Space matters too! Mutualistic dynamics between hydrogen fuel cell vehicle demand and fueling infrastructure

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Abstract

Pressures from human induced climate-change, pollution, and fossil fuel scarcity stimulate interest in alternative fuel vehicles, and in particular hydrogen fuel cell vehicles (HFCV's). The transition from internal combustion engine vehicles to HFCV's is complex as various 'chicken-egg' mechanisms interact in a highly integrated fashion, and the mechanisms are highly non-linear. This paper focuses on one of the most critical chicken-egg problems: the mutualistic dynamics of HFCV adoption and its fueling infrastructure. The effects of local demand-supply interactions on these dynamics are explored in depth.

This paper develops a dynamic, behavioral model of vehicle adoption and fueling infrastructure with explicit spatial structure. Simulations are performed for a reduced version. First, basic behavior is analyzed and shown to be robust. Further, a homogeneous market with strategically locating fuel-station entrants yields fast transition through the formation of adoption clusters (niches). However, under heterogeneous conditions the same micro-mechanisms can obstruct the emergence of a sustainable market. Policy implications are significant.

This spatial behavioral dynamic model (SBDM) can be used to compare targeted entrance strategies for hydrogen fuel supply. Insights can be used for an aggregate HFCV transition model that includes other mechanisms. Finally, the paper should stimulate a discussion on merits and limitations of spatial modeling as applied to more general socio-economic issues.

[1] I am grateful to John Sterman for many fruitful discussions.

Introduction

Interest in alternative fuel vehicles (AFV's) and especially hydrogen fuel cell vehicles (HFCV's) is on the rise. Much work explores potential opportunities for success (such as in (Lovins and Williams 1999)). However, while AFV's offer many long-term socio-economic advantages, adoption is hindered by the fact that few costs and performance factors are currently positive for hydrogen (e.g. (Romm 2004)). Many symbiotic interactions yield various so-called chicken-egg dynamics. For instance, investment in HFCV's and associated infrastructure will not take place while adoption is uncertain, adoption will not occur without such investment. Consequently, policy analysis to overcome these increasing returns to adoption (Arthur 1989) often proposes creating "momentum" by independently seeding one of the chicken-egg dynamics.

Large system transition dynamics (Kemp 1994) as these are much more complex than simple chicken-egg analogies suggest. They are determined by the interplay of several endogenous factors, such as consumer acceptance of new technologies, automotive learning-by-doing, vehicle performance, technology spillovers across competitive platforms, technology and investment synergies with non-automotive fuel cell applications, and government incentives. It is far from obvious how interactions among these factors generate a pattern in which the market conditions change such that HFCV's can successfully penetrate the market. Inability of governments to understand and anticipate the interactions of these dynamics have contributed to prior failures to stimulate transitions of considerable less complexity. For instance, Californian wind power collapsed (Karnoe 1999; Kemp 2001) after a huge surge; similarly, few alternative fuel have generated a sustainable share in the transportation market (Flynn 2002). For policy design to effectively stimulate adoption on a large scale, a quantitative, integrative, dynamic model with a broad boundary, long time horizon, and realistic representation of decision making by individuals and other key actors is essential.

This paper is part of a research program that attempts to explore this for the early stages of the HFCV transition (see also (Struben 2004)). The focus is on one of the mechanisms in more dept: the dynamics resulting from mutualistic interactions between HFCV adoption and its fueling infrastructure. Prior attempts to stimulate adoption of alternative vehicles, such as CNG, have foundered (Flynn 2002). In response, the infrastructure problem in the context of a prospective hydrogen economy has already sparked various amounts of research from government, industry and academia. (Jensen and Ross 2000) map the challenge of developing an infrastructure for a transition to hydrogen by considering the on-board technologies, storage devices, delivery to the vehicles. Their conclusion, based on qualitative arguments is that 10-15% of the 100,000 US refueling stations should be to maintain “tens of thousands of HFCV’s within the next decade. In a more recent study (Farrell, Keith et al. 2003) take a wider approach and develop guidelines to introduce hydrogen at minimum cost. They suggest to develop several protected niches for the initial adoption wave by a small number professional firms, of make-to-order fleets (incentive for innovation), intensively used along a limited number of point-to-point routes or within a small geographic area. (Melaina 2003) studies transition scenarios towards mass production, by comparing cumulative capital costs and cost of hydrogen and steady installation of hydrogen stations, including learning effects with exogenous diffusion rates . (Mintz, Molburg et al. 2003) compare central versus distributed supply options.

Studies as these as well as aggregate integrative ones are important. However, they are based on simplistic assumptions about the “chicken-and-egg problem” and how it relates to other hydrogen adoption challenges. For instance, fuel station entry and location decisions and consumer adoption of HFCV are predominantly driven by local interactions between the two: the propensity of households to purchase HFCV’s depends on the availability of fuel near the routes they drive, while entrepreneurs and hydrogen distributors firms seek to locate fueling infrastructure to maximize expected profits. Further, population density is non-uniform and consumers are heterogeneous on many dimensions including driving habits, income and preferences.

