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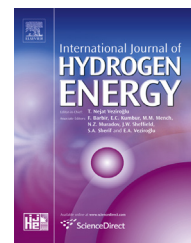
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Short Communication

Refueling hydrogen fuel cell vehicles with 68 proposed refueling stations in California: Measuring deviations from daily travel patterns



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ABSTRACT

This paper examines the deviation of refueling a hydrogen fuel cell vehicle with limited opportunity provided by the 68 proposed stations in California. A refueling trip is inserted to reported travel patterns in early hydrogen adoption community clusters and the best and worst case insertions are analyzed. Based on these results, the 68 refueling stations provide an average of 2.5 and 9.6 min deviation for the best and the worst cases. These numbers are comparable to currently observed gasoline station deviation, and we conclude that these stations provide sufficient accessibility to residents in the target areas.

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1. Background and motivation

Major automakers, fuel suppliers, and governments have announced ambitious partnerships in Germany [1], Japan [2], Nordic Countries [3], and the United States [4] for the introduction of commercially available fuel cell electric vehicles (FCEVs) and hydrogen refueling in 2015. Hydrogen fuel cell vehicles offer the promise of reduced criteria pollutant emissions, reduced greenhouse gas emissions, and an end to transportation dependence on petroleum derived fuels. The

biggest advantages of FCEVs over battery electric vehicles (BEVs) is its similarity to conventional internal combustion engine vehicles (ICEVs) such as refueling times and range. On the other hand, the refueling infrastructure provision has been the biggest challenge for the adoption of FCEVs. This so-called “chicken-and-egg” problem refers to the situation where there is no sufficient demand for refueling stations to be profitable, and there is no sufficient refueling opportunities for drivers to consider purchase of the vehicles. To achieve more sustainable transportation, both in terms of emissions and energy, it has been considered as the public sector’s role

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to initially provide the refueling opportunities to break out of the “chicken-and-egg” gridlock.

The determination of the location and number of hydrogen refueling stations required to both launch an initial FCEV market (coverage) and meet the needs of eventual FCEV drivers (capacity) has been an active field of research for some time. Melaina [5] has estimated that 4500 hydrogen refueling stations throughout the U.S. are required for an initial “Stage 1”, which supports early adopters’ travel, and that 17,700 stations are required for “Stage 2”, which supports travel for an initial mass production period. Given the number of gasoline stations in the United States, the Stage 1 estimate amounts to roughly 5% as many hydrogen stations as existing gasoline stations. However, since it is not likely that the adoption of FCEVs will occur at the same time nationally, additional studies have focused on specific target regions to determine more detailed infrastructure provision strategies. Stephens-Romero et al. and Stephens-Romero et al. [6,7] used a point-based approach for early adoption communities in Southern California targeted by auto-manufacturers. They applied the well-known set (“set” comprised of all nodes in the network) covering problem, and found that 11–14% of current gas stations “refitted for hydrogen refueling” would be comparable to current travel times (4 min) to gasoline stations in the areas. Some studies have used a path-based approach based on origin–destination (O–D) path demand. A *p*-median problem is applied in Nicholas et al. and Nicholas and Ogden [8,9] to minimize the total travel times to the nearest refueling stations. Another type of path-based approach is variations of the Flow Refueling Location Problem [10], which is an extension from the Flow Capturing Location Problem [11]. For detailed up-to-date refueling station siting work, with a focus on variations of Flow Refueling Location Problems, readers are referred to MirHassani and Ebrazi [12]. Kang and Recker [13] proposed a refueling siting formulation, in the category of a Location Routing Problem. While their work can be viewed as a tour-based model, it not only includes the tours, but also the capability of making the tour construction within the model. Xi et al. [14] goes further to integrate travel demand for station siting work; they used an activity-based travel simulation to generate synthetic travel patterns for the whole population in the study area.

In practice, the California Fuel Cell Partnership (CaFCP) Roadmap [15] proposed 68 hydrogen stations for Pre-commercial Clusters following the methodology in Stephens-Romero et al. and Stephens-Romero et al. [6,7]. The CaFCP Roadmap relied on additional analysis that has concluded 5–7% of current gasoline stations are sufficient to provide 6 min coverage [16,17] which appears to assuage driver concerns about refueling availability. The CaFCP Roadmap adopts the “clustering and bridging” strategy proposed by Kuby et al. [18], and for the “clustering” areas, they applied the set covering model – set comprised of all nodes on the network. It may be argued that CaFCP used rather simple modeling techniques albeit academic advances of previously mentioned state-of-art decision making models.

