An optimization framework for cost effective design of refueling station infrastructure for alternative fuel vehicles

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**A B S T R A C T**

Historically, gasoline and diesel fuels have been used for transportation, but the possible decline of oil supplies in the future is forcing nations to consider alternative fuels. Most technically and economically feasible alternative fuels have a lower energy density than gasoline, which results in a shorter range for these vehicles. This necessitates a greater need for convenient access to refueling facilities for alternative fuel vehicles. Since infrastructure development is expensive, there is a need to direct investments towards the establishment of refueling facilities in areas which result in maximum impact. This can be addressed by locating facilities at sites which service as many vehicles as possible. This work deals with the use of mathematical programming for determining the best locations for establishing alternative transportation fuel stations. The objective was to site the refueling stations at locations which maximize the number of vehicles served, while staying within budget constraints. The model used here is a modified form of the flow interception facility location model. For the case study we used the transportation network of Alexandria, Virginia, as a test bed for our model. Origin-destination travel demand data for this city is simulated through a transportation simulator to determine the routes taken by individual vehicles. The results are then compared with the service level offered by conventional gasoline refueling stations already located in the city. This work integrates the use of transportation modeling with mathematical programming for the solution of a complex large-scale problem on a real-life transportation network.

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1. Introduction

A large number of developed and developing nations import oil for the transportation sector to support economic activity and day-to-day transportation needs. This leads to a number of concerns about greenhouse gas emissions, trade deficits, and national energy security, among others. The looming possibility of a decline in the availability of oil is forcing nations to cut back on consumption. One of the ways to combat the problems associated with oil importation and consumption is the use of alternative energy sources like hydrogen, electricity, bio-fuels and natural gas to power the automobiles. Use of compressed hydrogen for powering fuel cell vehicles has seen some infrastructure development in California and the upper Midwest (Kuby & Lim, 2007). Recent advances in battery technology have enabled the development of reliable plug-in hybrid electric vehicles and pure electric vehicles. A major factor in the large scale adoption of these new vehicles is bringing their cost down to make them competitive with gasoline vehicles. Since these vehicles have a limited range, another important factor is convenient access to refueling facilities. After over a century of automobile use, gasoline stations are ubiquitous, but refueling stations for most alternative fuels are few and far in between. A lack of refueling stations would be an obstacle to the large scale adoption of these vehicles. On the other hand, if there is very little demand for alternative fuels then there is little incentive to invest in development of a refueling network. Since the establishment of refueling station infrastructure is costly in terms of capital, it makes sense to establish them at locations which see maximum traffic flow in the transportation network. In this paper, we investigate this problem using a mathematical programming framework for determining the best locations for establishing alternative transportation fuel stations. The objective was to site the refueling stations at locations which maximize the number of vehicles served, while staying within budget constraints. The model used is a modified form of the flow interception facility location model (Berman et al., 1992). For the case study we used the transportation network of Alexandria, Virginia, as a test bed for our model. An advanced transportation simulator was used to generate detailed and realistic traffic flow patterns which are used for the refueling station siting optimization model.
2. Background

2.1. Alternative fuel vehicles

Most modern day automobiles run on petroleum based liquid fuels like gasoline and diesel which are in limited supply. These fuels, although high in energy density, are known to cause high levels of air pollution and are blamed for contributing to climate change and global warming. These factors contribute to a shift towards alternative fuel sources for automobiles. Some of the options are described in the following sections.

2.1.1. Biofuels

Alternative fuel vehicles based on the internal combustion engine, modified to make use of non-petroleum based fuels, have gained popularity in various parts of the world in recent times. Some examples of such fuels are ethanol-gasoline blends and biodiesel derived from plant and animal sources. Although the use of such fuels helps in reducing dependence on petroleum, it does not ensure sustainability in the long term due to adverse impacts on the environment, food security, and land use (Fargione et al., 2008; Searchinger et al., 2008).

