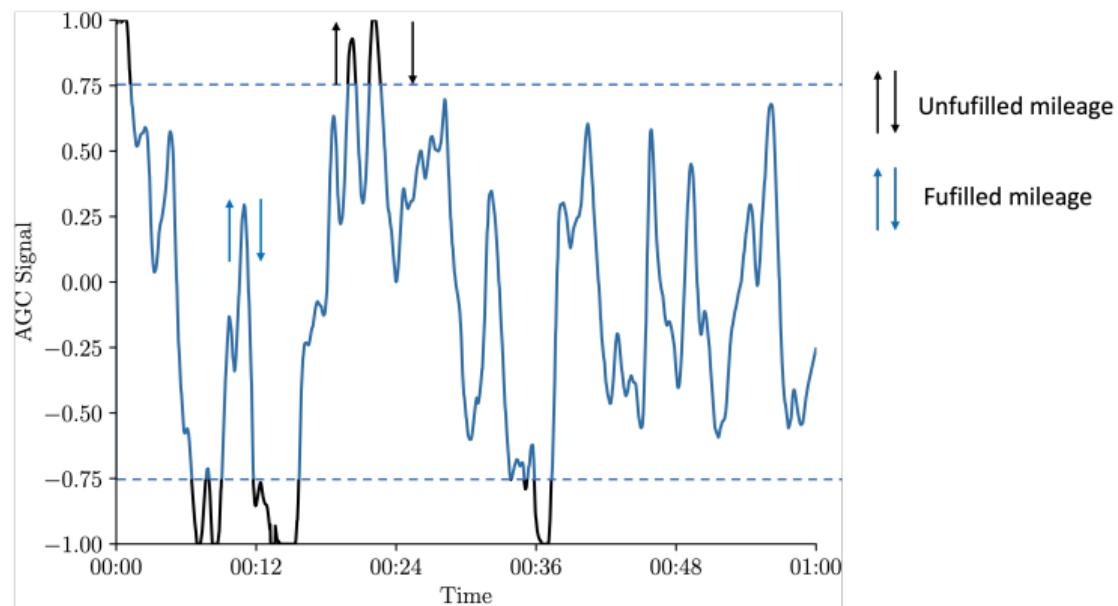
Regulation market side



AGC signal in a one-hour period of the PJM market

Frequency regulation market side

Mileage-based performance



Requirement: performance index = fulfilled mileage/total mileage $\geq 1 - \eta$

Regulation market side

- Challenge: the AGC signal is stochastic

$$P \left(\frac{\psi \tilde{K}_t}{\text{Total capacity from EV on charge}} - \frac{\tilde{r}_t C_t}{\text{AGC requirements}} \geq 0 \right) \geq 1 - \eta.$$

which is equivalent to the VaR expression

$$\hat{\phi}_{1-\eta}(\tilde{r}_t C_t - \psi \tilde{K}_t) \leq 0$$

We can use CVaR as a surrogate

$$\phi_{1-\eta}(\tilde{r}_t C_t - \psi \tilde{K}_t) \leq 0$$

Value-at-Risk

$(1 - \eta)$ -VaR:

$$\text{VaR}_{1-\eta}(v_0 + \mathbf{v}'\tilde{\mathbf{z}}) \triangleq \min \{t : P(-v_0 - \mathbf{v}'\tilde{\mathbf{z}} \leq t) \geq 1 - \eta\}$$

$(1 - \eta)$ -CVaR: the average of the values that fall beyond the VaR

$$\text{CVaR}_{1-\eta}(v_0 + \mathbf{v}'\tilde{\mathbf{z}}) \triangleq \min_a \left(a + \frac{1}{\eta} E(-v_0 - \mathbf{v}'\tilde{\mathbf{z}} - a)^+ \right).$$

We can use **forward and backward deviation** to bound CVaR.

Chen, X., Sim, M., & Sun, P. (2007). A Robust Optimization Perspective on Stochastic Programming. *Operations Research*, 55, 1058-1071.

Regulation market side

Definition.