To what extend can policy to generate sustainable take-off be supported by models that are approached by a simple uniform, mean-field perspective? The relevance of this question is illustrated by Figure 1. Left shows, for reference, the population distribution of California. The other show a proxy for availability of service, for gasoline (middle) and electric vehicles (right). Service is here approximated by fuel stations/person within a radius of 40 miles, relative to the average for that fuel. White areas are unpopulated, in the light areas service is below 50% of the average, medium dark areas have 0.5 - 4 times the average, dark areas have more stations per person.

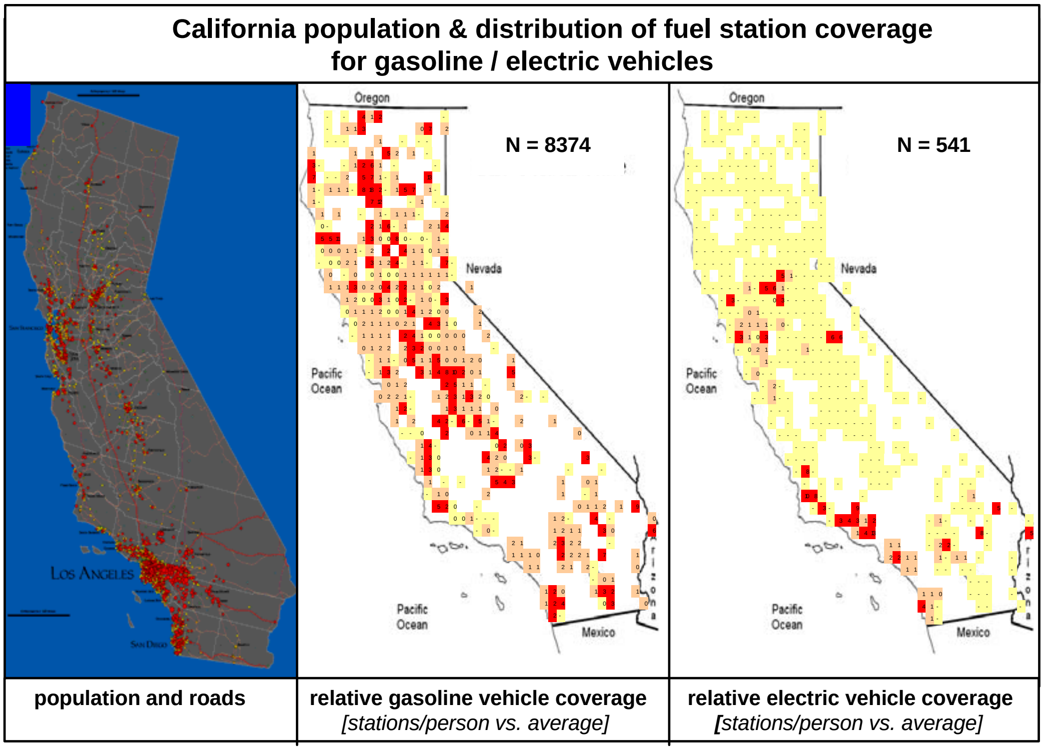

Figure 1 – a) California population distribution and road infrastructure, and b,c) service stations per person normalized to average per type: b) gasoline (n_g = 8374; 1 station every 4,000 persons), c) electricity (n_e=541; 1 station per 64,000 persons). Darker areas correspond with higher service. Complied from different sources ((Department of Energy 2004)).

The current fuel station infrastructure for gasoline is abundant (8374 fuel stations on a population of 34 million). Further, while highest close to transportation hubs/large roads, service appears to be close to uniformly/perfectly mixed distributed over the population[2]. However, the fuel/maintenance network has adjusted to the driver population (and vice versa) over a time span of over 100 years. The issue becomes clearer from Figure 1c) that exhibits an example of an emergent alternative fuel supply (electric). First, nearly all of the 512 high-voltage recharging stations are located in a few isolated “niches”. Further, availability of service is concentrated in urban sectors.

Unanticipated problems associated with the early dynamics of co-evolution between infrastructure and adoption during transitions are not unique, for example the telephone was nearly absent in rural areas (Fischer 1992). Similarly, the electric vehicle in the early

[2] The mean variance ratio of service is about 0.25, confirming the notion of a uniform distribution.

1900’s had good coverage in metropolitan areas as Manhattan, Pittsburgh and New Haven with electricity supply- and maintenance points. It was however very costly to maintain inventories and installations of the non-standardized new products and battery quality of electric vehicles could never improve through experience of longer distance trips, as was the case for internal-combustion-engine (ICE) vehicles. This in turn yielded little incentives for investors and repair shops to provide costly service (Kirsch 2000). The situation for hydrogen supply might be much more sensitive to successful policies – as relative up front investments, as well as multiplicity of stakeholders are many orders of magnitude higher than for electric charging stations. Further, HFCV will have to compete against a fully penetrated sustainable ICE-system. To overcome issues as these, current proposals include “energy parks” that make use of local complementarities (Clark, Rifkin et al. 2005). While potentially spurring entrance of fuel supply, they might also reinforce segregation of early service supply, reducing attractiveness for larger scale usage, further complicating the subsequent dynamics. To explore issues like this, spatial models are needed.

