Bayesian Optimization for BEV Charging Station Placement by Activity-based Demand Simulation

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The BEV market share in the U.S.

The U.S. BEV market has been growing rapidly since 2011 with an average annual growth rate of 42.2% [DOE. Transportation Energy Data Book 2021].

By 2020, the U.S. had 1.14 million registered BEVs, accounting for less than 1% of vehicles on the road [IEA. Global EV Outlook 2021].

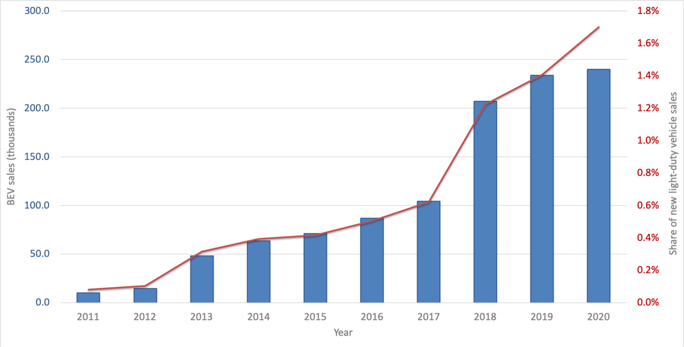


Figure 1: U.S. BEV sales from 2011 to 2020 [DOE. Transportation Energy Data Book 2021].

Restriction on BEV adoption

Lack of charging infrastructure

- BEVs rely heavily on charging infrastructure.
  - BEVs have shorter driving ranges than gasoline vehicles.
  - BEVs have longer recharge times than gasoline vehicles.
- Current charging infrastructure is not enough.
  - There are less charging stations than gas stations.

Table 1: Comparison of BEVs and gasoline vehicles

	BEVs	Gasoline vehicles
Maximum driving range (miles)	405	765
Refill time	30 min - 12 h	5 min
Number of refill stations in the U.S.	50,000	150,000

Research questions

Charging station location problem (CSLP): optimize the placement of charging infrastructure.

- How to place charging infrastructure in an economically sustainable way?
- How to find the optimal placement of multiple station types?
- How to account for demand uncertainty in station placement?
- How to efficiently solve it when the problem is computationally expensive?

Research objectives

Charging station placement by activity-based demand

- Optimize the location and capacity of multi-type charging infrastructure to maximize the net present value.
- Include uncertainty in demand addressed by individual travel and charging behaviors.

Solve the problem by random embedding Bayesian optimization (REMBO)

- First time solving the CSLP by simulating the behaviors of a large number of agents in a fine-divided region.
- Quantitatively evaluate the uncertainty of the optimal values.
- Significantly improve computation efficiency than the sate-of-the-art.

Charging station placement model I

A study region is partitioned into J areas, each area can hold a set of charger types I.

Decision variable:

$$\mathbf{x} = \{x_{ij} | i \in I, j \in J\} \tag{1}$$

x_{ij}: the number of charger type i at area j.

Objective function:

$$\begin{aligned} & \max_{\mathbf{x}} \ \mathbb{E}\left[g(\mathbf{x}, \xi)\right] \\ s.t. \quad & 0 \leq x_{ij} \leq M_{ij} \\ & x_{ij} \in \{0, 1, 2, \cdots\} \end{aligned} \tag{2}$$

$g(\mathbf{x}, \xi)$: net present value (NPV).

ξ: vector of random variables.

M_{ij}: maximum number of station type i at area j.

Simulation optimization problem

The optimization problem:

$$\max_{\mathbf{x}\in\Theta} \; f(\mathbf{x}) \tag{3}$$

- $f(\mathbf{x}) = \mathbb{E}\left[g(\mathbf{x}, \xi)\right]$.
- Θ is the search space.

Challenges of the problem:

- Evaluation of $f(\mathbf{x})$ is intractable.
- Dimension of $\mathbf{x}$ is large: $D =$ N. areas $\times$ N. charger types $\simeq 1,000$.
  $\Rightarrow$ Number of observations $= O(D^2) \sim 1,000,000$, computationally costly!

Solution algorithm:

Random embedding Bayesian optimization (**REMBO**)

Regional charging station placement: case study

Case study: Atlanta metropolitan area

- BEV market size: 5,000 - 30,000
- 21,504 - 113,569 daily commute trips
- Home charging: 0.13 $/kWh, 3.6 kW
- Number of areas: 951 census tracts
- Public charging: 0.43 $/kWh, 2 type chargers

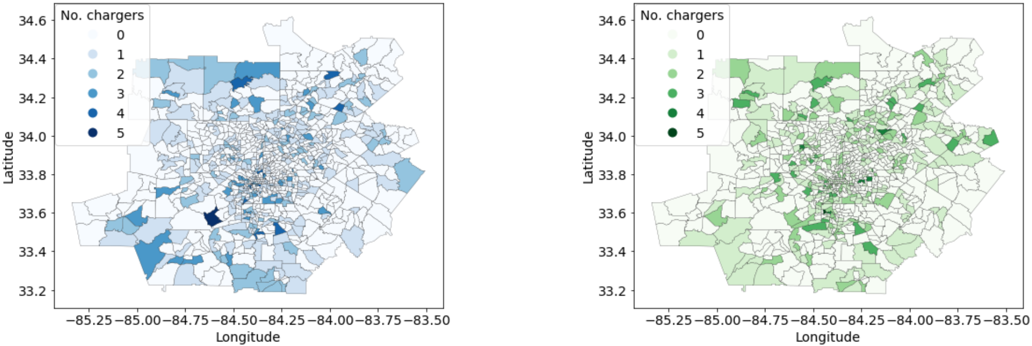
Table 2: Parameters of public charging options.

Charging mode	Charging rate (kW)	Purchase cost ($/unit)	Installation cost ($/unit)
Level 2	6.2	3450	3000
DCFC	150	25000	21000

Optimal charging station placement

Base case: 30,000 BEV, 591 areas.

- Number of level 2 chargers: 579; number of DCFC chargers: 553
- Best observed NPV mean: 30.9 M$



(a) Number of level 2 chargers (b) Number of DCFC chargers

Figure 2: Optimal charging placement.

Effect of charging behavior

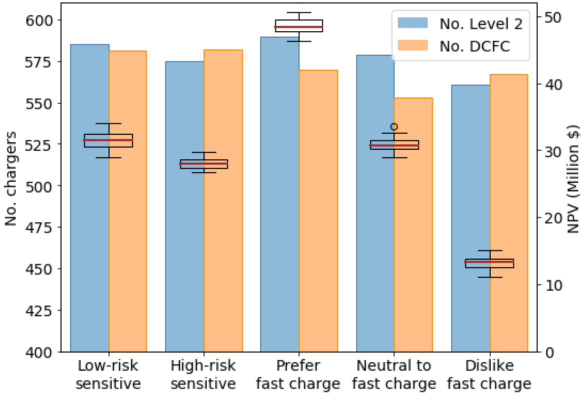


Figure 3: Optimal EVCS placements and NPVs for scenarios with different charging behaviors.

- The optimal number of chargers is not sensitive to users' behaviors.
- Users' preferences to fast charging can significantly affect the optimal NPV.

Effect of BEV market size

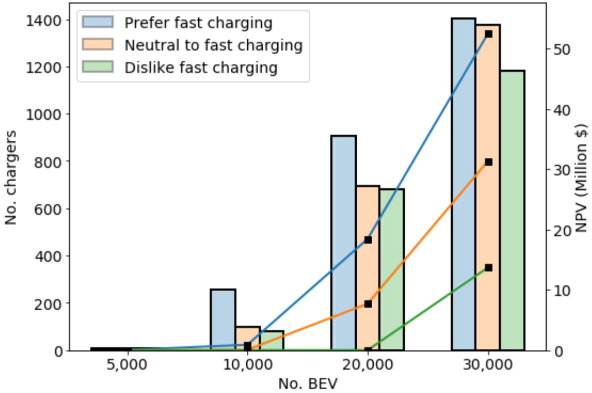


Figure 4: Optimal total number of chargers and NPVs for increasing BEV market size.

- The optimal number of charging infrastructure is highly related to the size of BEV market.
- The break-even BEV market size — the smallest market size that the EVCS project starts to be profitable — can be as small as 10,000.
- Users' charging preference can significantly affect the break-even BEV market size.

Discussion

- Both level 2 and DCFC chargers should be considered in the public charging station placement planning. In an optimal charging station placement, similar number of level 2 and DCFC chargers are needed to satisfy various demands.
- In an optimal charging station placement, small quantities of level 2 and DCFC chargers are scattered in areas that have a high number of parked vehicles.
- The BEV market size is the main factor deciding the optimal total number of charging infrastructure, which determines the initial investment budget of charging infrastructure.
- The profitability of charging infrastructure is not only related to the BEV market size but also users' preference for fast charging.
- The break-even market size can be as low as 10,000 BEVs if users prefer fast charging.

Future research

Charging demand estimation

- Charging behavior prediction (if charging behavior data in a mature market is available)
- Long distance trip charging demand estimation
- More accurate spatial demand distribution (if travel behavior model is available: e.g. if GPS data of general BEV users is available)

Life-cycle zero-emission system design of BEV charging supply

- Integrated charging infrastructure and renewable electricity generation
  - Charging infrastructure planning
  - Zero-emission electricity supply (e.g. photovoltaic field)
  - Energy storage system (e.g. vehicle to grid)

Conclusion

- Propose an activity-based BEV charging demand simulation model
- Estimate high-resolution spatio-temporal BEV charging demand.
- Propose a charging station placement model by activity-based demand
- Propose a solution algorithm by REMBO which allows quantitatively evaluate the uncertainty of the optimal values.
- Find the optimal placement and best NPV of charging infrastructure.

Thanks!

Q & A