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Early Hydrogen Station Economics Analysis

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Abstract

Deployment of the hydrogen supply infrastructure is one of most critical issues that must be addressed for a successful market transition to fuel cell electric vehicles (FCEV). Not only must hydrogen refuelling infrastructure be constructed, it must also be commercially viable and sell hydrogen to customers at retail prices that will encourage the continued expansion of the vehicle market. The objective of this study is to develop a station deployment optimization model and analyze station network economics and risk of investment. The model optimizes key deployment decisions to meet fuel demand by trading off infrastructure cost and fuel accessibility cost. Decision variables are when, where to build and the size of stations. Fuel accessibility cost is relative to gasoline, measured by additional detour time in order to access hydrogen refuelling stations. A case study is conducted for the City of Santa Monica in California. Deployment schemes generated from the optimization model are relatively robust to assumed level of fuel inconvenience cost, suggesting that the importance of station scale economy outweighs fuel convenience, subject to the caveats of model limitations. The model does not capture the dynamic interaction between vehicle demand and refuelling convenience. If vehicle demand was modelled endogenously, the importance of refuelling convenience would be valued higher by the model. Another factor might be that the area of study is small, which limits potential detour time savings that could be achieved from adding more stations. Cash flow analysis results suggest that the station network at the study area (the city of Santa Monica) may endure negative cash flows for about a decade. Driving patterns of early FCEV adopters matter to the economics of city station network. If FCEV users on average have long annual driving distance and trips are concentrated within the region, the profitability of local station networks would be improved.

Keywords: hydrogen station, optimization, cash flow analysis

1 Introduction

Deployment of the hydrogen supply infrastructure is one of the most critical issues that must be addressed for the success of fuel cell electric vehicles (FCEV). There are 10 hydrogen stations in operation now in the U.S. [1]. California has been the leading state that promotes the deployment of hydrogen stations. California Fuel Cell Partnership (CaFCP) has proposed to build 68 stations by 2018 [2]. As now, 8 stations are already open and 51 stations are under construction (Figure 1).

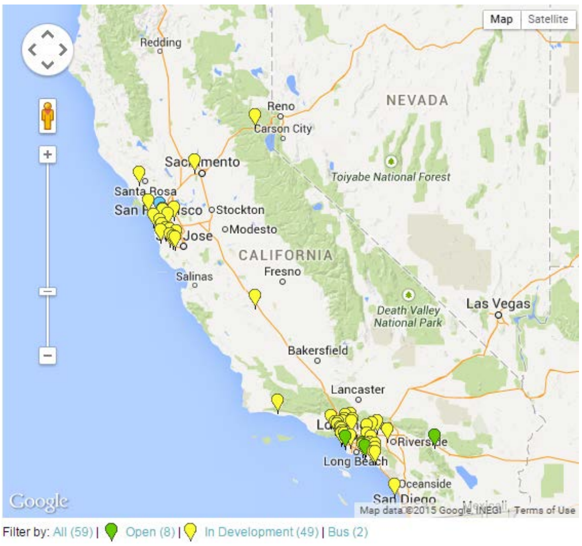

Figure 1: Hydrogen station rollout in CA

Source: http://cafcp.org/stationmap

Construction of hydrogen stations requires large up-front capital investment. However, station revenue during the early commercialization period is expected to be small when vehicle numbers are low. Thus the revenue is not sufficient to offset capital cost and maintenance expense for a long time. A good understanding of the economics of early stations is essential for investment decision making, risk management, and government policy design. Earlier work has studied the economics of early hydrogen stations in California from different angles. For example, Ogden and Nicholas [3] used cluster strategy to explore the scenarios of introducing early hydrogen stations and vehicles. Clustering refers to rolling out stations in a few concentrated geographic areas within a large region (e.g Irvine within Los Angeles Basin). Station cost and cash flows were estimated for Southern California. Eckerle and Garderet [4] also conducted cash flow analysis for proposed 68 stations in California with the purpose of designing suitable incentive schemes to encourage investment.

This paper builds on previous studies and analyses hydrogen station network economics at a cluster with rich supporting information. What is different in this paper is that the station rollout strategy is determined by an optimization model which trades off infrastructure cost and refuelling convenience. The model considers driving pattern heterogeneity in order to more accurately estimate hydrogen fuel demand at the area of interest. Besides cash flow calculations from 2015 to 2030, the paper also computes N-year net present value (NPV) at each year as a measure for investment risks. N-year NPV is defined as the NPV of the cash flow during the next N years.