This paper develops a dynamic behavioral model of adoption and infrastructure with explicit spatial structure. Any other relevant adoption mechanisms, such as word-of-mouth, learning-by-doing/using complicate dynamics and are ignored here and will be explored elsewhere. In what follows I first demonstrate how assumptions of static equilibria / mean-field interactions are not sufficient to capture the problem at hand. Thereafter I discuss a general formulation of a spatial-behavioral dynamic model (SBDM) in detail. Next, an analysis with a reduced version of the model shows some key dynamic characteristics. Finally I propose how to go forward with this research.

A simple model of randomly distributed stations

How can vehicle adoption and fuel infrastructure co-evolve to generate a high demand market as it exists for gasoline? What type of models produce valuable insights for policy, relative to the efforts of creating them? For this problem, especially the early stages of the transition dynamics are of interest. To illustrate that aggregate, mean-field assumptions are problematic consider first the question how adoption is affected by the availability of fuel stations. Cumulative adoption fraction F_{ad} for a given station density, found by summing adopters A_c that experience a critical service level c multiplied by the probability of occurrence p_c over all potential levels of coverage:

$$F_{ad} = \sum_{c=0}^{s} A_c * p_c \tag{2.1}$$

The population level adoption for a given coverage is derived by integrating over the product of a population density function for critical service levels and adoption fraction $a_{c,t}$ given service relative to a threshold t at:

$$A_c = \int_0^\infty \left(\rho_t * a_{c,t}\right) dt \tag{2.2}$$

In other words, in this model, the equilibrium adoption profile is determined by two aggregation effects. First there are non-homogeneous characteristics of service availability $a_{c,t}$.[3] Assuming for instance a standard logit-utility model for population adoption, the combined effect of all these factors can be captured by one sensitivity parameter σ_t.[4] A second determinant of the equilibrium adoption is a distribution of preferences ρ_t that captures the heterogeneity within the population with respect to individuals' adoption threshold. This threshold depends on the demographic, socioeconomic, and other characteristics of the population. For instance urban travelers can be expected to have a lower threshold than average, while the poor, those in rural areas and those who drive long distances to multiple locations will have a higher threshold. Most generally we can assume a symmetric two parameter function with average μ_t and sensitivity σ_t.

Suppose further the assumption that station entrance is uncorrelated with household distribution, adopters or with that of other stations. While clearly a false assumption, this allows determining analytically a static equilibrium adoption profile – that is, one that is history independent[5]. To see this, consider a geographical area of A square miles and a

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[3] Note that the first moment results for adoption fractions are independent of the *geographical* distribution of the population, this as a result of the assumption on random station entrance.

[4] For instance, a larger (smaller) population corresponds to a more uniform (homogeneous) distribution of factors, approximated by a lower (higher) σ_t.

[5] Note further that this is a necessary implicit assumption behind static equilibrium models

distribution of service stations s_i and households h, each having the same desired driving range of rd miles (Figure 2a) (A full derivation is provided in Appendix 1 – random model). Defining the number of stations in one's drives area as a metric for service, because of the Poisson properties of the model, the probability of having at least c stations within one's driving range can be derived analytically and equals:

$$p_c = 1 - e^{-\mu} \sum_{\gamma=0}^{c-1} \frac{\mu^{\gamma}}{\gamma!}; \qquad \mu = \frac{S * A_d}{A} \tag{2.3}$$

where μ represents the mean number of stations per driving area A_d , and thus the mean coverage for S stations and driving range r_d . Figure 2b) shows four adoption profiles, with a standard Logit formulation for $a_{c,t}$ and μ_t equaling the current average station density. Two different sensitivities, correspond with a 'large' and "small" population size ($\sigma_t = \{0.5, 2\}$), and distribution in preferences is either 'uniform' or is 'homogeneous'($t \in U[0, 2\mu_t]; t = \mu_t$).

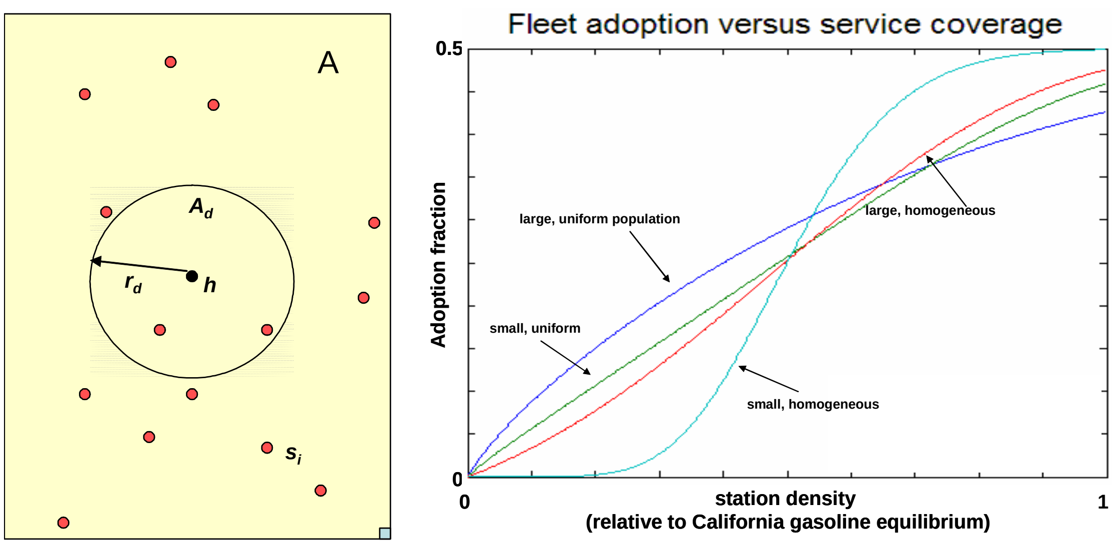

Figure 2 a) Hypothetical area A with S stations si randomly distributed. Households located in h have driving radius rd and mobility within disc Ad b) static adoption profiles for increasing station density, for 4 combinations of population distributions and preferences.

