Introduction

- The stochastic programming model is (EV-SP)
- The SAA counterpart of (EV-SP) is (EV-SAA)
- In the following, I briefly explain the model, more details about the model can be found at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3548028`
- I provide a sample code of solving the SAA problem using Python+Mosek in the HTML

Outline

Problem

Model description

Code description

A Large-scale Stochastic Program

The EV charging scheduling problem is

$$\min_{\boldsymbol{x}\in\mathcal{X}} \mathbb{E}_{\mathbb{P}^C} \left[\sum_{s\in[T]} e_s \sum_{v\in\mathcal{V}_s} x_{v,s}\tilde{z}_v + \max_{t\in[T]} \left\{ \sum_{v\in\mathcal{V}_t} x_{v,t}\tilde{z}_v \right\} \right] \qquad \text{(EV-SP)}$$

where

$$\mathcal{X} \triangleq \left\{ \boldsymbol{x} \;\middle|\; \begin{array}{ll} \sum_{t\in\mathcal{T}_v} \eta x_{v,t} = u_v & \forall v \in [V] \\ 0 \le x_{v,t} \le K/\eta & \forall v \in [V], t \in \mathcal{T}_v \end{array} \right\}.$$

SAA Problem

$$
\begin{aligned}
\min_{\boldsymbol{x}\in\mathcal{X}} \quad & \frac{1}{N}\sum_{i\in[N]}\left(\sum_{s\in[T]} e_s\left(\sum_{v\in\mathcal{V}_s} x_{v,s} z_v^i\right) + d\gamma^i\right) \\
\text{s.t.} \quad & \sum_{v\in\mathcal{V}_t} x_{v,t} z_v^i \le \gamma^i \qquad \forall t\in[T], i\in[N]
\end{aligned}
\tag{EV-SAA}
$$

where

$$
\mathcal{X} \triangleq \left\{ \boldsymbol{x} \;\middle|\; \begin{array}{ll} \sum_{t\in\mathcal{T}_v} \eta x_{v,t} = u_v & \forall v\in[V] \\ 0 \le x_{v,t} \le K/\eta & \forall v\in[V], t\in\mathcal{T}_v \end{array} \right\}.
$$

Outline

Model: Stochastic Demand

- Finite horizon $[T] \triangleq \{1, 2, ..., T\}$

Model: Stochastic Demand

- Finite horizon $[T] \triangleq \{1, 2, ..., T\}$
- Capacity C: number of chargers

Model: Stochastic Demand

- Finite horizon $[T] \triangleq \{1, 2, ..., T\}$
- Capacity C: number of chargers
- EV customer type $v \in [V]$: arrival period s_v, desired departure period τ_v, quantity to charge u_v

Model: Stochastic Demand

- Finite horizon $[T] \triangleq \{1, 2, ..., T\}$
- Capacity C: number of chargers
- EV customer type $v \in [V]$: arrival period s_v, desired departure period τ_v, quantity to charge u_v
- **Uncertainty**: number of EV customer type v: $\tilde{z}_v$, $\tilde{\boldsymbol{z}} \triangleq (\tilde{z}_v)_{v \in [V]} \sim \mathbb{P}^C$
  - $C = \infty$ (uncapacitated): $\tilde{z}_v \sim$ Poisson(λ_v) are independent
  - $C < \infty$ (capacitated): truncated from uncapacitated case with capacity constraints

$$\tilde{\boldsymbol{z}} \in \mathcal{Z} \triangleq \left\{ \boldsymbol{z} \geq \mathbf{0} \;\middle|\; \sum_{v \in \mathcal{V}_t} z_v \leq C, \quad \forall t \in [T] \right\}, \qquad (1)$$

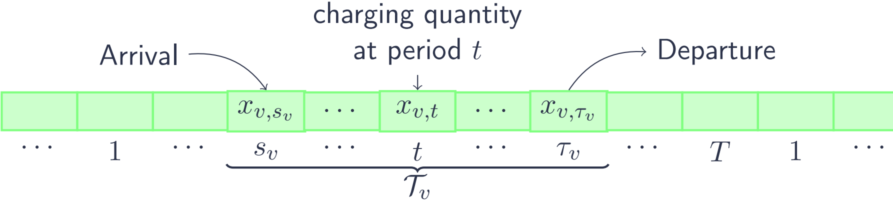
where $\mathcal{V}_t \triangleq \{v \in [V] \mid s_v \leq t \leq \tau_v\}$ with probability one.

Model: Charging Dynamics

- In each period $t = 1, ..., T$:
  1. Observe demand realization of $\tilde{z}_v$ with $s_v = t$.
  2. Charge all the EVs of type v with $v \in \mathcal{V}_t$ according to a **menu-based charging schedule**, i.e., a collection of $x_{v,t}$'s.
  3. Departure of EVs with $\tau_v = t$

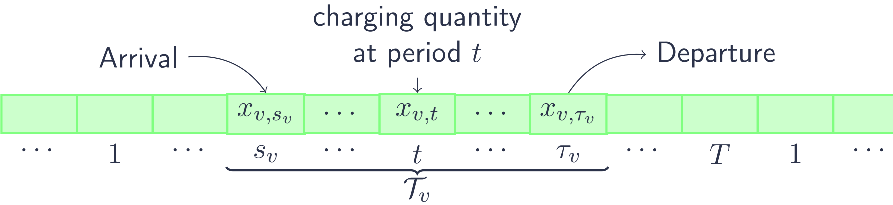
Model: Charging Dynamics

- In each period $t = 1, ..., T$:
  1. Observe demand realization of $\tilde{z}_v$ with $s_v = t$.
  2. Charge all the EVs of type v with $v \in \mathcal{V}_t$ according to a **menu-based charging schedule**, i.e., a collection of $x_{v,t}$'s.
  3. Departure of EVs with $\tau_v = t$
- EV charging: For a single EV of type v,