2 Approach

2.1 Optimal Station Deployment Model

The station deployment model optimizes key deployment decisions to meet exogenous fuel demand by minimizing system cost, which is the sum of infrastructure cost and fuel accessibility cost. Fuel accessibility cost is relative to gasoline, measured by additional detour time in order to access hydrogen refuelling stations. Decision variables are when, where to build and the size of stations.

Adopting the notations in table 1, the optimization model is described by equations (1) – (4).

Table 1: List of notations

Notations	variables
i	index for candidate station sites
t	index for year
T	planning horizon (*t=1 to T*)
x_{it}	binary decision variable, whether to build a station at site *i* in year *t*
s_i	decision variable, station size at site *i* in year *t*
C_t	infrastructure cost
A_t	fuel accessibility cost
Cc_t	capital cost
Cf_t	fixed O&M cost
Cv_t	variable O&M cost
d_t	exogenous hydrogen fuel demand
u_t	maximum station utilization rate
r	discount rate
m	lower bound for station size
M	upper bound for station size

$$\min_{x,s} \sum_{t=1}^{T} \frac{(C_t + A_t)}{(1+r)^t} = \sum_{t=1}^{T} \frac{(Cc_t + Cf_t + Cv_t + A_t)}{(1+r)^t} \quad (1)$$

S.t.

$$u \sum_i x_{it} s_i \geq d_t, \forall t \quad (2)$$

$$x_{it} \leq x_{i(t+1)}, \forall i, t \quad (3)$$

$$mx_{iT} \le s_i \le Mx_{iT}, \forall i \tag{4}$$

where the objective function defined in equation (1) is the NPV of infrastructure cost and fuel accessibility cost, which are functions of decision variables. Constraint (2) states that supply capacity (after discounted by station utilization rate) must exceed demand. Constraint (3) requires that once a station is open, it cannot be closed within the planning horizon. Constraint (4) restricts the station size either to be zero or a positive value confined by the lower and upper bound.

Infrastructure cost consists of capital cost, fixed operation & management (O&M) cost, and variable O&M cost. Hydrogen stations are assumed to be onsite Steam Methane Reformers (SMR) with the exception that the model can choose between a SMR and a mobile refueler in the first year. Cost numbers are collected from industry, as reported by Ogden [5].Capital cost and fixed O&M are fitted very well by power functions (Figure 2&3). Fitted cost functions are used in the model for deciding optimal station size. Variable O&M includes the cost of natural gas feed and the electricity cost of compressing hydrogen.

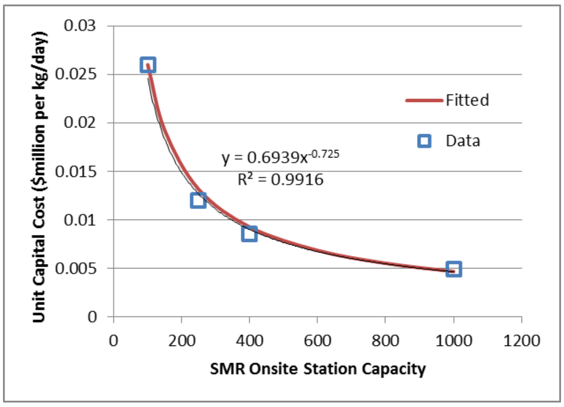

Figure 2: Station capital cost curve

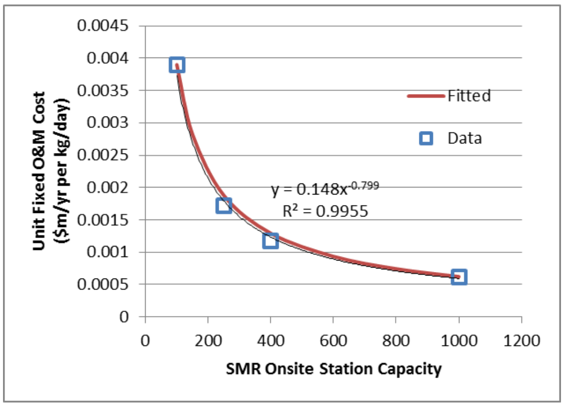

Figure 3: Station fixed O&M cost curve

2.1.1 Fuel accessibility cost

Apparently early FCEV buyers would prefer high fuel availability (measured by the ratio of the number of hydrogen stations and the number of gasoline stations); however, to achieve high fuel availability in early commercialization implies deploying more small-sized stations and/or lower station utilization, which in turn leads to the loss of station scale economy and increased hydrogen cost.

