Public refueling stations
Travel time from previous stop to 12-14 16-18
Least Deviation Analysis 4-6 14-16 20-30
18-20
Deviations 8-10
Stops immediately before / after station
Travel time between home and 60-70 10-20
Reasons for owning an AFV
60-70
10-20
Closest Facility Analysis 70-80
10-20

Introduction
Many challenges remain for commercializing alternative fuel vehicles (AFVs) for consumers. Academics and stakeholders in both public and private sectors cite the lack of a refueling infrastructure as the key barrier to AFV adoption (Melendez 2006). AFV refueling infrastructure build-out is a substantial investment, both economically and politically. Thus, automobile manufacturers are hesitant to produce more AFVs without a robust refueling infrastructure, and fueling stations owners are reluctant to build more facilities without a substantial population of vehicles. This mutual hesitancy is the so-called “chicken and egg problem.”

To overcome these barriers and construct an effective refueling station infrastructure, an understanding of AFV driving and refueling behavior is important. We update the landmark 1986 and 1987 studies by Kitamura and Sperling, interviewing 259 drivers of compressed natural gas (CNG), vehicles at five stations in Southern California. Based on observed refueling behavior of CNG drivers in Southern California, what do early adopters of AFVs consider to be convenient locations for refueling? Specifically, when faced with a choice, do drivers choose the station closest to home or one requiring the least deviation?

This research can help analysts select appropriate optimal facility location models when siting AFV refueling facilities. Models are generally either point-based models (e.g., p-median, max cover), or path-based (flow-intercepting, flow-refueling). Point-based models would prove more appropriate for early stage planning of refueling stations in Southern California, guiding refueling along the way between stops regardless of proximity to home points towards using flow-based models.

Survey
Why Los Angeles?
• Public refueling stations – Clean Energy / Trillium
• Commuter incentives
• Polycentric, many land uses
Honda Civic GX

Intercept methodology, stratified by time of day, n=259.

Questions focused on:
• Socio-demographic information
• Other vehicles in household
• Reasons for owning an AFV
• Reasons for refueling at that particular station
• Stops immediately before / after station

Home location

Methodology
Using ArcGIS 10 and Network Analyst
• Least travel-time path between each driver’s previous and next stops
• Least travel-time path from previous stop to station next stop
• Deviations
• Closest Facility Analysis
• Travel time between home and closest/CNG refueling facility
• Diagnostic for recommending point-based models
• Least Deviation Analysis
• Travel time from previous stop to all stations to next stop
• Diagnostic for recommending flow-based models

Categorize drivers into 2x2 matrix – did they choose a station that was closest to home or minimized detour? Neither? Both? Then categorize marginal cases, conduct t-tests between independent station choice groups to explore key population differences

Results

Publicly Available CNG Stations

Table 1. Deviation, Closest Facility, and Least Deviation

<table>
<thead>
<tr>
<th>CNG STATION</th>
<th>DEV. FROM HOME</th>
<th>% CLOSEST HOME</th>
<th>% LEAST DEVIATION</th>
<th>MEAN TRIP LENGTH (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bulktank</td>
<td>5.2</td>
<td>30.6</td>
<td>6.6</td>
<td>4.3</td>
</tr>
<tr>
<td>Delia Ave.</td>
<td>5.7</td>
<td>30.6</td>
<td>5.0</td>
<td>12.7</td>
</tr>
<tr>
<td>Santa Monica</td>
<td>8.5</td>
<td>60.0</td>
<td>6.7</td>
<td>19.4</td>
</tr>
<tr>
<td>Downtown</td>
<td>4.7</td>
<td>24.0</td>
<td>6.6</td>
<td>30.5</td>
</tr>
<tr>
<td>Baldwin</td>
<td>5.1</td>
<td>58.0</td>
<td>5.6</td>
<td>18.9</td>
</tr>
<tr>
<td>OVERALL</td>
<td>7.2</td>
<td>72.2</td>
<td>6.2</td>
<td>25.4</td>
</tr>
</tbody>
</table>

Table 2. Categorization of refueling station selection

<table>
<thead>
<tr>
<th>CATEGORIES</th>
<th>Closest to Home</th>
<th>Not Closest to Home</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Deviation</td>
<td>&quot;both&quot; 59</td>
<td>&quot;least deviation&quot; 102</td>
</tr>
<tr>
<td>Not Least Deviation</td>
<td>&quot;closest&quot; 10</td>
<td>&quot;neither&quot; 88</td>
</tr>
</tbody>
</table>