Model: Charging Dynamics

- EV charging: For a single EV of type v,



charging efficiency

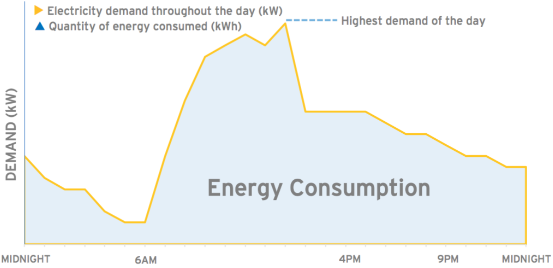
$$\sum_{t \in \mathcal{T}_v} \boxed{\eta}\, x_{v,t} = u_v$$

$$0 \le x_{v,t} \le \boxed{K} / \eta$$

maximal charging quantity

Model: Objective Function

- Energy charge (\$/kWh): usage cost of total energy consumption
- Demand charge (\$/kW): unit demand charge $\times$ highest demand



Source: https://www.sdge.com/businesses/pricing-plans/understanding-demand

Model: Objective Function

Minimize the expected total cost: $\mathbb{E}_{\mathbb{P}^C}\left[c(\boldsymbol{x}, \tilde{\boldsymbol{z}})\right]$ where

$$c(\boldsymbol{x}, \tilde{\boldsymbol{z}}) \triangleq \underbrace{\sum_{s \in [T]} \underbrace{e_s}_{\text{time-dependent unit energy charge}} f_s(\boldsymbol{x}, \tilde{\boldsymbol{z}})}_{\text{energy charge}} + \underbrace{\underbrace{d}_{\text{unit demand charge}} \max_{t \in [T]}\{f_t(\boldsymbol{x}, \tilde{\boldsymbol{z}})\}}_{\text{demand charge}}$$

where

$$f_t(\boldsymbol{x}, \tilde{\boldsymbol{z}}) = \sum_{v \in \mathcal{V}_t} x_{v,t} \tilde{z}_v$$

is the total amount of electricity purchased in period t.

Outline

On the code in HTML

In the HTML, we show how to set model parameters and solve SAA problems using Mosek.

- The SAA problem we solve in the code is slightly complicated: we use multiple demand charges, i.e., the demand charge

  $$d \max_{t \in [T]} \{f_t(\boldsymbol{x}, \tilde{\boldsymbol{z}})\}$$

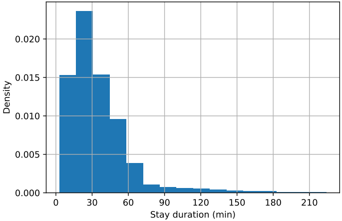
  in (EV-SP) is replaced by

  $$d_{all} \max_{t \in [T]} \{f_t(\boldsymbol{x}, \tilde{\boldsymbol{z}})\} + d_{on} \max_{t \in \mathcal{T}_{on}} \{f_t(\boldsymbol{x}, \tilde{\boldsymbol{z}})\} + d_{mid} \max_{t \in \mathcal{T}_{mid}} \{f_t(\boldsymbol{x}, \tilde{\boldsymbol{z}})\}$$

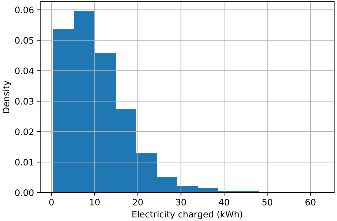
  where $\mathcal{T}_{on}$, $\mathcal{T}_{mid}$ are `PeakOn`, `PeakMid` and d_{all}, d_{on}, d_{mid} are `cdFa`, `cdOn`, `cdMid`, respectively in the code
- I also provide parameter setting in the next page for your references.

Calibrated parameters from public data

- $T = 96$: one-day horizon with each period 15 minutes
- Longest stay duration: 16 periods
- Maximal energy charged $U = 62$kWh



(a) Normalized stay duration



(b) Normalized electricity charged

- Other parameters: Maximal charging power $K = 43$kW, Charging efficiency $\eta = 0.9$

Calibrated parameters from public data

- $T = 96$: one-day horizon with each period 15 minutes
- Longest stay duration: 16 periods
- Maximal energy charged $U = 62$kWh
- Other parameters: Maximal charging power $K = 43$kW, Charging efficiency $\eta = 0.9$
- Time-of-use (TOU) unit energy charge and demand charge

$$\hat{e}_t = \begin{cases} \$0.1466/\text{kWh} & \text{if } 13 \le \lceil t/4 \rceil \le 18 \text{ (on-peak hours)} \\ \$0.0895/\text{kWh} & \text{if } 9 \le \lceil t/4 \rceil \le 12 \text{ or } 19 \le \lceil t/4 \rceil \le 23 \text{ (mid-peak hours)} \\ \$0.0582/\text{kWh} & \text{otherwise (off-peak hours),} \end{cases}$$

$$\hat{d}_t = \begin{cases} \$0.465/\text{kW} & \forall t \in [T] \doteq [96] \text{ (all-period)} \\ \$0.540/\text{kW} & \text{if } 13 \le \lceil t/4 \rceil \le 18 \text{ (on-peak hours)} \\ \$0.165/\text{kW} & \text{if } 9 \le \lceil t/4 \rceil \le 12 \text{ or } 19 \le \lceil t/4 \rceil \le 23 \text{ (mid-peak hours),} \end{cases}$$

Calibrated parameters from public data

- Average number of EVs at station in different periods: