Comparative Assessment of Geospatial Models for Electric Vehicle Supply Equipment (EVSE) Planning

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Background

- There are 16,555 public electric stations and 45,371 charging outlets in the United States by Dec. 2017.
- The average density is 43/1000 EVSE/PEV at U.S. county level.

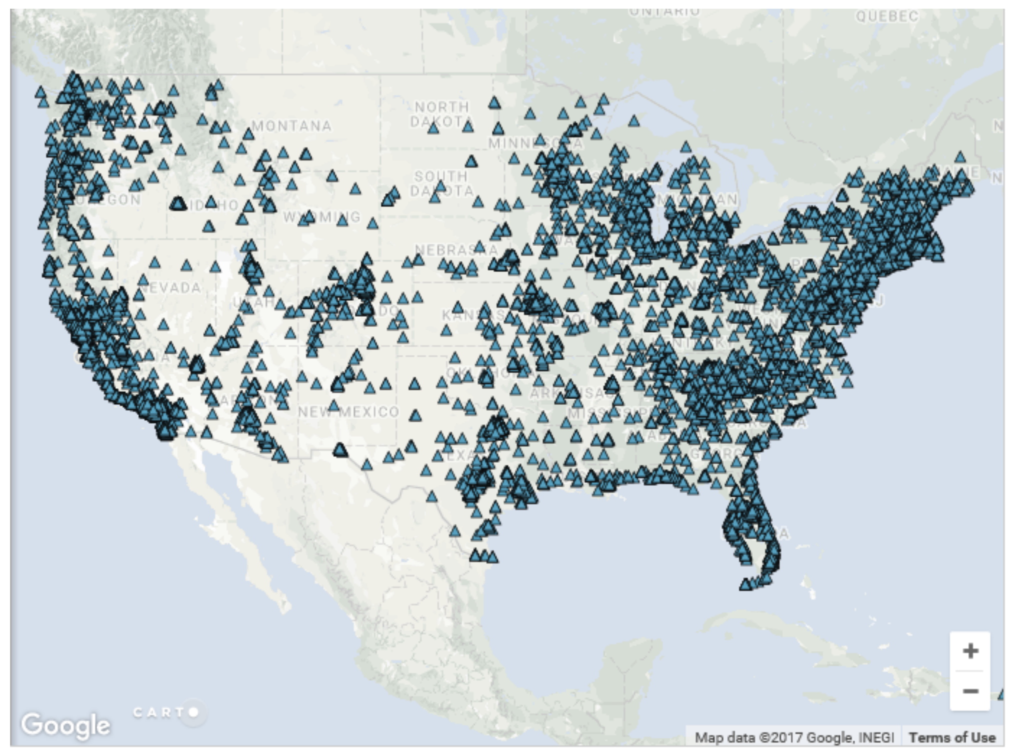

Fig. 1 U.S. Public EVSE Distributions

Source: Alternative Fuel Data Center

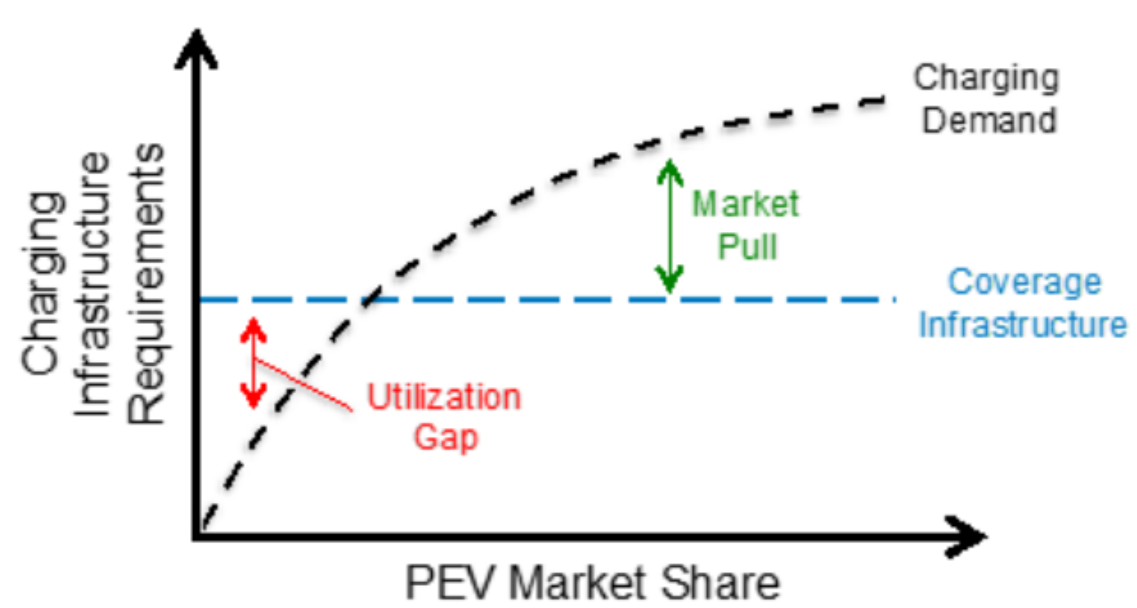

Fig. 2 EVSE Requirements with Different Market Stages

Source: National Plug-In Electric Vehicle Infrastructure Analysis

Results