Fuel accessibility cost is estimated by the following equation:

$$A_t = (\delta v \eta) * \frac{d_t}{h} \tag{5}$$

where δ is average incremental detour time for a hydrogen refuelling trip, compared with gasoline refuelling, v is the value of time, and η is a multiplier ($\eta \ge 1$) to reflect the annoyance and frustration perceived by FCEV early adopters. The term $\frac{d_t}{h}$ calculates the number of refuelling trips at all stations, where d is total hydrogen demand at the region and h is FCEV tank capacity. Detour time δ is a function of hydrogen station coverage, as represented by the ratio of the number of hydrogen stations and gasoline stations.

2.1.2 Determining hydrogen demand

Hydrogen demand (d_t) is calculated outside of the optimization model, as a function of the number of FCEVs, driving pattern, and FCEV fuel efficiency. FCEV market penetration at the region of interest is assumed to be exogenous, constrained by the Zero Emission Vehicle (ZEV) mandate [6].

Since this paper concerns station deployment and economics in a city, driving pattern data are used to distinguish between miles refuelled at local stations and miles refuelled outside the city. Driving pattern data is obtained from 2009 National Household Travel Survey (NHTS) [7]. We classified California drivers into 6 groups: frequent driver & long commute (FLC), frequent driver & short commute (FSC), average driver & long commute (ALC), average driver & short commute (ASC), moderate driver & long commute (MLC), and moderate driver & short commute (MSC). Driving profile at each group is characterized by parameters of mean daily distance and commute distance, which are used to define a Gamma distribution function (Figure 4). As shown in [8] and [9], Gamma distributions are a convenient and reliable way to describe day to day variations of daily driving distance.

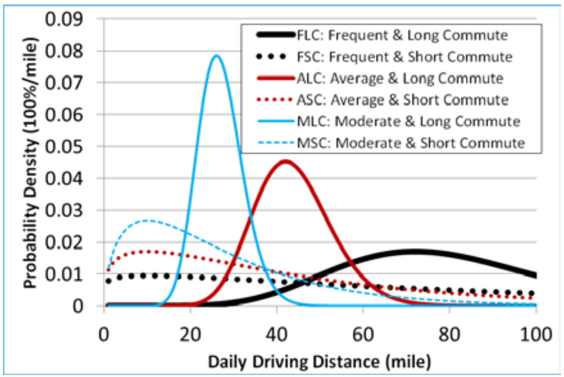

Figure 4: Heterogeneous driving profiles

For each driver group, the number of days when daily driving distance exceeds a threshold value (e.g. 100 miles) is calculated using the Gamma distribution. Then miles driven at these days and associated fuel demand are assumed to be refuelled at local stations. A higher share of frequent drivers with long commute distance (and consequently less trips exceeding the threshold) is expected to contribute more to local station business.

3 Results

The project developed an Excel-based model, which takes input of FCEV attributes and penetration assumptions, driver characteristics including driving pattern, value of time, and discount rate, as well as infrastructure assumptions including station capital cost and O&M cost as a function of station size and type. The model outputs station deployment solutions (when & where to build and station size) and calculates cash flow and total system cost.

Based on clustering strategy of station deployment, the case study focuses on station network in the city of Santa Monica. FCEV market penetration is assumed to follow the path in figure 5, which is consistent with ZEV-compliance scenario in [3]. Average time to refuelling stations in Santa Monica is a function of fuel availability, as plotted in figure 6.

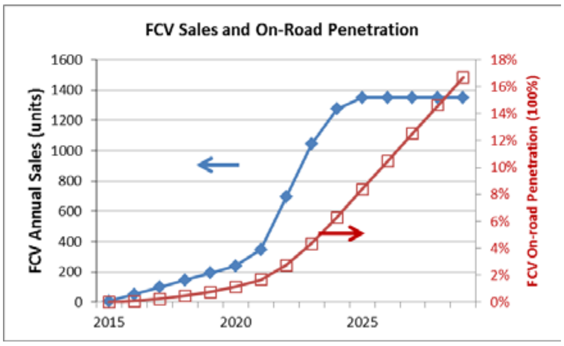

Figure 5: Assumed FCEV sales and on-Road number

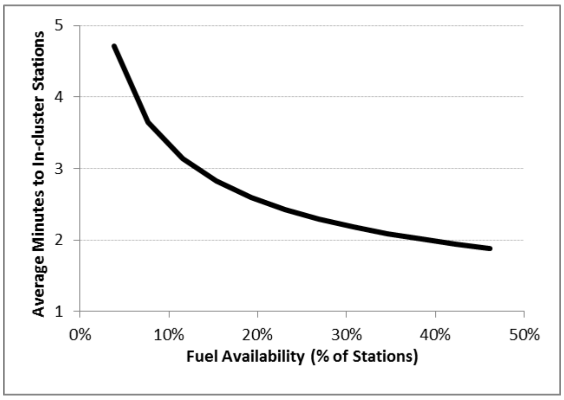

Figure 6: Aveage time to stations in Santa Monica
Note: Fitted curves based on figure 6 in [10]

Given the maximum number of stations to deploy (10 stations in this case), the problem is to decide to build what size of stations at which year. The factors in consideration are station scale economy and refuelling convenience. Large stations have better scale economy in terms of both capital cost and O&M cost but have lower utilization rate, particularly in the early market. To reduce refuelling inconvenience, building more small stations is desirable but at the price of decreased scale economy. The optimization approach is expected to find the right balance of these factors and minimize the system cost. Besides solving the problem using optimization approach, we also tried a heuristic method, named as small station first strategy, where stations sizes are predefined and increase linearly over time. A new station is built whenever existing capacity cannot meet exogenous fuel demand. The small station first strategy is designed to mimic ad hoc decision making in project planning.

The solution from the optimization model is listed in the 2nd column of table 2, which builds 9 stations in total. Station sizes do not increase monotonically over time. The system cost (infrastructure cost + fuel accessibility cost) from the optimal solution is 24.67 million dollars (equivalently, 9.04$/kg hydrogen), compared with 28.99 million dollars (10.63$/kg hydrogen) from the small station first strategy.

Table 2: Station deployment (size in kg/day & year) from two build-out strategies

Year	Optimal Solution	Small Station First
2015	100	100
2016		
2017		
2018	739	444
2019		
2020		
2021		514
2022	875	583
2023		653
2024	775	722
2025	902	792
2026	934	861
2027	630	931
2028	821	1000
2029	823	

Cash flow analysis was conducted (Figure 7 for the optimal solution and Figure 8 for the small station first strategy). Positive cash flow includes hydrogen sales revenue. Hydrogen price is assumed to be $10/kg. Negative flow includes annual O&M cost and capital cost as a lump sum payment at each year when a station is open. Station owners endure net loss for about a decade before the break-even point. Figure 7 shows annual cash flow becomes positive in 2025 and cumulative flow is negative until 2027. Figure 8 for small station first strategy shows a little worse station economics: cumulative cash flow is not positive until 2029.

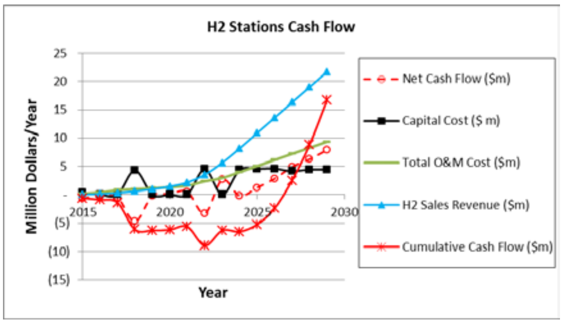

Figure 7: Station network cash flow from the optimal solution

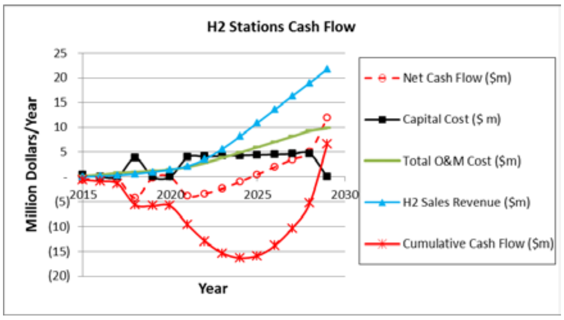

Figure 8: Station network cash flow from the small station first strategy

In the next we examined investment risks and implications for public-private partnership. Since station cash flow is negative for at least a decade, Investors' planning horizon is an important factor which determines how they perceive the risk of the investment. Figure 9 shows the next-N-year net present value (NPV) at each year, which is defined as the NPV of the cash flows during the next N years. As expected, investment risk will be (perceived) smaller if the investors enter the market late or if they are more patient (indicated by a longer planning horizon). Figure 9 also shows government buy-down cost, which is defined as the cumulative sum of negative cash flows over the period. Namely, buy-down cost measures government subsidy cost if it wishes to pay for all losses before positive cash flows.