For a zero-mean random variable \tilde{z} , the forward and backward deviations are defined as follows, respectively:

$$\sigma^f(\tilde{z}) = \sup_{\theta > 0} \left\{ \frac{1}{\theta} \sqrt{2 \ln(E[\exp(\theta \tilde{z})])} \right\}$$

$$\sigma^b(\tilde{z}) = \sup_{\theta > 0} \left\{ \frac{1}{\theta} \sqrt{2 \ln(E[\exp(-\theta \tilde{z})])} \right\}$$

- $\sigma^f \geq \sigma$ and $\sigma^b \geq \sigma$.
- If \tilde{z} follows a Normal distribution, $\sigma^f = \sigma^b = \sigma$.
- For any $\theta \geq 0$, $P(\tilde{z} \leq \theta \sigma^f) \leq \exp(-\theta^2/2)$ and $P(\tilde{z} \geq -\theta \sigma^b) \leq \exp(-\theta^2/2)$.
- For any $\theta \geq 0$, $E[\exp(\theta \tilde{z})] \leq \exp \theta^2 (\sigma^f)^2 / 2$ and $E[\exp(-\theta \tilde{z})] \leq \exp \theta^2 (\sigma^b)^2 / 2$.

Value-at-Risk

Proposition.

Consider a random vector $\tilde{\mathbf{z}} \in \mathbb{R}^I$ whose components are mutually independent, and have zero means and finite forward and backward deviations. Then,

$$\phi_{1-\eta} \left(\alpha_0 + \sum_{i=1}^I \alpha_i \tilde{z}_i \right) \leq \alpha_0 + \sqrt{-2 \ln \eta} \sqrt{\sum_{i=1}^I u_i^2} \quad (1)$$

where $u_i = \max\{\sigma_i^f \alpha_i, -\sigma_i^b \alpha_i\}$

$$\phi_{1-\eta} \left(\alpha_0 + \sum_{i=1}^I \alpha_i \tilde{z}_i \right) \leq \alpha_0 + \frac{1-\eta}{\eta} \sqrt{-2 \ln(1-\eta)} \sqrt{\sum_{i=1}^I v_i^2} \quad (2)$$

where $v_i = \max\{-\sigma_i^f \alpha_i, \sigma_i^b \alpha_i\}$.

Chen, Wenqing, Sim, Melvyn (2009). Goal-Driven Optimization. *Operations Research*, 57(2), 342-357.

Regulation market side

Proposition.

Let \bar{r}_t , σ_t^f and σ_t^b be the mean, forward deviation and backward deviation of \tilde{r}_t , respectively. Then either of the following is a sufficient condition that guarantees the CVaR constraint holds:

$$\bar{r}_t C_t - \psi M y_t + \sqrt{-2 \ln \eta} \sqrt{\psi^2 M y_t (1 - y_t) + (\sigma_t^f C_t)^2} \leq 0 \quad (3)$$

$$\bar{r}_t C_t - \psi M y_t + \frac{1 - \eta}{\eta} \sqrt{-2 \ln(1 - \eta)} \sqrt{\psi^2 M y_t (1 - y_t) + (\sigma_t^b C_t)^2} \leq 0. \quad (4)$$

Chen, X., Sim, M., & Sun, P. (2007). A Robust Optimization Perspective on Stochastic Programming. *Operations Research*, 55, 1058-1071.

Put everything together

Platform (leader)

$$\max_{C,s} \sum_{t=1}^T (\bar{p}_t C_t - s_t y_t M)$$

$$\text{s.t. } P(\psi \tilde{K}_t - \tilde{r}_t C_t \geq 0) \geq 1 - \eta, \text{ for } t = 1, \dots, T$$

Drivers (follower)

$$\max \sum_{a \in A} \left(\mu_a y_a + \sigma_a \sqrt{y_a(1-y_a)} \right)$$

$$+ \sum_{t=1}^T \left((\mu_t + s_t) y_t + \sigma_t \sqrt{y_t(1-y_t)} \right)$$

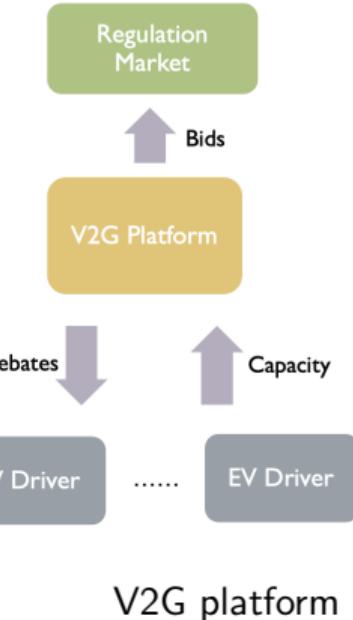


Table of Contents

1 Introduction

2 Literature

3 Model

4 Solution approach

5 Case study

6 Conclusion

Bilevel Problem

Calculate the dual of drivers problem:

$$\min_{\rho} \frac{1}{2} \sum_{a \in A \cup A'} \left(\lambda_a + \sqrt{\lambda_a^2 + \sigma_a^2} \right) + \sum_{n \in N} f_n \rho_n.$$

$$\text{s.t. } \lambda_a = \mu_a - \sum_n b_{na} \rho_n, \quad \forall a \in A,$$

$$\lambda_a = \mu_a + s_a - \sum_n b_{na} \rho_n, \quad \forall a \in A',$$

Then the follower's problem can be converted to the following constraint:

$$\begin{aligned} & \sum_{a \in A} \left(\mu_a y_a + \sigma_a \sqrt{y_a(1-y_a)} \right) + \sum_{t=1}^T ((\mu_t + s_t) y_t + \sigma_t w_t) \geq \\ & \frac{1}{2} \sum_{a \in A} \left(\lambda_a + \sqrt{\lambda_a^2 + \sigma_a^2} \right) + \frac{1}{2} \sum_{t=1}^T \left(\lambda_t + \sqrt{\lambda_t^2 + \sigma_t^2} \right) + \sum_{n \in N} f_n \rho_n. \end{aligned}$$

Full model

$$\begin{aligned}
 & \max \quad \sum_{t=1}^T (\bar{p}_t C_t - u_t M) \\
 \text{s.t.} \quad & \sum_{a \in A} \left(\mu_a y_a + \sigma_a \sqrt{y_a(1-y_a)} \right) + \sum_{t=1}^T (\mu_t y_t + u_t + \sigma_t w_t) \geq \\
 & \frac{1}{2} \sum_{a \in A} \left(\lambda_a + \sqrt{\lambda_a^2 + \sigma_a^2} \right) + \frac{1}{2} \sum_{t=1}^T \left(\lambda_t + \sqrt{\lambda_t^2 + \sigma_t^2} \right) + \sum_{n \in N} f_n \rho_n \\
 & \sum_{a \in A \cup A'} b_{na} y_a = f_n, \quad \text{for } n \in N; \quad 0 \leq y_a \leq 1, \quad \text{for } a \in A \cup A' \\
 & \lambda_a = \mu_a - \sum_{n \in N} b_{na} \rho_n \text{ for } a \in A \\
 & \lambda_t = \mu_t + s_t - \sum_{n \in N} b_{nt} \rho_n \text{ for } t = 1, \dots, T. \\
 & \bar{r}_t C_t - \psi M y_t + \sqrt{-2 \ln \eta} \sqrt{\psi^2 M w_t^2 + (\sigma_t^f C_t)^2} \leq 0 \\
 & w_t^2 + y_t^2 \leq y_t \text{ for } t = 1, \dots, T \\
 & s_t = \sum_{h \in H} \hat{s}_{th} z_{th} \\
 & \sum_{h \in H} z_{th} = 1; \quad z_{th} \in \{0, 1\} \text{ for } h \in H \\
 & y_{th} \leq z_{th} \text{ for } h \in H \\
 & u_{th} \leq z_{th} \hat{s}_{th} \text{ for } h \in H \\
 & u_{th} \leq y_{th} \hat{s}_{th} \text{ for } h \in H \\
 & \sum_{h \in H} y_{th} = y_t
 \end{aligned}$$

MISOCP: Mixed integer second-order cone programming

Computational enhancement

Denote by \underline{y}_t the optimal flow for charging arc $t \in A'$ in the pricing optimization model with extra constraints $s_{t'} = 0$, for $t' \in A' \setminus \{t\}$. Similarly, denote by \bar{y}_t the optimal flow for charging arc $t \in A'$ in the pricing optimization model with the extra constraints $s_{t'} = \bar{s}$, for $t' \in A' \setminus \{t\}$. Then, the following holds:

Proposition.