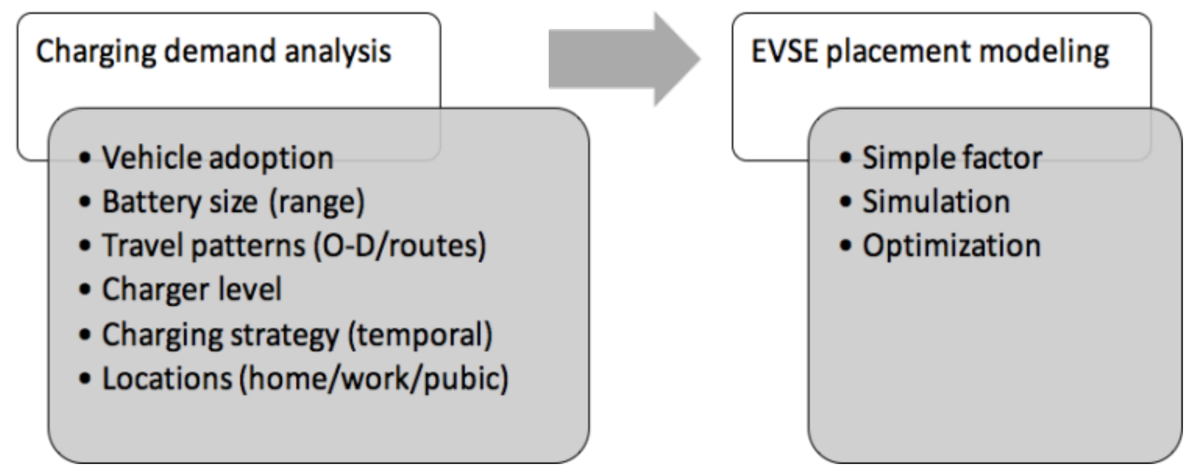

Fig. 3 General Model Algorithm

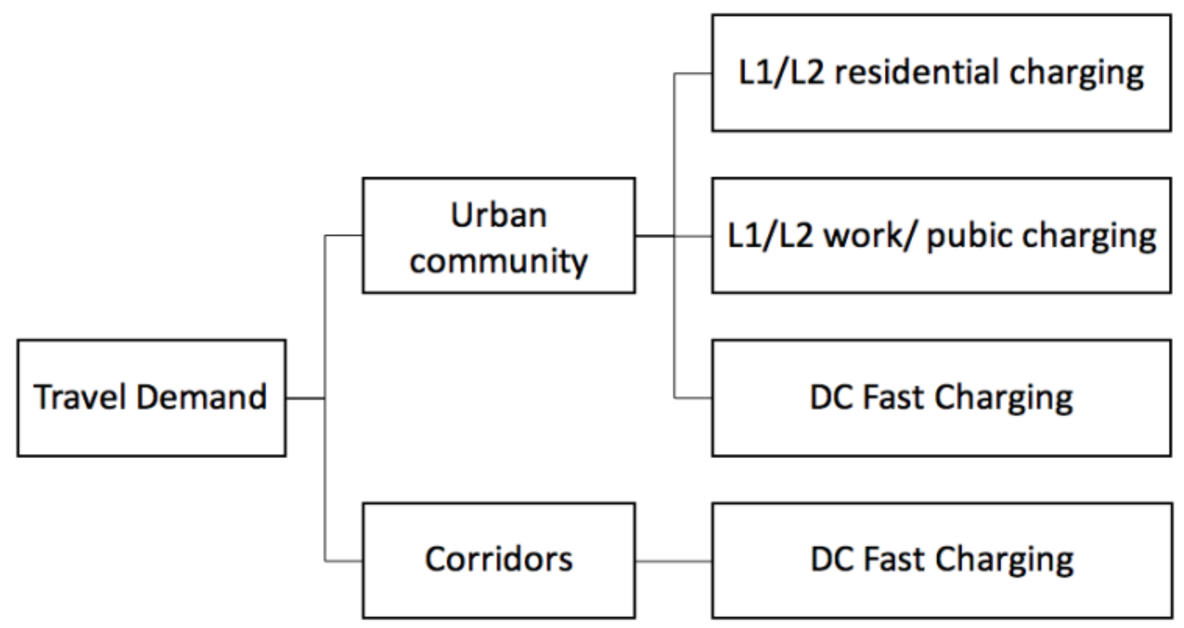

Fig. 4 EVSE Applications by Travel Demand

- *Node-based modeling* views charging demand at nodes, which are determined as origins or destinations of trips, e.g. garage at home, parking lots at workplace, shopping mall, and universities. Mostly used to estimate L2 non-residential EVSE for satisfying urban community trips.
- *Flow-based modeling* regards demand as flows, assuming refilling completed during trips, indicating a relative short refilling time. Used in long-distance corridor trips for identifying fast charging locations.