Increasing size/uniformity in the distribution of population strengthens a decreasing returns effect, and yields more relative adoption for low station densities. Second, uniformity in the distribution of preferences/circumstances diminishes a threshold effect, also yielding faster adoption for low distributions.

While the foregoing model is overly simplistic and its assumptions of uncorrelated station entrance are wrong, a key point can be learned: heterogeneity can matter a lot. This effect becomes larger when assuming that station location decisions are strategic, that is, when entrance is higher for areas that have higher expected profitability. The combination of stratification and heterogeneities might further strengthen driver adoption locally. However, the implications of this are not necessarily positive – as was argued to be the case for the electric vehicle in the introduction. This, however, can never be tested with a model with aggregate assumptions.

Modeling local interactions

This problem is part of a class of diffusion models that incorporate the presence of a spatial component. Spatial modeling allows heterogeneities or local deviations away from the global mean to be introduced in cases where these phenomena can drastically affect the global dynamics. Since (Turing 1952) introduced physio-chemical diffusion reaction structures, or “Turing Structures”, research in this area has increased. These types of spatial patterns are increasingly likely to be found where the movement and range of influence of actors is small compared to the global scale, leading to strong local correlations. Due to the increasing processing capabilities, problems as these are addressed more, in both the natural and social sciences, on problems related to statistical physics (Ising models), material physics (crystal growth and the process of solidification, or, dendrites - (Langer 1980)), and organic surface growth (diffusion limited aggregation, (Witten and Sander 1981)), Aggregration - and geographical economics (e.g. von Thunen’s land use model, (Krugman 1996)), and transportation research (Domencich, McFadden et al. 1975; Ben-Akiva and Lerman 1985). Co-evolutionary diffusion problems are increasingly studied (e.g. (Keeling 1999)).

A useful model should track the interaction of a supply-side that involves fuel and other services (stations) and a demand-side (drivers, miles driven and fuel consumption) in an as simple possible way, but not too simple to not be able to capture the central to the problem, the effect of local interactions. Spatial dynamics are driven by two types of interactions: self-induced and from underlying heterogeneities. In the light of this, especially three assumptions are revisited of which the first two are of the self-induced type and the third is the result of underlying heterogeneities. First, the assumption of absence of (local) strategic behavior is relaxed. Entrants form expectations about the profitability of a particular location, depending on the (expected) concentration of demand but also to existing supply from other stations – this also implies introducing time dynamics. Second, as a result of this is essential to introduce more sophisticated behavioral assumptions on the psychology of adoption and driving behavior. For instance, while attractiveness should increase with increasing coverage within one's driving range, more frequented regions will count more heavily; on the other hand, if barely frequented, but important destinations are not covered how attractive will it be to adopt? Finally, the population distribution is not homogeneous (illustrated by Figure 1, a), influencing effective coverage and baseline attractiveness for entrance.

The model

this section describes a generic version of the model. Figure 3 offers a compact representation of the model structure. Top shows a hypothetical geographical landscape of area “A” is shown that is divided in a grid of so-called “patches”.[6]

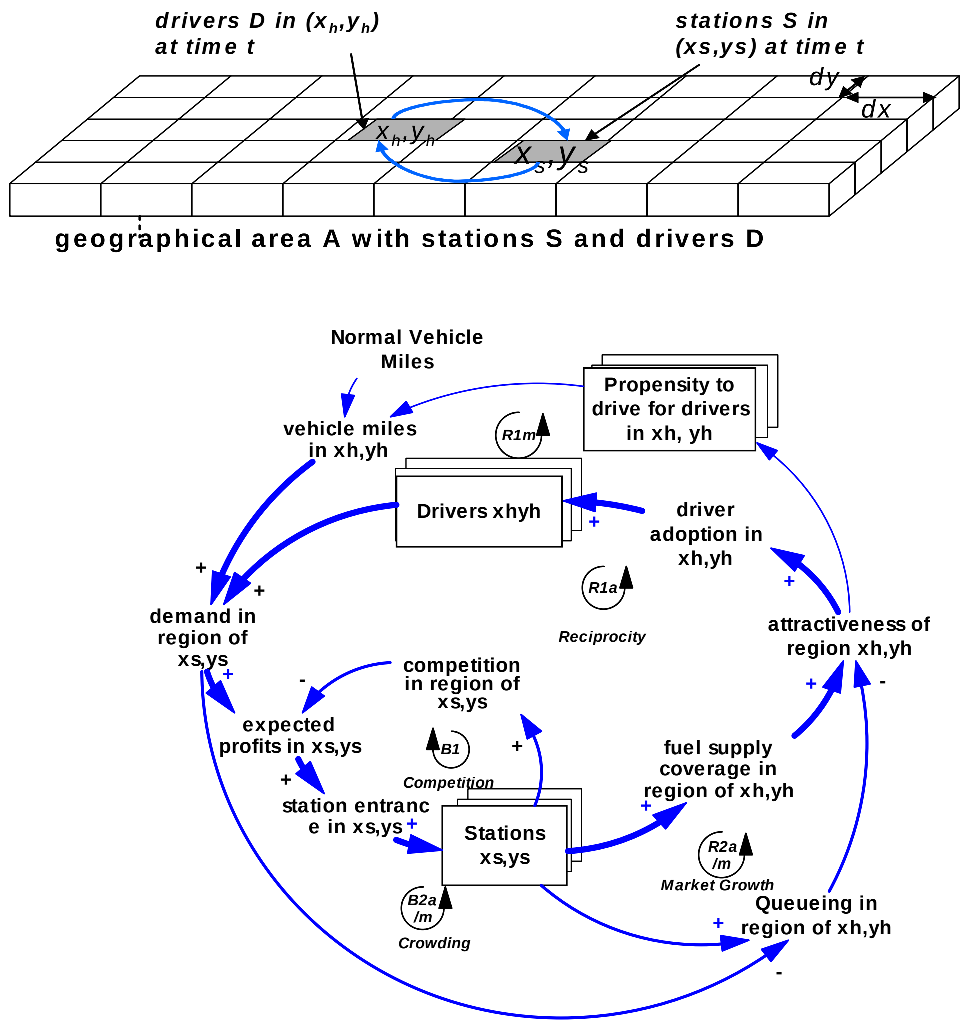

Figure 3 – Basic model structure. Top: geographical area “A” contains drivers D and stations S, both distributed in homogenous patches of size dxdy. Bottom: conceptual representation of causal structure for interaction between households in (x_h,y_h) and stations in (x_s,y_s).

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[6] In this paper the patches are either depicted as squares, to illustrate the operational idea of a grid of finite sized, connected elements, and sometimes depicted as “dots”, to create a sense of infinitesimal size, relative to the other dimensions.

Each patch potentially contains drivers of HFCV's in their home location and stations S. While distributions are spatially heterogeneous, each individual "patch" has area $dx * dy$, chosen to be small enough so that they can be considered homogeneous. The different populations interact across space: households situated in a particular patch (x_h, y_h) adopt with increasing fuel supply within their region; for instance coming from location (x_s, y_s) as shown. Likewise, potential fuel/service station entrants consider the relative attractiveness for locating at a particular site by estimating expected profitability in the different regions, derived from actual sales and expected drivers and competitive effects. Further, while dynamics for driver adoption and vehicle miles are spatially dependent, the behavior in each location can be described by the same structure that is described below for one arbitrary location. Figure 3 , bottom, shows a conceptual diagram. When stations increase, coverage in the region increases, that in turn leads to driver adoption In addition the vehicle miles for adopters also increase. In turn, with increasing total demand, attractiveness to enter by fuel stations also increases that again leads to higher coverage in (somewhat different) neighboring regions.
Households face two types of decisions: adopting a HFC vehicle, subsequently use it driving vehicle miles. Following (Domencich, McFadden et al. 1975), these choices are modeled hierarchically (nested).

While for each location drivers and their vehicle miles are treated as continuous variables that adjust deterministically as a function of attractiveness, individual stations enter in discrete time. Thus, following the typology of (Keeling 1999), the model is a hybrid between a metapopulation (patch) model and interacting particle system (as cellular automata). Aggregate behavior is derived after capturing individual adoption and mobility at patch level by integrating over each patch and averaging over ensemble outcomes.

Demand dynamics

Household adoption

The structure for household adoption is shown in Figure 4 and is discussed below.

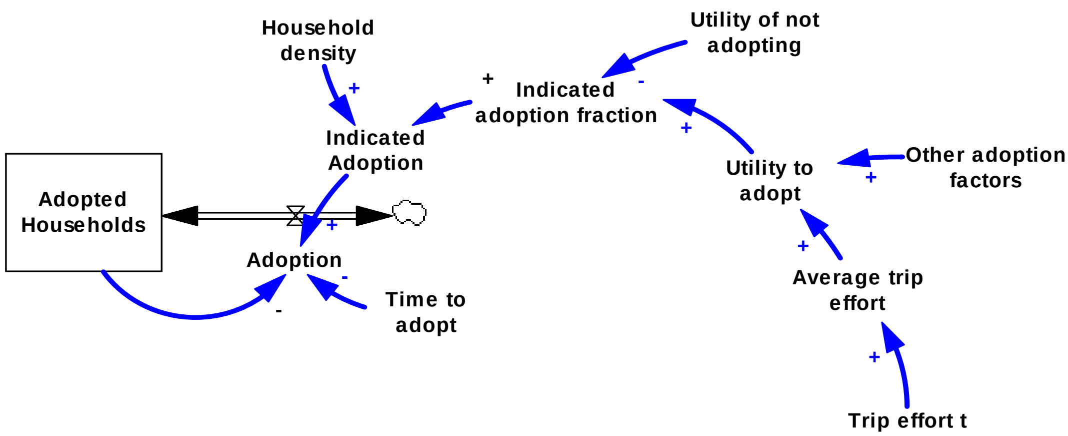

Figure 4 – Household adoption structure

The level of adopted households of type ∂ , h_a^{∂} ,in an arbitrary location, adjust to the indicated level $h_a^{*\partial}$ over an adoption time τ_a (see Appendix 1 for the clarification of indices)

$$\frac{d\,h_a^{\partial}}{dt} = \frac{h_a^{*\partial} - h_a^{\partial}}{\tau_a} \tag{2.4}$$

Indicated households are the product of household density, ρ_h^{∂} , and the indicated adoption fraction $a^{*\partial}$:

$$h_a^{*\partial} = \rho_h^{\partial} * a^{*\partial} \tag{2.5}$$

The adoption fraction is derived through a multinomial logit formulation that is in line with those used in transportation research (e.g. Domenchich and McFadden 1975;(Ben-Akiva and Lerman 1985) and in the automobile industry (Berry e.a. 1995; Train 2004), The indicated adoption fraction is given by the utility of adoption, relative to the sum of utility of adoption U_a^{∂} and an (unknown) alternative U_{na}^{∂} (no adoption), or [7]

$$a^{*\partial} = \frac{U_a^{\partial}}{U_a^{\partial} + U_{na}^{\partial}} \tag{2.6}$$

Utility of not adopting includes utility of all alternatives (in particular, the gasoline vehicle). This utility is defined to equal one[8]:

$$U_{na}^{\partial} \equiv 1 \tag{2.7}$$

Determinants of utility are, vehicle related factors V_a, such as net vehicle performance and price, insurance cost, yearly fuel (cost relative to the alternative); socio-economic factors (per type and/or location), given by the vector $\overrightarrow{se_a^i}$ ($i \in \{,l,l\partial;\partial\}$); and, average effort required to drive, e^{∂}. For this model, all factors except efforts are assumed constant and are replaced by one vector $\overrightarrow{E_a^i}$. Further, assuming utility to be multiplicatively separable in its determinants: [9]

$$U_a^{\partial} \quad = f\left(\overrightarrow{E_a^i}, c^{\partial}\right) = f\left(\overrightarrow{E_a^i}\right) f\left(e^{\partial}\right) \tag{2.8}$$

with $\widehat{x_j} \equiv x_j / x_{n,j}$ being the normalized attribute j and $f\left(\widehat{x_j}\right)$ chosen to be exponential:[10]

$$f\left(\widehat{x_j}\right) = \exp\left[\beta_j\left(\widehat{x_j} - 1\right)\right] \tag{2.9}$$

Here β_j captures the sensitivity to a fractional change in the attribute[11]. The one parameter formulation is justified as long as the region of operation is small, which is the case for

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[7] An individual adopts once its perceived utility exceeds that of alternatives, while for aggregate adoption a univariate binary formulation is appropriate

[8] As utility of the alternative is fixed, IIA, embedded in equation (2.6) is of no concern.

[9] Utility is also derived from the purpose of the trip, but as this is identical for all alternatives and can be ignored.

[10] $x_{n,i}$ are the normal, or indifference points, defined such that when all attributes equal their indifference points, utility equals one.

our problem that involves early stages of adoption[12]. Further, data (such as parameter estimations, trip tables) are available from related research.

Aggregate effort is a weighted average over the coverage of each trip part of the trip set T ,

$$e^{\partial} \equiv e^{\partial,\overline{T}} \tag{2.10}$$

where $\overline{T}$ indicates a weighted averaging.

Vehicle miles

The key variable of interest is determining the local demand per driver as a function of service availability. This entails determining the adopter's vehicle miles, through a convolution integral over desired trip frequency times distance per trip and the relative attractiveness per trip, as a function of effort. Trip effort, besides having a fixed component, is a function of refilling hassle, which depends on travel distance/time to a service station, refilling time, and risk to be out of fuel. This all depends on station concentration (and demand).

To represent heuristics that constitute "average efforts" one could make use of the technique of Voronoi diagrams (e.g. (Okabe, Boots et al. 1992)), often applied to determine effective coverage in spatial related problems (e.g. for cellular phone networks). This method would imply determining the nearest service station to each location and allows uncovering several characteristics parameters. However, a key implication of assuming strategic fuel station entrance is their non uniform (nor randomly) distribution in space. The same then holds true for a driver's efforts (or

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[11] Note that the model can be used to intitalize parameters by applying it to conventional gasoline U_a^{∂} as the utility of adopting gasoline and setting $U_{na}^{\partial} \equiv 1$ for all other options. However, it must be noted that for that vehicle more "unobserved" factors play a role.

[12] To examine the effect of trip coverage on utility over all ranges (zero stations to "full coverage", where all locations contain a station) a functional form form that exhibits an s-curve is desired – which will require one more parameter. For instance the logistic formulation can be used: $f\left(e^{\partial}\right)=1/\left(1+\exp\left[-4*\beta_e\left(e^{\partial}-e_{0.5}\right)\right]\right)$, with $e_{0.5}$ being the locus where f equals 50% of its range. This expression has been used for testing the model under extreme conditions.

expected efforts) to obtain service. This in turn necessitates the derivation of efforts for each individual trip, rather than using any mean field approximation from each adopter's home location, or the Voronoi technique.

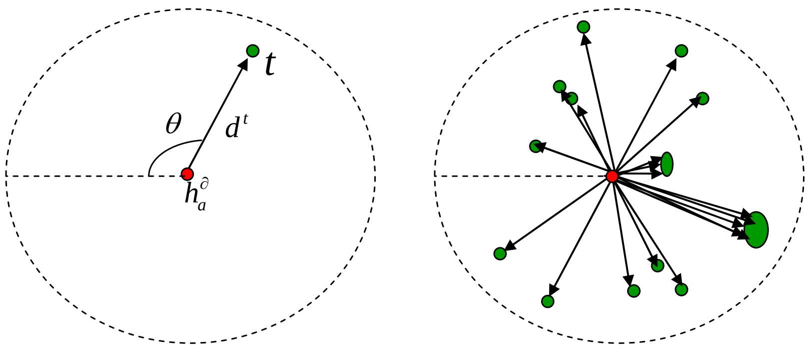

Figure 5 modeling driving behavior. An individual trip t of length d in polar coordinates. Right shows a typical spatial count of trips for a hypothetical individual.

As shown in Figure 5, individuals are assumed to have a probabilistically fixed driving pattern in space and time, defined through trip destinations t, and frequencies $f^{\partial,t}$ that differ per location and type. For each trip several modes of transportation are compared, of which the most favorable is selected. Thus, individuals, once owning a HFC vehicle, consider on a per trip basis, weather to use it or not. The total miles for an individual can be found by integrating over all potential angles and length: $m^{\partial} = 2\int_{r,\theta} d^t * f^{t,\partial}(r,\theta)\,dr\,d\theta$:

From hereon, notation (r,θ) will be replaced by the single letter t.

Trip frequencies and utility to drive

The structure of the trip frequency are shown in Figure 6 and explained below.

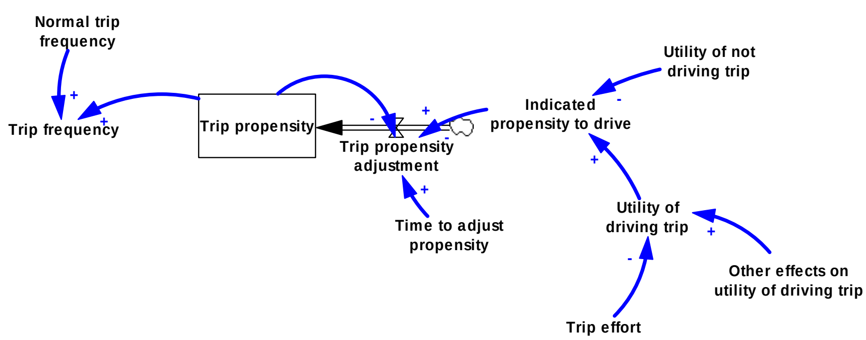

Figure 6 Vehicle miles of trip t

The average trip frequency (trips/year) per person while using the HFCV is the product of the propensity $p_d^{\partial,t}$ to drive trip t (with the HFCV) and the normal trip frequency:[13]

$$f^{\partial,t} = p_d^{\partial,t} * f_n^{\partial,t} \tag{3.1}$$

Propensity per trip (given $t \in T^{\partial}$) adjusts over an adjustment time τ_T to its indicated level $p_d^{*\partial,t}$:

$$\frac{d\, p_d^{\partial,t}}{dt} = \frac{p_d^{*\partial,t} - p_d^{\partial,t}}{\tau_T} \tag{3.2}$$

which is defined to be of univariate binary form, identical to (2.6):

$$p_d^{*\partial,t} \quad = \frac{U_d^{\partial,t}}{U_d^{\partial,t} + U_{nd}^{\partial,t}} \tag{3.3}$$

Utility of not using the vehicle is defined to equal one,[14]

$$U_{nd}^{\partial,t} \equiv 1 \tag{3.4}$$

and similarly to the case of adoption (see equation (2.8), utility has two main components:[15]

$$U_d^{\partial,t} \quad = f\left(\overrightarrow{E_d^i}, e^{\partial,t}\right) = f\left(\overrightarrow{E_d^i}\right) * f\left(e^{\partial,t}\right) \tag{3.5}$$

where $\overrightarrow{E_d^i} = \left\{V_d, \overrightarrow{se_d^i}\right\}$ ($i \in \{l, \partial, t, l\partial, lt, \partial t\}$) and functional forms are identical to equation(2.9).

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[13] One can obtain a distribution for $f_n^{\partial,t} \quad \equiv f_n\left(l, t\left(r,\theta\right) | \partial\right)$ (for instance) by transforming to polar coordinates, and demanding that the integrated vehicle miles $\left(1/H\right)\int_{l,\partial,(r,\theta)} h_a^{l,\partial} 2d^t f_n^{\partial,t} = m$ and the integrated trip frequency $\left(1/H\right)\int_{l,\partial,(r,\theta)} h_a^{l,\partial} f_n^{\partial,t} = F_T$ observed/desired. Similarly one can constrain the frequency through higher moments, or particular distributions as a function of (r,θ).