The optimal flow for arc $t \in A'$ satisfies $\underline{y}_t \leq y_t \leq \bar{y}_t$.

We can add these valid inequalities during the branch-and-bound process to reduce the search space.

Granot F, Veinott AF (1985) Substitutes, complements and ripples in network flows. *Mathematics of Operations Research* 10:471-497

Table of Contents

1 Introduction

2 Literature

3 Model

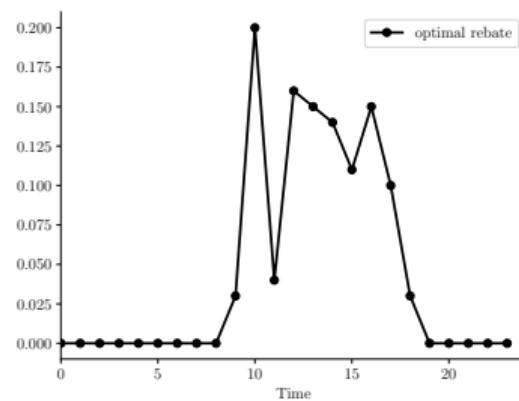
4 Solution approach

5 Case study

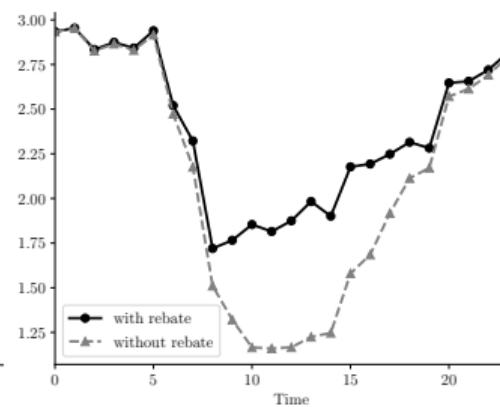
6 Conclusion

Case Study

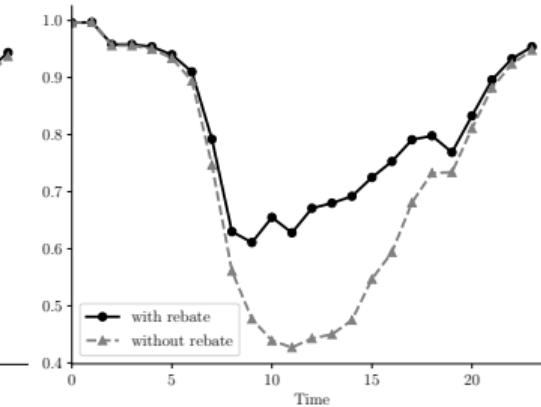
Overall, the fleet of 200 EVs generates a monthly profit of **\$220.60 (per EV)** for the platform, and **\$20.52** in rebates on average for each driver. Compared with the case of not offering rebates, offering such incentives helps improve the platform's profit by **4.37%**.



optimal rebates



optimal bids



optimal persistency values

Sensitivity Analysis

Impact of Fleet Size

Fleet size	Profit per EV (with rebates)	Profit per EV (without rebates)	Improvement	Total rebate (monthly)
100	216.063	205.475	5.15%	23.163
150	219.021	209.301	4.64%	23.193
200	220.598	211.358	4.37%	20.517
250	221.587	212.652	4.20%	20.514
300	222.271	213.544	4.09%	20.589
350	222.790	214.197	4.01%	20.499
400	223.169	214.698	3.95%	20.499

Observation: Both increasing the participating EV fleet size and offering plug-in rebates help improve the platform's profits due to a pooling effect. Furthermore, the two work as strategic substitutes in improving profits.

Sensitivity Analysis

Comparison of different chargers' power rates

Charging rate (kW)	Profit per EV (with rebates)	Profit per EV (without rebates)	Improvement	Total rebates (monthly)
7.2	154.360	152.178	1.43%	11.028
10	220.598	211.358	4.37%	20.517
15	346.865	317.038	9.41%	45.000
20	479.788	422.717	13.50%	62.811
30	756.814	634.075	19.36%	89.781
40	1042.483	845.434	23.31%	111.582

Observation: Upgrading the chargers' powering rating is a strategic complement with offering rebates, and can benefit EV drivers even more than the platform.

