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.

We investigate the assumptions, inner logic and importance of range of possible results, underscoring the environmental performance of electric vehicles.

Proper placement of EVSE is of great importance to most important factors affecting PEV adoption.

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.

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.

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.

Results

Table 1 Categories of existing models and methods

<table>
<thead>
<tr>
<th>Category</th>
<th>Characteristics</th>
<th>General descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple factor</td>
<td>Node-based</td>
<td>Based on ratios of EVSE/PEV, EVSE/urban area or EVSE/interstate miles</td>
</tr>
<tr>
<td>Simulation</td>
<td>Node-based</td>
<td>Simulate the driving patterns and charging behaviors in the real world</td>
</tr>
<tr>
<td>Optimization</td>
<td>Node-based &amp; flow-based</td>
<td>Optimal allocate the charging demand among the candidate EVSE locations, or various charger types</td>
</tr>
</tbody>
</table>

General objectives as max demand coverage, min EVSEs, min distance between EVSE and node/flow distribution.

Table 2 Models and methods comparison

<table>
<thead>
<tr>
<th>Method</th>
<th>Characteristics</th>
<th>Temporal Granularity</th>
<th>Regional Resolution</th>
<th>EVSE Level</th>
<th>Data Inputs</th>
<th>Outputs</th>
<th>Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>National EVSE Analysis</td>
<td>Apply EVSE/PEV ratios to 3623 areas covering U.S. at city/county/interstate levels</td>
<td>Yearly</td>
<td>Urban areas, state &amp; national</td>
<td>Nonresidential L2, DCFC</td>
<td>State</td>
<td>Total PEV, %PEV, Work L2 chargers, Public L2 chargers, Public DCFCs</td>
<td></td>
</tr>
<tr>
<td>Simulation</td>
<td>ITS Toolbox - Workplace</td>
<td>Site EVSE at workplace location; simulate the utilization of each EVSE</td>
<td>Daily</td>
<td>California at MPOs level</td>
<td>Workplace L2</td>
<td>Market size, location at zip code level</td>
<td>Number of charging events, electricity demand (Wh) at EVSE</td>
</tr>
<tr>
<td>Optimization</td>
<td>EM-Pro</td>
<td>Cluster charging demand notes and site EVSE within 0.1 mile</td>
<td>ZEV goals in 2025</td>
<td>Hourly</td>
<td>CA, San Francisco Bay Area</td>
<td>State</td>
<td>EVSE/PEV ratios by PEV type and EVSE type</td>
</tr>
<tr>
<td>Optimization</td>
<td>BEAM</td>
<td>Random draw EVSE from discrete probability distributions of roads’ charging needs</td>
<td>Existing &amp; potential EVSE</td>
<td>Hourly</td>
<td>9 counties in San Francisco Bay Area</td>
<td>Public L2</td>
<td>Travel and charging data for calibration</td>
</tr>
<tr>
<td>Optimization</td>
<td>SCP/MClP</td>
<td>Min EVSEs, Max coverage, Min distance</td>
<td>Potential EVSE</td>
<td>Daily or yearly</td>
<td>Mostly regional</td>
<td>Nonresidential L2, DCFC</td>
<td>Total travel data, Optimal EVSE distributions</td>
</tr>
<tr>
<td>Flow-based</td>
<td>Traffic Equilibrium</td>
<td>Min travel and charging cost, Network-based</td>
<td>Potential EVSE</td>
<td>Daily or yearly</td>
<td>Regional</td>
<td>Nonresidential L2, DCFC</td>
<td>Total travel cost and time, Optimal EVSE distributions</td>
</tr>
</tbody>
</table>

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.

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