Table 1 Categories of existing models and methods

Category	Characteristics	General descriptions
Simple factor	Node-based	• Based on ratios of EVSE/PEV, EVSE//urban area or EVSE//interstate miles • Approximately estimate the magnitude of EVSE requirements
Simulation	Node-based	• Imitate the driving patterns and charging behaviors in the real world • Site EVSE at destinations or locations when the batteries reach some low state of charge
Optimization	Node-based & flow-based	• Optimally allocate the charging demand among the candidate EVSE locations, or various charger types • General objectives as max demand coverage, min EVSEs, min distance between EVSE and node/ flow

Table 2 Models and methods comparison

Method	Characteristics	Perspec-tives	Temporal Granularity	Regional Resolution	EVSE Level	Data Inputs	Outputs	Availabi-lity
Simple factor								
National EVSE Analysis	Apply EVSE/PEV ratios to 3623 areas covering U.S. at city/ town/ rural/ interstate highway levels	15M PEVs in 2030; 88% home charging	Yearly	Urban areas, state & national	Nonresidential L2, DCFC	State	Total PEV, %BEV, Work L2 chargers, Public L2 chargers, Public DCFCs	Created by DOE for public guidance
Simulation								
ITS Toolbox-Workplace	Site EVSE at workplace locations; Simulate the utilization of each EVSE	Existing, proposed & future potential EVSE	Daily	California at MPOs level	Workplace L2	Market size, location at zip code level	Number of charging events, electricity demand (kWh) at EVSE	Free download GIS interface
EVI-Pro	Cluster charging demand notes and site EVSE within 0.1 mile	ZEV goals in 2025	Hourly; Weekday/ weekend	CA, MA, Columbus	Nonresidential L2, DCFC	State	EVSE/PEV ratios by PEV type and EVSE type	Website interface
BEAM	Random draw EVSE from discrete probability distributions of roads' charging needs	Existing & potential EVSE	Hourly	9 counties in San Francisco Bay Area	Public L2	Travel and charging data for calibration	Possible EVSE distributions under given number of EVSE	Lawrence Berkeley National Laboratory
Optimization								
Node-based								
SCP/MCLP / p-median	Min EVSEs, Max coverage, Min distance	Potential EVSE	Daily or yearly	Mostly regional	Nonresidential L2, DCFC	Travel data	Optimal EVSE distributions	Literatures
Flow-based								
Flow-capturing	Max flows been captured by EVSE	Potential EVSE	Daily or yearly	Mostly regional	DCFC	Travel data	Optimal EVSE distributions	Literatures
Traffic Equilibrium	Min travel and charging cost, network-based	Potential EVSE	Daily or yearly	Regional	Nonresidential L2, DCFC	Travel and cost data	Optimal EVSE distributions	Literatures

Motivation

- A widespread EVSE system is identified as one of the most important factors affecting PEV adoption.
- Proper placement of EVSE is of great importance to the development of EV industry, the operation and demand management of electric grid, as well as the environmental performance of electric vehicles.
- A variety of proposed tools, models, and metrics to address EVSE location decisions displays the wide range of possible results, underscoring the importance of appropriate method in specific situation.
- We investigate the assumptions, inner logic and applicability of each model, and further discuss their capabilities, limitations and results disparities.

Discussion

- Market stage

Initial market stage when PEV adoption is low, it is hard to predict PEV and investigate PEV/EVSE relations: simple factor estimation.

Intermediate transition stage with early adopters' PEV purchasing and charging behaviors, to fascinate EV adoption: simulation & optimization.

long-term transportation planning: flow-based traffic equilibrium considering congestions and its impacts on route and EVSE choice.

- Area dimension

National/ state level: choose simple factor or simulation, depending on data availability, and research objective.

MPOs/ county/ city level: optimization is often used in small planning areas due to computational limitation for complex optimization problem.

Future Study

- Further understand different methods by conducting a case study developing a node-based/ flow-based optimization model to estimate work L2 in Sacramento areas, then comparing the result with simulation from ITS Toolbox – workplace tool.
- Consider the temporal and geospatial disparity in GHG intensity of the electricity, and develop a multi-objective optimization problem with max flows being captured and min GHG emissions.
- Consider the constraints of electric grid, or the benefits to renewables integration into EVSE design.
- Expand the objective fleets, and include the infrastructure demand for battery electric trucks.

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