2.1.2. Hydrogen

Hydrogen has been in consideration as an alternative automotive fuel for a long time (Bockris, 1975). It can be burned in an internal combustion engine to generate mechanical energy or it can generate electric power through a reaction with oxygen in a fuel cell. One of hydrogen’s primary advantages is that its only major oxidation product is water vapor; it produces no carbon dioxide. Although hydrogen has been a candidate alternative fuel for quite some time, the development of hydrogen powered vehicles has not advanced too much for several reasons. Theoretically hydrogen can be produced by electrolysis of water but currently most of the production is from methane or other fossil fuels since electrolysis of water is not cost competitive (Agrawal et al., 2005). This goes against the idea of moving away from carbon based fossil fuels. The main drawback of using hydrogen as a transportation fuel is the need for large on-board storage tanks, which are required because of hydrogen’s extremely low density. Hydrogen can be stored on-board a vehicle as a compressed gas, as a liquid in cryogenic containers, or in metal hydrides but because of the low density, compressed hydrogen will not be able to give a comparable range to that of gasoline (Balat, 2008). In recent times, several major automobile manufacturers have dropped their plans to develop hydrogen cars in favor of electric vehicles (Dennis, 2009; Taylor & Spector, 2008).

2.1.3. Electricity

An electric vehicle uses an electric motor for propulsion instead of an internal combustion engine. Electric motors can deliver high torque at low revolution speeds which makes for a simpler and lighter powertrain and transmission when compared to internal combustion engine powered vehicles. The conversion of electrical energy to mechanical energy by an electric motor is much more efficient than deriving mechanical energy from fossil fuels in an internal combustion engine. A pure electric powertrain is also able to gain greater efficiency using regenerative braking. This leads to a much larger ‘tank-to-wheel’ efficiency for an electric vehicle. The comparison might become less favorable when we take into account the energy losses during the production and transmission of electricity. As more and more power production is moved from fossil fuels like coal and natural gas to more efficient renewable energy sources such as wind and solar power, electric vehicles will become more favorable due to increased efficiency as well as lower costs and carbon emissions (Thomas, 2009). Even with these apparent benefits pure electric vehicles are virtually non-existent on the road today. With optimistic assumptions about battery cost and weight, the electric vehicle is still quite expensive and is limited in range (Kromer, 2007). While these limitations might be tackled with advancements in battery technology over time, electric vehicles would still need a reliable recharging infrastructure to compete with gasoline engine vehicles. This infrastructure can either be battery charging stations which are classified as level 1, 2 or 3 depending on the current amperage or battery swapping stations which replace a used battery with a fresh one.

We notice that some alternative vehicle technologies like an all electric powertrain seem to be more attractive in the long run than others like hydrogen powered fuel-cell vehicles and biofuel powered internal combustion engines. Nevertheless petroleum based fuels still have a much higher energy density than competing alternative fuels (Chalk & Miller, 2006). Due to size and weight limitations on vehicles, alternative fuels cannot be stored in large amounts onboard, which leads to a shorter vehicle range. Since refueling infrastructure availability is a major obstacle to large scale adoption of alternative fuels, it becomes all the more important to direct refueling infrastructure investment decisions for maximum impact.

2.2. Flow interception facility location problem

Most topics in transportation planning are concerned with activity locations which are either the starting or end points for trips. Some examples of such trips are those which start at home and end at the workplace, or start at home and end at a shopping mall. These are instances when travel is done to use a service which can only be obtained at a particular destination. Apart from these, we also travel to other places to avail discretionary services such as a trip to a convenience store, trip to a gas station, or picking up weekly groceries on the way back from work. For these types of trips, the customer is most likely on a pre-planned trip between two points. Locating the discretionary service on the pre-planned route increases the attractiveness of the facility, since it is conveniently placed. This enables the travelers to use the facility without having to deviate from their planned route (Berman et al., 1992). We recognize that occasionally a traveler would embark on a one-stop journey to consume a discretionary service, but overall it would be more convenient if such facilities were placed on paths which would ‘intercept’ as many travelers as possible. A path is considered intercepted when a facility is placed somewhere on a pre-planned travel route, thereby enabling service without any deviation from the original route.