It is, however, also arguable that it may be sufficient to use rather straight forward modeling techniques for early stage hydrogen station siting in the real world. The reason is that hydrogen refueling infrastructure decision making

involves various stakeholders from both public and private sectors, resulting in a complicated decision making process. For example, the current California hydrogen infrastructure model involves the addition of hydrogen equipment to an existing gasoline station. In theory, a mathematical optimization model can take input of quantified data of qualitative conditions. In practice, however, qualitative conditions such as safety, lot size, gasoline station owners, local permission, public investment guidelines, public acceptance, result in complicated and interconnected effects that cannot be easily formulated. Consequently, the funding strategy in California has relied not on specific optimized locations, but more broadly on “polygons” that encompass optimum locations and provide enough geographic flexibility to enable various hydrogen stakeholders to negotiate viable business decisions without straying too far from an optimized solution [19].

Additionally, data collection is not always easy or accurate. For many path-demand based models, path demand input is often from Statewide Travel Demand Models. Trip Distribution which is mostly done by a gravity model is a key component in deriving O–D path demand. However, the goal of this process is to match the total production and the total attraction of each zone rather than deriving – or collecting – a set of real path demand [20]. In an effort to include individual traveler’s fundamental travel decision making procedures, some studies incorporate recent advances in activity-based travel modeling within station siting work; Kang and Recker [13] used Statewide Travel Survey Data and integrated travel demand models in their proposed formulation. However, they used a small sample data set, and such a sample size may be sufficient for model development but not for representing real demand. Although the work by Xi et al. [14] appropriately represents the integration of travel demand given the status of currently available state-of-art demand models, due to the huge data requirements of such models, the travel demand process is not always conveniently integrated within a location model. However, for these studies, the goal is not to derive the accurate path-demand but rather matching observed or predicted total demands.

Also, path-based approaches are more suitable for analyzing long-distance travel than daily travel within a metropolitan area. Many path-based studies include multi-refueling capability based on fuel inventory. However, given the fact that average daily driving distance is less than 65 km (40 miles), and that the range of FCEVs is greater than 400 km (250 miles), fuel inventory-based refueling need is not useful for the scope of a metropolitan area. By the property of their formulation, many of path-based approaches are better suited for analyzing long distance travels’ refueling needs.

Methodology from Stephens-Romero et al. [6] and Stephens-Romero et al. [7] depends quantitatively on the network properties and path demands are accounted for in a more qualitative method. This means it is independent of route choice/traffic assignment (particularly for metropolitan planning) and long-term travel demand changes, which have not been addressed in any of hydrogen station siting models but are significant factors when dealing with travel demand. This gives policy makers static but resilient basis for this long-term infrastructure investment.