Sensitivity Analysis

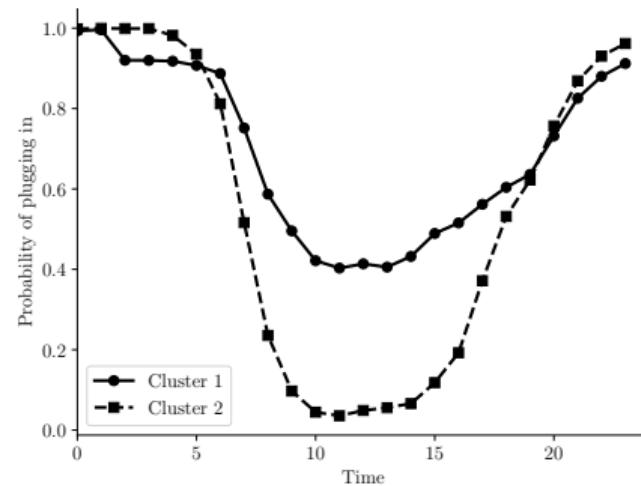
Impact of Baseline Utility Value $\bar{\mu}$

$\bar{\mu}$ (in dollars)	Profit per EV (with rebates)	Profit per EV (without rebates)	Improvement	Total rebate (monthly)
100	239.679	211.358	13.40%	27.042
150	227.931	211.358	7.84%	27.336
200	220.598	211.358	4.37%	20.517
250	216.205	211.358	2.29%	17.265
300	213.448	211.358	0.99%	10.413
400	211.403	211.358	0.02%	1.509
500	211.358	211.358	0.00%	0.000

Observation: When EV drivers have lower valuations for using their EVs, they become more sensitive to rebates. Consequently, the platform offers higher rebates and thereby obtains higher profits.

Computational performance

To generate different instances, we first apply agglomerative hierarchical clustering on the travel patterns of residents.



Travel Pattern Clusters in CHTS Sample

Computational performance

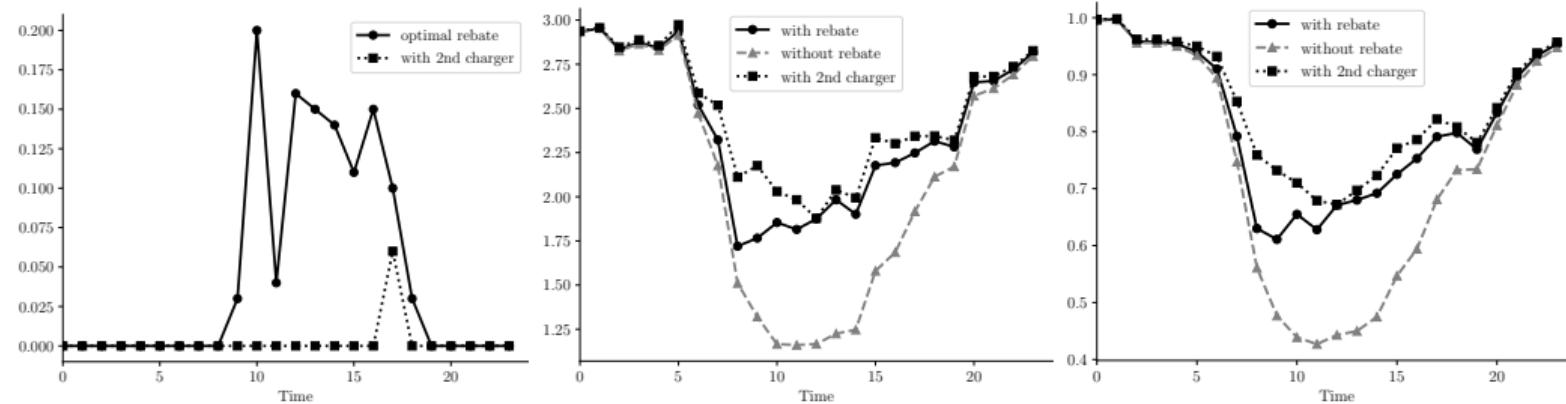
Computational Performance

Composition		without valid inequalities			with valid inequalities		
Cluster 1	Cluster 2	Time(s)	Gap	% Solved	Time(s)	Gap	% Solved
0.4	0.6	174.02	-	100%	42.46	-	100%
0.45	0.55	202.68	-	100%	58.31	-	100%
0.5	0.5	298.45	2.38%	94%	54.78	-	100%
0.55	0.45	490.88	2.23%	86%	102.80	-	100%
0.6	0.4	676.23	2.41%	62%	171.98	2.13%	98%
0.65	0.35	758.29	2.46%	40%	330.58	2.20%	86%
0.7	0.3	994.54	2.60%	18%	473.09	2.29%	64%