The objective of this flow interception facility location model (FIFLM) is to maximize the number of vehicles intercepted by at least one facility. Apart from smaller test networks the model has been solved for a real life transportation network based in Edmonton, Canada (John Hodgson et al., 1996). Several improvements over the original FIFLM model have been made over the years, both in deterministic and in stochastic scenarios. The FIFLM problem is NP-hard which makes it difficult to solve for large number of nodes. Several heuristics have been applied for solving such large scale problems (Berman et al., 1995; Cendreau et al., 2000; Suh et al., 2006). The classical model has been extended to more advanced ones which have competing facilities (Berman & Krass, 1998), limited range of flow constituents (Kuby & Lim, 2007; Upchurc et al., 2009; Wang & Lin, 2009), and ones which incorporate consumer preference over facility locations (Zeng et al., 2009).

2.3. Data requirements and transportation planning

Historically, most transportation planning and forecasting has been done using the conventional four-step model (McNally, 2000;
Ortuzar & Willumsen, 2002) as shown in Fig. 1. The FIFL model requires the vehicular flow data for every distinct path through the network. Metropolitan planning agencies collect travel demand data in the form of origin-destination (OD) matrices for different times of the day, where each element of the matrix represents the number of travelers moving from the origin to the destination. This travel demand data has to be processed through the four-step model to generate the paths through which vehicles travel to reach their destination. Solving the four-step model requires iterative load balancing among candidate paths to achieve equilibrium. Since this is hard to do for a large real life network, shortest paths for all vehicles have been used thus far in the literature for the flow interception facility location problem (John Hodgson et al., 1996). This assumption neglects congestion effects and behavioral influences in the choice of path by the travelers. Another simplistic assumption is to combine activity location together into zones. Activity locations are the starting or end points in a trip. Since this assumption decreases the granularity of the problem specification, the results from the model are only good at a zonal level and fail to specify the exact location of the facilities.

3. The model

\( G(N, A) \) is a transportation network where \( N \) is the set of nodes and \( A \) is the set of arcs. \( P \) is the set of non-zero flow paths through the network and \( f_p \) is the rate of traffic flow along any path \( p \in P \). The total network flow is \( f = \sum_{p \in P} f_p \). Let \( I \) be the total investment budget and \( c \) be the cost of installing a single facility. Then \( m = I/c \) is the maximum number of facilities that can be installed with the given budget. The objective is to find the best set of network locations for the facilities on the network which maximize intercepted traffic flow while staying within the budget constraints.

\[
\begin{align*}
    x_j &= \begin{cases} 1 & \text{if a facility is located on node } j, \\ 0 & \text{otherwise} \end{cases}, \quad \forall j \in N \\
    y_p &= \begin{cases} 1 & \text{if at least one facility is located on path } p, \\ 0 & \text{otherwise} \end{cases}, \quad \forall p \in P
\end{align*}
\]

Maximize \( \sum_{p \in P} f_p y_p \)

such that

\[
\begin{align*}
    \sum_{j=1}^{n} x_j &\leq m \quad (1) \\
    \sum_{j \in p} x_j &\geq y_p \quad \text{for all } p \in P \quad (2) \\
    m &= \frac{I}{c} \quad (3)
\end{align*}
\]

The binary integer linear programming model here is a modified version of the classical flow interception facility location model (Berman et al., 1992). The objective function expresses the maximization of the intercepted traffic flow. Constraint (1) ensures that the number of facilities do not exceed the maximum number possible due to budget constraints. Since addition of more facilities on the network may or may not increase the amount of intercepted flow, but will lead to additional cost, we have used an inequality sign in the constraint. The inequality condition in constraint (1) prevents the addition of such redundant facilities. Constraint (2) ensures that a path is considered as intercepted if one or more facilities are located on the path. Eq. (3) relates the maximum number of facilities to total capital investment.