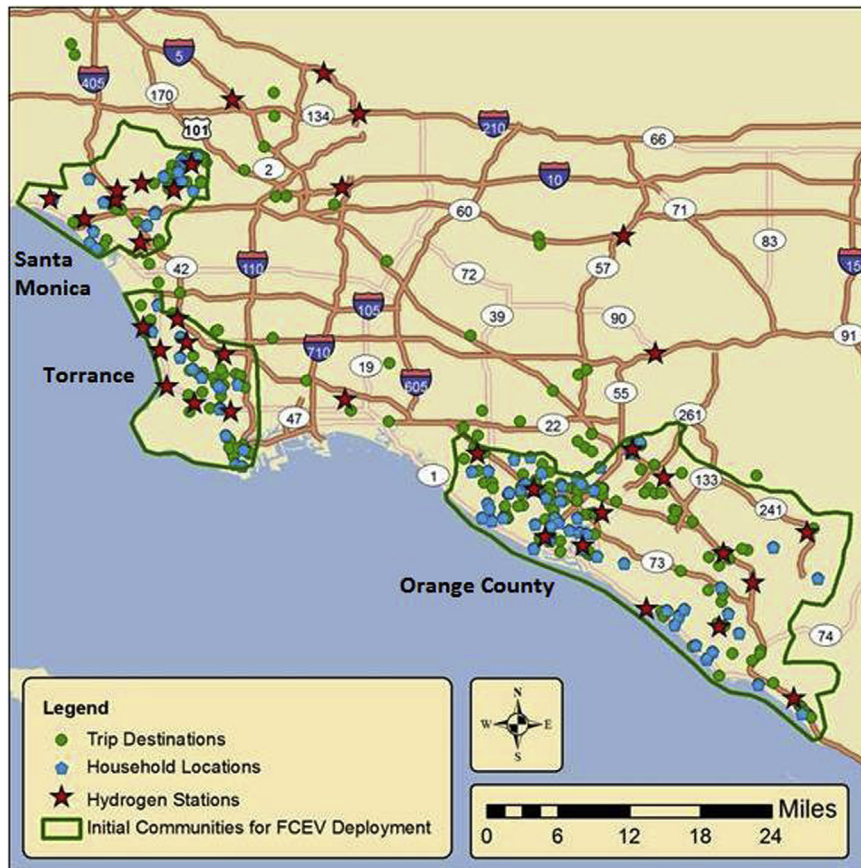


Fig. 1 – Clusters, hydrogen stations, and household samples.

Due to these reasons, it has been more practical for agencies to take an approach of providing “everyone” accessibility in the target clusters of early adoption. In this paper, we analyze the realistic feasibility of the 68 hydrogen refueling stations proposed by the California Fuel Cell Partnership [14] by measuring the deviation from the reported travel patterns required for refueling trips. Deviation is a measure of inconvenience for hydrogen refueling. The purpose of this analysis is to characterize the inconvenience level of the proposed stations for sample travel patterns, compare the results to the inconvenience level for current gasoline refueling infrastructure, and determine if the “simple methods” used to determine the 68 hydrogen stations actually provide the desired level of coverage. It is noted that whether state-of-art models could have delivered more efficient solution is not the focus of this paper due to the above mentioned reasons.

2. Data and methodology

Sample travel patterns are derived from the California State-wide Travel Survey (CSTS) [21] including information on departure/arrival times, trip purpose, durations of trips/activities, geo-coded activity locations, and vehicle mode. Households residing in the initial target market clusters [15] with travel patterns that rely on one vehicle are selected as

the target population as shown in Fig. 1. For the 81 travel patterns selected, each traveler/vehicle averaged 4.3 trips (minimum 2 trips, maximum 12 trips), 0.79 h of total travel time (minimum 0 h and maximum 3.31 h), 65.20 km (34.92 miles) of total travel distance (minimum 0.05 km and maximum 448.01 km), and spent a total of 7.29 h away from home (minimum 0.17 h and maximum 14.64 h).

It is assumed that drivers will try to keep their current travel sequences. To analyze the increased travel times required to reach limited refueling opportunities, one refueling trip is inserted per day. This is not to impose that all drivers need to refuel on a daily basis, but to analyze the increased inconvenience each driver faces within the spatial and temporal constraints of performing daily activities.

Given the sequence of activities of household h , along with arrival/departure times, travel patterns are generated with all possible insertions, k , of a refueling trip. For each insertion, the closest (least deviant) refueling station by travel time is selected.¹ Then for each household, the best insertion and the worst insertion are selected since vehicle fuel level is not tracked and refueling trips are not always preplanned.

¹ Travel times are derived from the OCTAM network, using the shortest path between two geo-coded locations. Refueling time is assumed to be 10 min based on current hydrogen refueling time [22].

Although it was witnessed that drivers plan refueling trips when refueling opportunities are limited [23,24], having both the best and the worst cases provides a better understanding of limited refueling inconvenience of lower and upper bounds. It is noted that the “worst” refueling deviation still utilizes the closest refueling station: it refers to the refueling trip that has to divert from the travel patterns between two activity locations that are located the furthest from the closest refueling stations. The algorithm is as follows.

Let n^h be the number of out-of-home and at-home activities performed by household h : each household’s activity locations are $P^h = \{P_0^h, P_1^h, \dots, P_i^h, \dots, P_{n^h}^h, P_0^h\}$ where P_0^h denotes the home location of household h , and P_i^h denotes the location for activity i of household h . It is noted that in-home activities during the day are also considered as separate activities. Corresponding arrival times are $a^h = \{NA, a_1^h, \dots, a_i^h, \dots, a_{n^h}^h, a_0^h\}$ and departure times are $b^h = \{b_0^h, b_1^h, \dots, b_i^h, \dots, b_{n^h}^h, NA\}$. There are a total of $n^h + 1$ trips for household h .