When Cluster 2 takes a larger proportion, the platform will offer less (often close to zero) rebates, and the corresponding optimization problem becomes easier to solve. Yet, for all instances, the tightened formulation is computationally tractable.

Model extensions

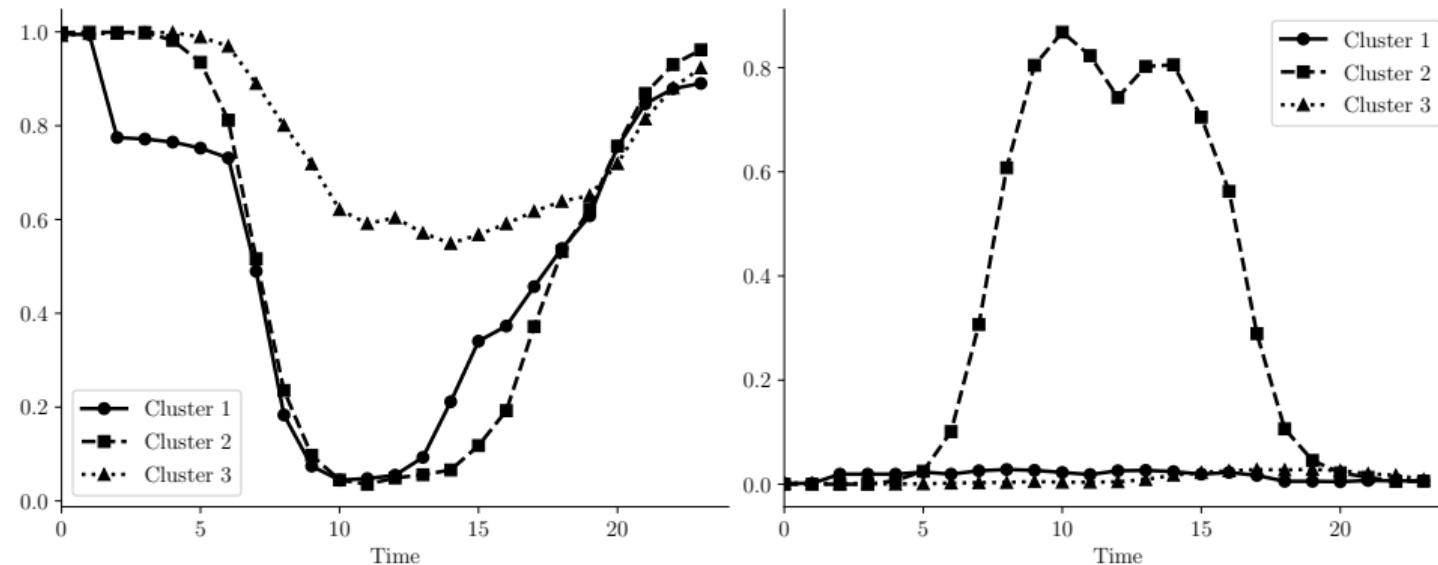
Workplace charging



Observation: Two alternative strategies to promote V2G participation, installing workplace chargers and providing plug-in rebates, work as strategic substitutes in improving the platform's profits.