4. Case study – Alexandria, VA

As mentioned in Section 2.3, large scale flow interception facility location problems have been solved for real life networks in the past. Various simplistic assumptions were used for solving the problems due to several reasons. Most models were solved for small hypothetical transportation networks for demonstration purposes (Berman et al., 1992; Hodgson, 1990; Kuby & Lim, 2007). Real world transportation networks were used from time to time but the input data was aggregated and simplified. This was due to two different reasons. First, detailed transportation data is often difficult to compile since transportation planning has historically been done using the conventional four-step model (McNally, 2000) which aggregates activity locations into traffic zones. Second, smaller problem size leads to a faster solution for NP-hard problems, such as the one here.

Historically transportation planning has been done by dividing the area into traffic analysis zones, and representing all travel in terms of trips that occur between these zones. In recent times however, there has been a shift towards using activity-based multi-agent models which highlight the fact that trips occur due to the activities that individuals carry out on a day to day basis.
TRANSIMS is an agent-based transportation forecasting model developed by Los Alamos National Laboratory, which has been implemented for several places such as Portland, Oregon (Marfia et al., 2007) and Chittenden County, Vermont (Lawe et al., 2009). In this work we have used TRANSIMS for providing detailed input data to our flow interception model. Our case study is conducted on the city of Alexandria, Virginia, a Washington, DC suburb.

4.1. Data requirements

The model described in Section 3 needs several inputs, namely, network topology with nodes (i) and the links connecting them, paths taken by individual vehicles (p), traffic on each path (fp), cost of establishing a refueling station (c) and the capital investment budget (l). City of Alexandria network and travel data is available as a test case provided with TRANSIMS. This data includes a GIS map of the city with detailed information about the nodes and the links on the network. This network contains 2620 nodes and 3653 links and a Geographical Information System (GIS) representation of the network is shown in Fig. 2. Travel data is available in the form of trip tables between different zones from the Metropolitan Washington Council of Governments (MWCOG)2005 regional daily trip tables. Since Alexandria is a subarea within the Washington, DC region, the external station demands were developed through simple aggregations of MWCOG zones outside of the subarea and manually adjusted to help demonstrate some of the through movements more realistically.

TRANSIMS distributes the zonal origin-destination trips over the activity locations within the zone and assigns a vehicle to each trip. Output from the simulator gives detailed second by second snapshot data for the network. This output contains information about location, velocity, acceleration, etc. for each vehicle.

4.2. Input processing

The flow interception model in Section 3 needs the individual vehicle paths as well as the flow on each path as its input. Second by second snapshot data from the TRANSIMS traffic micro-simulator needs to be processed before it can be used in our model. We used SQL queries on a relational database for our data processing needs. Vehicle paths were obtained by analyzing their co-ordinates over the day and aggregating them to form vehicle trails. Vehicles traveling on the same paths were then aggregated together to obtain the daily flow on each path. There were 2476 nodes (xi) in the network and 114,942 unique paths (p) travelled by vehicles in the network.

4.3. Solution procedure

The model was implemented in General Algebraic Modeling System (GAMS) coupled with the ILOG CPLEX 10.0 solver. The problem has 117,418 variables (xi and yp) and 114,944 constraints (one for each yp in constraint (2) and two from constraints (1) and (3) in Section 3). Total investment budget (l) and cost of installing a single refueling station (c) would vary from case to case, so we ran the model for several values of maximum number of facilities (m). The results from these runs show how the number of vehicles serviced goes up as we increase the number of refueling stations. These results are then compared with the location of existing gasoline refueling stations to underline the benefits of using an optimization procedure for facility location. We have also analyzed a scenario where existing gasoline stations are retrofitted to dispense alternative fuels.

5. Results

The facility interception model was executed for several integer values of maximum number of facilities (1 < m < 20). The results of model execution are listed in Table 1 and shown in Fig. 3.

Fig. 3 also shows the capital investment required for setting up the refueling stations. We have assumed that a $500,000 investment is required for setting up a single refueling station based on initial cost estimates for a typical battery swapping station (Galbraith, 2009). We note that while the capital investment required keeps increasing with increasing number of refueling stations most of the traffic interception gains occur with the first few refueling stations. This clearly shows the diminishing return on the capital investment with increasing number of refueling stations. Establishing refueling stations at these points not only leads to higher interception rates but also leads to a high visibility of these stations which would relieve ‘range anxiety’ among owners and thereby lead to faster adoption and greater penetration of these new technologies. A refueling station developer can invest a minimal amount of money towards establishing a small number refueling stations and use the returns for expanding the network with time.

5.1. Computational insights

Maximum number of refueling stations that can be established (m) affect the solution time for the problem. Total number of feasible solutions to the problem is equal to the binomial coefficient Cm. This number increases as m increases, until m = n/2 and then it starts to decrease. For our case studies, n = 2620 and 1 < m < 21, therefore in this range the feasible set is continuously increasing. The CPLEX optimization routine uses a branch and cut method which keeps searching for a binary integer solution until it is within 1% of the best possible solution. The solid line in Fig. 4 shows the solution time required for the problem for various values of m. The model was run on a PC with a 2.8 GHz Intel Core 2 duo T9600 CPU and 4 GB RAM. Although we see a general trend of increasing solution time with increasing m, it is hard to be certain about this trend by looking at just this one scenario.

Sensitivity analysis was performed by varying the traffic flow (fp) on each path in the case study. 2x, 3x and 4x in Fig. 4 denote doubled, tripled and quadrupled traffic flows on each path. A large number of such perturbation scenarios need to be considered to definitively comment on how the solution times change with a change in problem size (Cm). Due to time and computational resource limitations we limited our sensitivity analysis to four different path flow rates. The results in Fig. 4 indicate that in general the solution time is increasing with increasing values of m.

Several heuristic and meta-heuristic methods exist for solving large sized flow interception problems (Berman et al., 1992). The structure of this problem can be exploited to find a faster solution for larger values of m. The problem for large values of m can be broken down into a series of sub-problems. These sub problems can be solved consecutively for increasing values of m, starting with m = 1. The solution from problem where m = k (k is a integer constant) can be consecutively used to solve the problem for m = k + 1, by assuming that the first k refueling station locations remain the same, on increasing m from k to k + 1, thereby reducing the search space for a feasible solution. This hypothesis is valid since we assumed that vehicles need to encounter only one refueling station on their path to be refueled. The presence of multiple stations on a path does not change the interception rates for vehicle flows on these paths. Therefore, in each consecutive problem the additional refueling station is placed so as to maximize the interception rates of previously untouched traffic flows.
5.2. Comparison with existing infrastructure

While Alternative fuels are expected to gain more popularity in the future, most existing automobiles run on petroleum based fuels. Due to the widespread availability of gasoline vehicles, gasoline refueling stations are ubiquitous. It is worthwhile to compare the locations of existing gasoline refueling stations with the locations recommended by our results.

The model in Section 5 was modified to calculate the percentage of vehicles directly intercepted when the location of refueling stations is available as an input. The location of existing gasoline stations in city of Alexandria is widely available through various web-based mapping services. Multiple gas stations at the same location were treated as a single gas station for our modeling purposes. Using this data and our model, results show that the 20 gasoline station locations in the city of Alexandria as shown by

![Fig. 2. A GIS representation of city of Alexandria, VA.](image1)

<table>
<thead>
<tr>
<th>Number of refueling stations</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicles intercepted (%)</td>
<td>30</td>
<td>40</td>
<td>47</td>
<td>53</td>
<td>58</td>
<td>62</td>
<td>66</td>
<td>69</td>
<td>72</td>
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</table>

![Fig. 3. Percent of vehicles intercepted vs. maximum number of refueling stations.](image2)

Table 1
Percentage of vehicles refueled with increasing number of refueling stations.

<table>
<thead>
<tr>
<th>Number of refueling stations</th>
<th>1</th>
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<th>7</th>
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<th>20</th>
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dark squares in Fig. 5, directly intercept 55% of the traffic. The location set, from our results is able to intercept over 57% of the traffic with just 5 facilities as shown in Fig. 6. Fig. 7 shows the location of facilities for a maximum available budget for 20 facilities. This configuration would be able to refuel over 84% of the vehicles as compared to 57% in the case of existing infrastructure. We note that the suboptimal location of the existing gasoline stations have a much lower interception rate when compared to the locations determined using our optimization technique. This is because the optimization scheme in our work locates the refueling stations on most popular roadways and population centers.

5.3. Retrofitting existing filling stations

As we mentioned earlier, setting up new refueling stations is capital intensive. Current gasoline stations would face a shortage in fuel demand as more and more vehicles move to alternative fuels. Most gasoline filling stations in the current day have multiple fuel dispensers to service several vehicles at the same time. In the short term, it might be more cost effective to replace one or more gasoline dispensers with an alternative fuel dispensing unit, at an existing filling station. This would be cheaper and more practical than setting up a new refueling station altogether. Table 2 shows how the
Fig. 6. Location of refueling stations for $m = 5$ (57% traffic intercepted).

Fig. 7. Location of refueling stations for $m = 20$ (85% traffic intercepted).

Table 2
Percentage of vehicles refueled with increasing number of retrofitted refueling stations.

<table>
<thead>
<tr>
<th>Number of retrofitted stations</th>
<th>1</th>
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<th>5</th>
<th>6</th>
<th>7</th>
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<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicles intercepted (%)</td>
<td>10</td>
<td>19</td>
<td>27</td>
<td>32</td>
<td>37</td>
<td>41</td>
<td>43</td>
<td>45</td>
<td>47</td>
<td>49</td>
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percentage of vehicles refueled increases as more and more filling stations are retrofitted with alternative fuel dispensing units. We notice that a large majority of the originally intercepted traffic can be intercepted by retrofitting a small number of gasoline filling stations.

6. Conclusions

Concerns about greenhouse emissions and declining fossil fuel reserves have prompted nations to explore alternative technologies. This necessitates the development of an appropriate
infrastructure for convenient access to refueling facilities for alternative fuel vehicles. Since infrastructure development is expensive, there is a need to direct investments towards the establishment of refueling facilities in areas which result in maximum impact. We have addressed this problem using a mathematical programming framework for determining the best locations for establishing alternative transportation fuel stations. The objective was to site the refueling stations at locations which maximize the number of vehicles served, while staying within budget constraints.

The model used here is a modified form of the flow interception facility location model. For the case study we used the transportation network of Alexandria, Virginia, as a test bed for our model. Origin-destination travel demand data for this city is simulated through a transportation simulator to determine the routes taken by individual vehicles. Agent based modeling methods such as the one used in TRANSIMS, are becoming increasingly popular in transportation planning. Due to their emphasis on microscopic details, these models generate large amounts of output data. Relational database tools are useful for manipulating such large amounts of data, to process and aggregate it into a form which can be used by mathematical programming models. As transportation planning moves to more microscopic models the need for extensive data processing with the help of relational databases is increasingly important. This work uses such an approach for providing input data to a flow capturing facility location model implemented on a large scale real-life network. The case study in Section 5 determines the optimal location of such refueling stations when a refueling network is being designed from scratch. The results when compared with the location of existing gasoline stations show that this optimization approach will lead to a more effective use of infrastructure investments.

While we propose setting up refueling stations at new locations we understand that there might be several barriers to entry for new investments. Zoning laws and prior occupancy may prevent setting up refueling station on some of the proposed locations. It is proposed that retrofitting existing gasoline filling stations with alternative fuel dispensing units would be a good low-cost starting point before full scale alternative fuel stations are set up. We have also shown how retrofitting only a small number of gasoline stations can refuel a relatively large proportion of alternative fuel vehicles.

The framework proposed in this work is applicable to any alternative fuel infrastructure design but at this point in time electric vehicles seem to have an advantage over other alternative fuel technologies. Since these vehicles have a simpler drive-train, electric batteries are the single cost component, usually more than 50% of the vehicle cost. While advances in battery technology will reduce this cost, easy access to refueling facilities will obviate the need for carrying large onboard batteries. This will lead to reduction in vehicle costs, thereby making these vehicles an attractive alternative to a large majority of consumers.

References