For $\forall k$ s.t $0 \leq k \leq n^h + 1$

Initially, start with a sequence of activities of home:

$$P_k^h = \{P_0^h\}, a_k^h = \{NA\}, b_k^h = \{b_0^h\}$$

For all activities before refueling, $0 \leq i \leq k$

Add activities and corresponding times:

$$P_k^h = P_k^h \cup P_i^h, a_k^h = a_k^h \cup a_i^h, b_k^h = b_k^h \cup b_i^h$$

For $\forall r \in R$

Add a refueling activity at refueling station r :

$$P_{k,r}^h = P_k^h \cup P^r$$

$$a_{k,r}^h = a_k^h \cup (a_k^{r,h} = a_k^h + t_{k,r}^h)$$

$$b_{k,r}^h = b_k^h \cup (b_k^{r,h} = b_k^h + t_{k,r}^h + s_R)$$

where

P^r denotes the refueling location of station r

$t_{k,r}^h$ denotes the travel time from activity location k of household h to refueling station r

$a_k^{r,h}/b_k^{r,h}$ denote arrival/departure time at refueling station r when the refueling trip is following activity k of household h

s_R denotes refueling time

Then, add a trip from the refueling station to the next activity location:

$$P_{k,r}^h = P_{k,r}^h \cup P_{k+1}^h$$

$$a_{k,r}^h = a_{k,r}^h \cup (a_{k+1}^h = a_k^h + t_{k,r}^h + t_{r,k+1}^h - t_{k,k+1}^h + s_R)$$

$$b_{k,r}^h = b_{k,r}^h \cup (b_{k+1}^h = b_k^h + t_{k,r}^h + t_{r,k+1}^h - t_{k,k+1}^h + s_R)$$

where

$t_{r,k+1}^h$ denotes the travel time from refueling station r to activity location $k + 1$ of household h

$t_{k,k+1}^h$ denotes travel time from activity location k to $k + 1$. $t_{k,r}^h + t_{r,k+1}^h - t_{k,k+1}^h$ is the deviation time caused by refueling at station r between activities k and $k + 1$

s_R refers to refueling duration

Then select the least deviated pattern among r different generated patterns:

$$P_k^h = P_{k,r^*}^h, a_k^h = a_{k,r^*}^h, b_k^h = b_{k,r^*}^h$$

where r^* represents a refueling station with the least deviation:

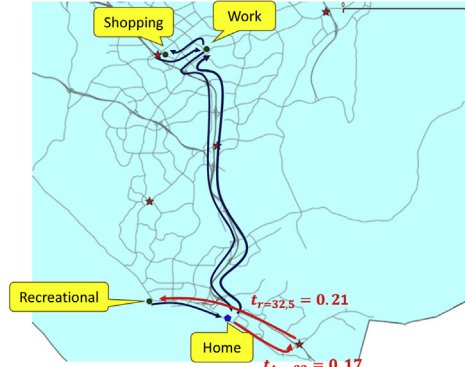
$$r^* = \arg \min_r (t_{k,r}^h + t_{r,k+1}^h - t_{k,k+1}^h)$$



(a) Reported travel pattern



(b) Best Case Insertion of a refueling trip



(c) Worst Case Insertion of a refueling trip

Fig. 2 – Illustration of deviation analysis.

$d_k^h = t_{k,r_s}^h + t_{r_s,k+1}^h - t_{k,k+1}^h$ refers to the deviation time when visiting r^h between activities k and $k + 1$

Then, for the remaining activities of the sequence, $k + 1 < i \leq n + 1$

Add activities and corresponding times:

$$p_k^h = p_k^h \cup p_i^h, \quad a_k^h = a_k^h \cup (a_i^h = a_i^h + d_k^h + s_R),$$

$$b_k^h = b_k^h \cup (b_i^h = b_i^h + d_k^h + s_R)$$

Following activities arrival/departure times are delayed by the deviation and refueling time

Select the smallest deviant insertion and the largest deviant insertion and measure by the earliest and the latest return home times:

$$P_{k_best}^h \text{ where } k_best = \arg \min(a_k^h(a_0^h))$$

$$P_{k_worst}^h \text{ where } k_worst = \arg \max(a_k^h(a_0^h))$$

Algorithm: Finding the least and most deviated patterns with an insertion of a refueling trip

