Energy-sponge Electric Vehicle Sharing System Design

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Abstract

We propose a new vehicle sharing service where a spatially-distributed EV fleet serves as a backup reservation interfacing with both the transportation and power grid systems. We build a two-stage stochastic model to generate sustainable management strategies considering the stochastic spatiotemporal fluctuations of the requests for this new service. In our model, the bid process of an EV fleet operator in the day-ahead energy and reserve market constitutes the first stage, which is optimized based upon macroscopic modeling on the next-day operations of the EV fleet as the second stage. Interesting managerial insights on bid strategies are obtained through numerical experiments.

Introduction

The car-sharing market has experienced prosperous growth recently. With economic benefits and government policy incentives, electric vehicles (EVs) are expected to be adopted by more carshare operators.

With a wise management strategy, a shared EV fleet of a sufficient scale can mitigate the demand disturbance in both transportation and power grid systems. In this way, the shared EV fleet forms an energy sponge service (ESS) that improves the resilience in both energy and transportation systems.

However, the implementation of ESS is challengeable. First, the fleet charging strategy needs to consider the infrastructure limitations and the regulation requirements from the power grid. Second, the fleet's planning and operations should consider the spatiotemporal demand uncertainty and the energy consumption constraints.

To counter these challenges, we establish a profit-driven planning framework for the proposed ESS, which integrates both the power and transportation systems, to provide a sustainable energy-sponge service.

Conclusion

This paper proposes an innovative ESS for a large-scale shared EV fleet and presents a stochastic optimization model for the day-ahead bidding strategies and next-day operations. This optimization identifies several optimal management strategies from a macroscopic perspective, which includes the economically optimal bids in the day-ahead energy and reserve market, as well as the corresponding optimal charging schedules and service level while facing variable trip requests.

Model: Stochastic Optimization Problem (SP)

$$\max \quad r^R - c^E + r^V - c^G$$

$$\text{s.t.}\, Y_t^{up}, Y_t^{down} \geq 0, \forall t \in T, \tag{1}$$

$$(\phi_t[s] - \phi_{t-1}[s])N = \sum_{t': t' + \tau_{t'}[s] = t-1} z_{t'}[s]\,\lambda_{t'}[s] - z_{t-1}[s]\,\lambda_{t-1}[s], \forall t \in T, s \in S, \tag{2}$$

$$\phi_0[s] = \phi_{|T|}[s] = 1, \forall s \in S, \tag{3}$$

$$0 \leq \phi_t[s], z_t[s] \leq 1, \forall t \in T, s \in S, \tag{4}$$

$$z_t[s]\,\lambda_t[s] \leq N\phi_t[s], \forall t \in T, \tag{5}$$

$$\mu_t[s] = \alpha_1 N(1 - \phi_t[s]), \forall t \in T, s \in S, \tag{6}$$

$$N\alpha_2\phi_t[s] \leq x_t[s] \leq N\alpha_3\phi_t[s], \forall t \in T, s \in S, \tag{7}$$

$$y_t^{up}[s] = x_t[s] - N\alpha_2\phi_t[s], \forall t \in T, s \in S, \tag{8}$$

$$y_t^{down}[s] = N\alpha_3\phi_t[s] - x_t[s], \forall t \in T, s \in S, \tag{9}$$

$$\varepsilon_t[s] - \varepsilon_{t-1}[s] = (x_{t-1}[s] - \mu_{t-1}[s])\Delta T, \forall t \in T, s \in S, \tag{10}$$

$$N\underline{\varepsilon} \leq \varepsilon_t[s] \leq N\overline{\varepsilon}, \forall t \in T, s \in S, \tag{11}$$

$$\varepsilon_0[s] = \varepsilon_{|T|}[s] = N\varepsilon^{intial}, \forall s \in S, \tag{12}$$

$$c^E = \sum_{s\in S} \mathbb{P}[s] \left[\sum_{t\in T} p_t^e x_t[s]\Delta T\right], \tag{13}$$

$$r^R = \sum_{t\in T} \left(p_t^{up} Y_t^{up} + p_t^{down} Y_t^{down}\right)\Delta T, \tag{14}$$

$$r^V = \sum_{s\in S} \mathbb{P}[s] \sum_{t\in T} \left(\rho_t^d \tau_t^d[s]\,\lambda_t[s]\,z_t[s]\right)\Delta T - \sum_{s\in S} \mathbb{P}[s] \sum_{t\in T} \left(\rho_t^r \tau_t^d[s]\,\lambda_t[s]\,(1 - z_t[s])\right)\Delta T, \tag{15}$$

$$c^G = \sum_{s\in S} \mathbb{P}[s] \left[\sum_{t\in T} \left(\rho_t^e |X_t - x_t[s]| + \rho_t^{up}\left(Y_t^{up} - y_t^{up}[s]\right)^+ + \rho_t^{down}\left(Y_t^{down} - y_t^{down}[s]\right)^+\right)\Delta T\right]. \tag{16}$$

Solution Algorithm

(SP) is a two-stage stochastic programming model considering demand uncertainty. Notice that the term (16) in the objective function can be linearized by introducing auxiliary variables $l_t[s]$, $m_t^{up}[s]$, $m_t^{down}[s]$, and adding extra constraints.

$$c^G = \sum_{s\in S} \mathbb{P}[s] \left[\sum_{t\in T} \left(\rho_t^e l_t[s] + \rho^{up} m_t^{up}[s] + \rho^{down} m_t^{down}[s]\right)\Delta T\right] \tag{17}$$

$$\text{s.t.}\, l_t[s] \geq X_t - x_t[s], \forall t \in T, s \in S, \tag{18}$$

$$l_t[s] \geq x_t[s] - X_t, \forall t \in T, s \in S, \tag{19}$$

$$m_t^{up}[s] \geq Y_t^{up} - y_t^{up}[s], \forall t \in T, s \in S, \tag{20}$$

$$m_t^{up}[s] \geq 0, \forall t \in T, s \in S, \tag{21}$$

$$m_t^{down}[s] \geq Y_t^{down} - y_t^{down}[s], \forall t \in T, s \in S, \tag{22}$$

$$m_t^{down}[s] \geq 0, \forall t \in T, s \in S. \tag{23}$$

It is easy to show that (SP) with modified term (17) and additional constraints (18) to (23) is equivalent to the original version.

Since (SP) is a two-stage linear stochastic model with continuous variables and complete recourse, we apply the L-shaped method to solve it efficiently. For simplicity, we abbreviate (SP) as follows

$$\begin{aligned} &\max \mathbf{c}^T\mathbf{x} + \sum_{s\in S} \mathbb{P}[s]\,\mathbf{q}^T[s]\,\mathbf{y}[s], \\ &\text{s.t.}\, \mathbf{A}\mathbf{x} \leq \mathbf{b}, \\ &\quad \mathbf{T}[s]\,\mathbf{x} + \mathbf{W}[s]\,\mathbf{y}[s] \leq \mathbf{h}[s], \end{aligned}$$

The L-shaped algorithm is described based on the above abbreviated (SP) in Algorithm 1.

Algorithm 1 L-shaped Algorithm

- Step 0: Set $s = \nu = 0$.
- Step 1: Set $\nu = \nu + 1$. Solve the following LP1:

$$\begin{aligned} &\max \mathbf{c}^T\mathbf{x} + \theta \\ &\text{s.t.}\, \mathbf{A}\mathbf{x} \leq \mathbf{b}, \\ &\quad \mathbf{E}_l\mathbf{x} + \theta \geq \mathbf{e}_l, l = 1, 2, ..., s. \end{aligned}$$

Let $(\mathbf{x}^\nu, \theta^\nu)$ be an optimal solution of LP1.