Model extensions

Workplace charging



Model extensions

Workplace charging

Table 6 Comparison of different traveling patterns

Composition			without workplace charger				with workplace charger			
C2	C1	C3	Reb	NoReb	Imp	TotReb	Reb	NoReb	Imp	TotReb
0.2	0.3	0.5	214.983	208.983	2.87%	17.256	235.397	234.277	0.48%	5.975
0.2	0.4	0.4	212.127	205.499	3.23%	18.019	229.541	227.988	0.68%	5.250
0.25	0.3	0.45	214.847	206.785	3.90%	21.855	238.389	237.395	0.42%	5.437
0.25	0.35	0.4	209.651	199.304	5.19%	23.522	231.500	230.339	0.50%	3.617
0.3	0.2	0.5	215.696	208.607	3.40%	17.113	248.120	247.629	0.20%	3.947
0.3	0.25	0.45	214.254	205.938	4.04%	20.525	241.374	240.532	0.35%	4.878
0.3	0.35	0.35	209.174	199.223	4.99%	26.711	235.252	233.694	0.67%	4.819
0.3	0.4	0.3	209.210	195.533	6.99%	24.971	232.267	230.987	0.55%	4.246
0.3	0.3	0.4	213.574	202.351	5.55%	20.603	236.926	235.699	0.52%	2.984
0.345	0.227	0.428	213.709	206.029	3.73%	21.686	244.611	243.896	0.29%	2.604
0.35	0.25	0.4	211.672	200.108	5.78%	23.428	246.446	245.892	0.23%	4.682
0.35	0.2	0.45	213.592	203.307	5.06%	19.276	247.127	246.222	0.37%	3.980
0.35	0.3	0.35	210.982	198.612	6.23%	21.965	240.995	239.821	0.49%	3.986
0.4	0.2	0.4	213.157	202.176	5.43%	23.210	249.396	248.726	0.27%	3.367
0.4	0.25	0.35	212.019	200.159	5.93%	21.898	246.158	245.814	0.14%	3.871
0.4	0.3	0.3	209.972	195.990	7.13%	24.701	241.781	240.880	0.37%	4.435
0.5	0.2	0.3	211.905	191.842	10.46%	26.576	249.109	248.226	0.36%	4.069

Observation: The benefits of offering workplace chargers are robust with respect to the population composition of drivers.

Model extensions

Alternative objective

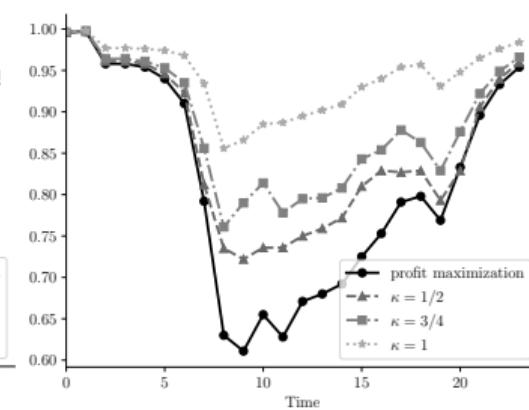
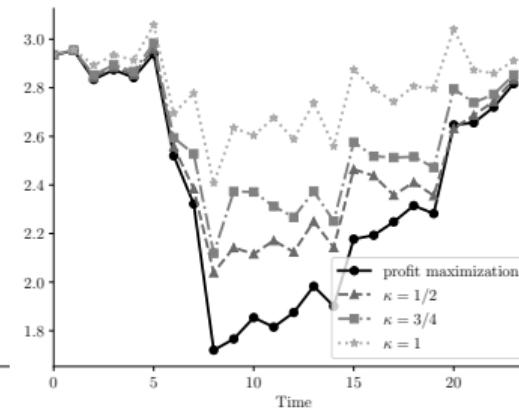
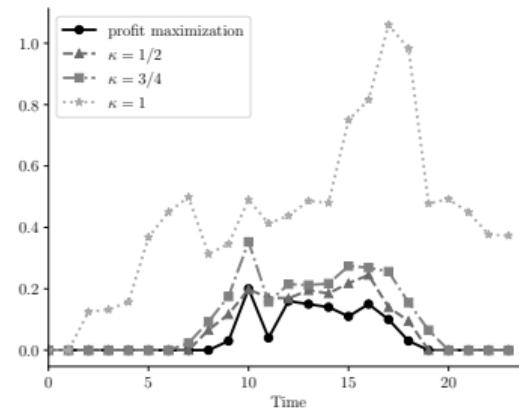
We consider the case where the platform is jointly owned by the drivers.

$$\begin{aligned}
 \max_{\mathbf{C}, \mathbf{s}, \rho} \quad & \sum_{a \in A} \left(\mu_a y_a + \sigma_a \sqrt{y_a(1-y_a)} \right) + \sum_{t=1}^T \left((\mu_t + s_t) y_t + \sigma_t \sqrt{y_t(1-y_t)} \right) \\
 & + \frac{1}{\kappa M} \sum_{t=1}^T (\bar{p}_t C_t - s_t y_t M) \\
 \text{s.t.} \quad & \sum_{t=1}^T (\bar{p}_t C_t - s_t y_t M) \geq 0,
 \end{aligned}$$

Other Constraints.