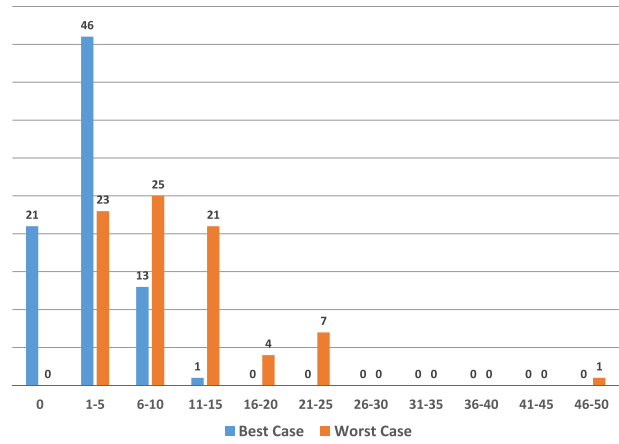
The deviation analysis can be illustrated as follows. Household number 1047602 with one household member with one vehicle had 6 total trips: Home → Work → Shopping → Work → Home → Recreation → Home as seen in Fig. 2-(a). The refueling trip that results in the least deviation from the reported path is shown in Fig. 2-(b) when this traveler refuels while traveling from home to work. The increased travel time is $t_{0,r=23}^{h=1047602} + t_{r=23,1}^{h=1047602} - t_{0,1}^{h=1047602} = 0.26 + 0.18 - 0.42 = 0.02$ hours (1.2 min). The worst case refueling trip insertion occurs on the way from home to the recreational activity as seen in Fig. 2-(c). The increased travel time is $t_{4,r=32}^{h=1047602} + t_{r=23,5}^{h=1047602} - t_{4,5}^{h=1047602} = 0.17 + 0.21 - 0.24 = 0.14$ hours (8.4 min).

3. Results and analysis

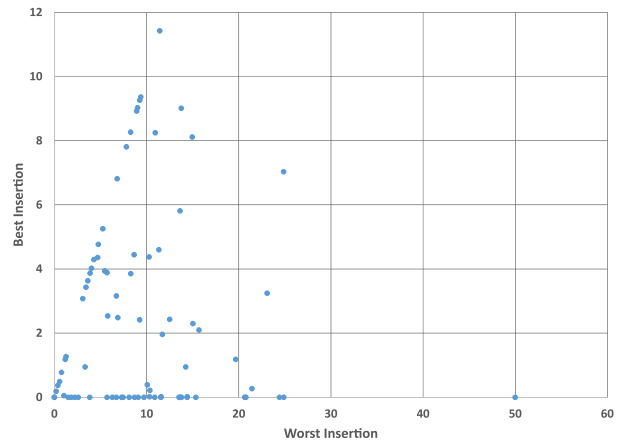
On average, the sample households experience 2.5 min of increased travel times (minimum of 0 min and maximum of 11.4 min) when refueling at the best possible times given their sequences of activities/trips. When refueled at the worst possible times given their sequences of activities/trips, households experience increased times of 9.6 min on average (minimum of 0 min and maximum of almost 50 min). In terms of distance, the best refueling trip takes an average of 2.09 km (1.30 miles) (minimum 0 km, maximum 13.16 km) of detour from the reported patterns.² For the worst case, the average was 7.95 km (4.94 miles) (minimum 0 km, maximum 61.2 km). In addition, when the best and worst cases are plotted together as seen in Fig. 3-(b), it is witnessed that there is no dominant correlation, which means drivers can always pre-plan their refueling to avoid the worst case. For example, the driver with the worst case scenario resulting in 50 min of additional travel time can actually refuel with no time delay if fueling occurs during a different portion of the daily tour.

The results of refueling detour can also be compared to actual recorded gasoline refueling trips from the CSTS data

² No additional time/distance occurs when their activity location is right at the hydrogen stations. At that location, a driver performs his/her activity, and refuels (or refuels before the activity), leading to no detour time/cost.



(a) Histogram of Increased Travel Times (Minutes)



(b) Best vs Worst Insertion Increased Travel Times (Minutes)

Fig. 3 – Best and worst case insertion of a refueling trip.

set. In the data set, there are 6 recorded refueling trips with full geo-coded information. These households are not within the defined hydrogen clusters, but are located in adjacent Orange or Los Angeles County areas – and it is sufficient to assume that these households show similar driving patterns to those of households within the clusters. Compared to directly traveling from the activity location preceding the refueling activity, to the activity location following the refueling activity, travelers traveled an additional 6.3 km (3.9 miles) and 4.7 min. Consequently, the best average insertion from the deviation analysis for hydrogen refueling of 2.5 min is well below the average deviation times of current refueling trips. Even the worst case insertion of 9.6 min is only double that of the travel survey data.

4. Conclusion

This paper examines the deviation of reported travel patterns in order to refuel a FCEV at one of the proposed 68 hydrogen stations in early adoption clusters. Both the best (average of 2.5 min) and the worst case (average of 9.6 min) insertions are

examined, and even for the worst case, the deviation time is not drastically different than currently reported refueling travel deviation (4.7 min).

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