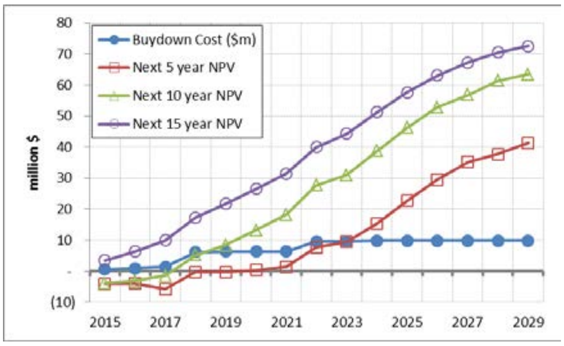

Figure 9: Next N-year NPV

At the early market for FCEVs, much of the market behaviour remains unknown. Thus it is necessary to examine the sensitivity of model results to important model parameters. We have analyzed the sensitivities of the annoyance multiplier in fuel accessibility cost calculation (η in equation 5) and the mix of driver groups which is used to determine fuel demand. The default value of the annoyance multiplier is 3, which reflects other cost (e.g. annoyance) perceived by early FCEV adopters in addition to the cost of the detour time for refuelling trips. The cost of the time is assumed to be $20/hour. We tried different values of the annoyance multiplier: 1 for no annoyance cost and 10 for high annoyance cost. Solutions from the optimization model do not change when these two values are used. In fact, the model generates different solutions only when the annoyance multiplier is very large (e.g. 100), which opts to build more small stations early on. These results suggest station rollout strategies are relatively robust to assumed level of annoyance multiplier, implying the importance of station scale economy outweighs fuel accessibility in station planning. However, our model does not represent the dynamic interaction between station deployment and FCEV market penetration. If FCEV sales were endogenous to the model and dependent on refuelling convenience, then the importance of fuel accessibility should be higher than reflected in our current model. Integrated modelling of station deployment and FCEV demand will be one of future research directions.

Reference driving pattern assumes that drivers consist of 2% frequent driver & long commute (FLC), 2% frequent driver & short commute (FSC), 25% average driver & long commute (ALC), 25% average driver & short commute (ASC), 23% moderate driver & long commute (MLC), and 23% moderate driver & short commute (MSC). The mix is calibrated to NHTS data such that the calculated average annual driving distance matches the actual average annual driving distance in California in NHTS database. As discussed in section 2.1.2, different driver groups contribute differently to local station business, i.e., they have different share of fuel demand met by local stations. It is unknown whether early FCEV adopters are driving differently from the average drivers. Thus we designed alternative cases to test the sensitivity of model results to assumed mix of different driver groups. "100% FLC" case assumes that early FCEV drivers are all FLCs who have the highest share of fuel demand met by local stations in the city.

"100% FLC" case has larger fuel demand than the reference case, though FCEV numbers are the same. As a result, "100% FLC" case has improved profitability. Figure 10 shows that the cumulative cash flow becomes positive in 2023, 4 years earlier than the reference case.

4 Discussions and Conclusions

This study develops a station optimal deployment model that trades off infrastructure cost and fuel accessibility cost to find out station size and rollout timing while meeting exogenous fuel demand. A little surprisingly, model solutions are relatively robust to assumed level of fuel inconvenience cost, suggesting that the importance of station scale economy outweighs fuel convenience. The caveat is that the model does not capture the dynamic interaction between vehicle demand and refuelling convenience. If vehicle demand was modelled endogenously, the importance of refuelling convenience would be valued higher by the model. Another factor might be that the area of study is small, which limits potential detour time savings that could be achieved from adding more stations.

Cash flow analysis results suggest that station network at the study area (the city of Santa Monica) may endure negative cash flows for about a decade. Driving patterns of early FCEV adopters matter to the economics of city station network. If FCEV users on average have long commuting distance and less long trips outside the cluster, the profitability of local station networks would be improved. This result implies that it is important to incorporate FCEV driving pattern into station planning.

Investment risks perceived by investors would depend on their planning horizon, as illustrated by next N-year NPV results. To reduce the amount of public investment for subsiding early stations, private investors would need to have longer planning horizon or more investor patience. Investors may be more patient if they perceive less technological and policy risk.

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