Model extensions

Alternative objective



Observation: As more EV drivers become stakeholders in the community V2G platform, the optimal rebate schedule **more closely resembles the pattern of regulation prices**.

Model extensions

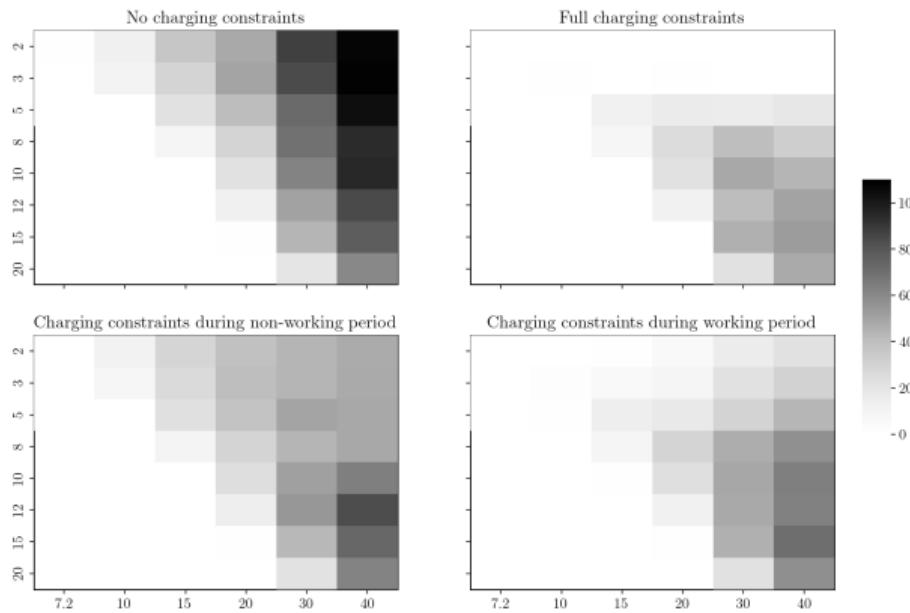
State-of-charge guarantees

Within each hour that the EV is plugged in, the platform will ensure that the EV is charged at an *average* rate of ω kW, and that the EV will not lose charge (i.e., end the hour with lower state-of-charge than it started) with at least $1 - \hat{\eta}$ probability (e.g., 95%).

$$P\left(\omega \tilde{K}_t - \tilde{\gamma}_t C_t \geq 0\right) \geq 1 - \hat{\eta},$$

$$P\left((\psi - \omega)\tilde{K}_t - \tilde{r}_t C_t \geq 0\right) \geq 1 - \eta.$$

Model extensions



Observations:

From the EV owner's perspective, requiring the platform to maintain state of charge throughout periods of V2G participation can lead to reduction in rebates.

Table of Contents

1 Introduction

2 Literature

3 Model

4 Solution approach

5 Case study

6 Conclusion

Main Take-away

- Bilevel problem for platform-driver game
 - ▶ Bilevel convex optimization
 - ▶ Persistency model for drivers' behavior (temporal substitution)
 - ▶ Dist-Robust Optimization for chance constraint
 - ▶ Inverse optimization for parameter calibration
- Observations
 - ▶ **Mismatch** between the availability of regulation power (parked EVs) and the regulation revenue. → offering rebates.
 - ▶ The infrastructure enhancements of increasing the power rating of chargers and providing workplace chargers work as a *strategic complement* and a *strategic substitute* with the pricing strategy of offering rebates.
 - ▶ In an alternative, community-based business model, the optimal rebates will be higher.
 - ▶ SOC guarantee generally lowers the amount of rebates offered to EV owners, and especially so when the nominal charging rate is low.