Table 3. Marginal cases of 2x2 classification, by rank

<table>
<thead>
<tr>
<th>CHARACTERISTIC</th>
<th>HOME</th>
<th>WORK</th>
<th>SCHOOL</th>
<th>TOTALS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Age</td>
<td>39</td>
<td>36</td>
<td>34</td>
<td>37</td>
</tr>
<tr>
<td>% Employed</td>
<td>89</td>
<td>90</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>% Male</td>
<td>65.5</td>
<td>61.2</td>
<td>60</td>
<td>60.2</td>
</tr>
<tr>
<td>% Home-anchored</td>
<td>79.4</td>
<td>75</td>
<td>70</td>
<td>77.5</td>
</tr>
<tr>
<td>% Work-anchored</td>
<td>60.5</td>
<td>75.7</td>
<td>60</td>
<td>65.9</td>
</tr>
<tr>
<td>Average Age</td>
<td>37.5</td>
<td>38.6</td>
<td>38.2</td>
<td>38.8</td>
</tr>
<tr>
<td>Total Trip Distance</td>
<td>27.5 miles</td>
<td>20.9 miles</td>
<td>20.6 miles</td>
<td>21.9 miles</td>
</tr>
<tr>
<td>Median Distance</td>
<td>15.1 miles</td>
<td>13.8 miles</td>
<td>13.8 miles</td>
<td>13.8 miles</td>
</tr>
<tr>
<td>Median Deviation</td>
<td>3.5 min</td>
<td>6.8 min</td>
<td>6.6 min</td>
<td>6.6 min</td>
</tr>
<tr>
<td>Maximum Deviation</td>
<td>16.7 min</td>
<td>16.2 min</td>
<td>16.2 min</td>
<td>16.2 min</td>
</tr>
</tbody>
</table>

Table 4. Summary statistics for independent groups

When drivers refueled at a CNG station that is either the closest station to home or the least-deviation station – but not both – they selected the latter by an order of magnitude: 102:10 (Table 2).

Summary statistics (Table 4) show little variation across groups. Gender has the most dramatic difference, where the “closest” groups is 70% female. This same group also have the lowest percentage of work-related trips. Group size, however, is very small (n=10).

For the two groups that refueled at a station that met only one criteria, t-tests showed that deviations differed significantly, but trip length and travel time were not significant (Table 5). This eliminates the explanation that those who minimize deviations are taking longer trips than those refueling close to home.

Table 5. Difference of means tests: choice groups

When no CNG station exists that is both closest to home and most on their way, ten times as many drivers refueled at the station that minimized deviation as opposed to the one closest to home.

An additional 88 chose a station that fit neither absolute classification, but many of these drivers were closer to minimizing detour than to refueling closest to home.

Conclusion and Implications
When no CNG station exists that is both closest to home and most on their way, ten times as many drivers refueled at the station that minimized deviation as opposed to the one closest to home.

Trip distances and travel time were not significantly different between the choice groups: those who refueled closest to their home cannot be explained merely by inherently shorter trips.

This empirical evidence suggests that flow-based location models may be more appropriate for early infrastructure planning of AFV refueling station locations, rather than point-based models.

Based on these results, we suggest that the initial wave of AFV refueling stations should be focused along frequently traveled paths of drivers, rather than home-work commute routes.

Related analyses underway (not shown here): (1) Comparison of CNG and gasoline driver refueling; (2) Survey of commercial drivers refueling at another fleet’s station; (3) Similar survey of EV public recharging in Phoenix. Other geographies should be examined for consistency.

References

We would like to acknowledge NSF Grant 1025313, “Spatial Refueling Patterns of Drivers of Alternative-Fuel and Conventional Vehicles.” We thank Clean Energy Fuels and Trillium for permission to conduct interviews at their CNG stations. We also acknowledge the valuable contributions of ASU graduate student Joseph Schiemenz, who provided many hours of GIS support for the project; undergraduate students Patrick Zwolinski and Jeff Martinez, who conducted the survey in Los Angeles; and Michael McLean of the ASU Institute of Social Science Research, for help with survey and sampling design.