- Step 2: For $s \in S$, solve the following LP2:

$$\begin{aligned} &\min \mathbf{q}^T[s]\,\mathbf{y}[s], \\ &\text{s.t.}\, \mathbf{W}[s]\,\mathbf{y}[s] \leq \mathbf{h}[s] - \mathbf{T}[s]\,\mathbf{x}. \end{aligned}$$

Let $\pi^\nu[s]$ be the simplex multipliers associated with the optimal solution of LP2.

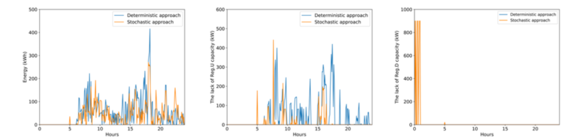
- Step 3: Define

$$\mathbf{E}_{s+1} := \sum_{s\in S} \mathbb{P}[s]\left(\pi^\nu[s]\right)^T \mathbf{T}[s],$$

$$\mathbf{e}_{s+1} := \sum_{s\in S} \mathbb{P}[s]\left(\pi^\nu[s]\right)^T \mathbf{h}[s].$$

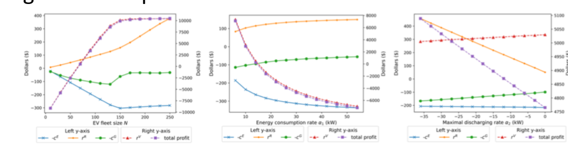
If $\mathbf{e}_{s+1} - \mathbf{E}_{s+1}\mathbf{x}^\nu \leq \theta^\nu$, stop; $\mathbf{x}^\nu$ is an optimal solution. Otherwise, set $s := s + 1$, and return to Step 1.

Results

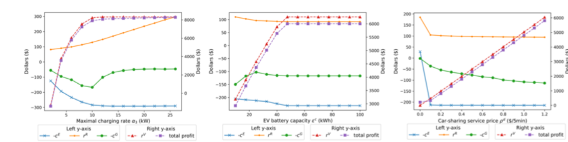


(a) The expected gap between the targeted charging rate X and the real-time charging rate x ($\mathbb{E}_S[|X_t - x_t[s]|]$) (b) The expected lack of Reg.U capacity $\mathbb{E}_S\left[\left(Y_t^{up} - y_t^{up}[s]\right)^+\right]$ (c) The expected lack of Reg.D capacity $\mathbb{E}_S\left[\left(Y_t^{down} - y_t^{down}[s]\right)^+\right]$

Figure 1. Comparison between deterministic and stochastic solutions

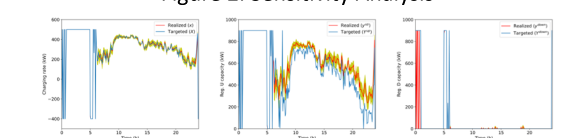


(a) Variation of EV fleet size N (b) Variation of energy consumption rate α_1 (c) Variation of maximal discharging rate α_2

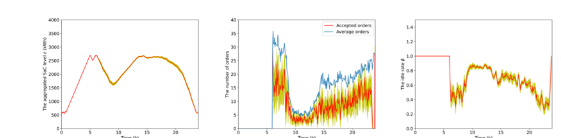


(d) Variation of maximal charging rate α_3 (e) Variation of EV battery capacity ε^c (f) Variation of car-sharing service price ρ^d

Figure 2. Sensitivity Analysis



(a) Targeted charging rate X and the realized charging rate x with its 95% C.I. (b) Targeted Reg.U capacity Y^{up} and the realized Reg.U capacity y^{up} with its 95% C.I. (c) Targeted Reg.D capacity Y^{down} and the realized Reg.D capacity y^{down} with its 95% C.I.



(d) The aggregated SoC level ε with its 95% C.I. (e) The average orders and the accepted orders with its 95% C.I. (f) The idle rate ϕ with its 95% C.I.

Figure 3. Stochastic Solution for Austin case