[14] Note that the utility has three components: the fixed utility of doing the trip, the fixed effort, or hassle of doing the trip and the hassle of doing the trip as a function of availability of service.

15 Second order effects such as habitualization are ignored. All else equal, considering this in combination with equation (2.6), implies that if utility equals one, the trip pattern will be identical to that for gasoline vehicles

Trip effort

Average trip effort is determined by capturing the average experienced effort over the whole trip (Figure 7). Consider a driver on a trip from San-Francisco to Los-Angeles, starting at a half-full tank. Non-uniformity of service availability requires averaging over all points underway (u) where service requirements can occur.

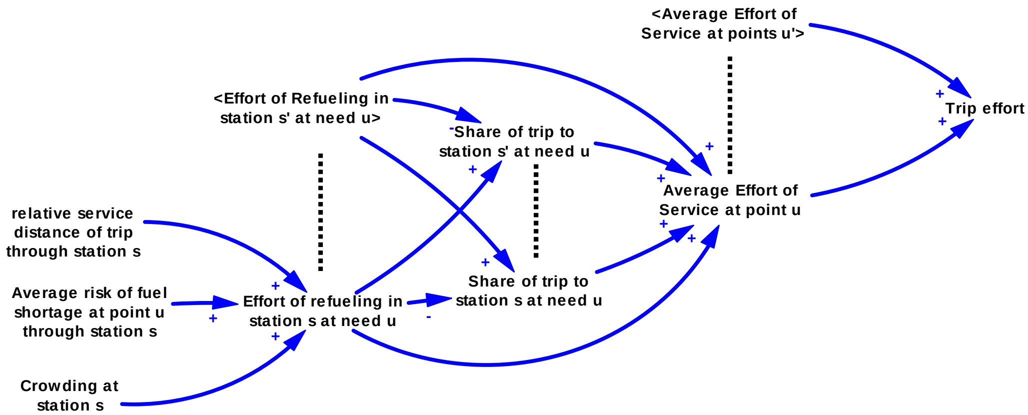


Figure 7 deriving the trip effort

When it is assumed that service requirements are uniformly distributed over the whole trajectory, trip effort, relative to the normal effort e_n^t equals

$$e^t = \frac{p_f^t * e^{t,\overline{U}}}{e_n^t} \tag{3.6}$$

where p_f^t is the probability of refueling for trip t, $t,\overline{U}$ indicates the averaging over all underway locations of trip t and e_n^t is the normal effort per trip – for instance as experienced with gasoline times the same probability of refueling.

Average experience of effort entails integrating over effort for all underway sites:

$$e^{t,\overline{U}} = \frac{1}{d^t} \int_{u=0}^{t} e^{t,u} \tag{3.7}$$

where d^t is the trajectory distance.

For averaging over contributions of all service locations to an underway location, the respective efforts are weighted by the share distribution of demand:

$$e^{t,u,\bar{S}} = \int_s \sigma^{t,u,s} e^{t,u,s} \quad (3.8)$$

with the share that station s receives in case of requirements at u being a function of the relative attractiveness of all stations:

$$\sigma^{t,u,s} = \frac{f\left(e^{t,u,s}\right)}{\int_l f\left(e^{t,u,l}\right)} \quad (3.9)$$

The functional form is identical to (2.9). Sensitivity parameter β_s is bounded below zero. If a driver has complete control and full information on where to make use of the service, it selects the station that requires least effort over the whole trip ($\beta_s \to -\infty$). On the other extreme, if a driver would distribute its demands randomly $\beta_s = 0$. Thus for the sensitivity parameter holds: $-\infty < \beta_s \leq 0$

Actual effort is represented by a linear combination of the different factors that contribute to this, each potentially having a different weight of importance[16]:

$$e^{u,s} = e_{\bar{I}}^{u,s} = \sum w^i e_i^{t,u,s};\ \sum w^i = 1 \quad (3.10)$$

As discussed, three factors are considered to constitute the endogenous trip effort. First, there is hassle associated with driving further than the desired trip trajectory (indicated as trip-distance, or td); second, with limited supply, there is a risk of getting out of fuel, or hassle to tank much earlier than needed (risk, or ri); finally, when locally demand exceeds supply, people will have to wait too long, increasing the annoyance of refilling (time to fill, or tf) (For instance, first phase service stations are expected to have capacity for not more than 10-15 vehicles per day). Thus:

$$i \equiv \{td, ri, tf\} \quad (3.11)$$

First, people prefer to drive a minimum distance/time, relative to a direct trip to the final destination (Figure 8 a), represented by:[17]

[16] Note that $w^i / w^{i'}$ represents the cost of the attribute i relative to that of i'.

[17] There is a significant difference in terms of the effect of this factor between 1D and 2D. This will be discussed later

$$e_{td}^{t,u,s} = \frac{d^{t,s}}{d^t} \tag{3.12}$$

with $d^{t,s}$ is the shortest trip distance via the service station. This effect captures that for a short trip a deviation weights much heavier than for a large trip.

The second attribute captures that individuals prefer to refill as close as possible to the underway location where the need occurs (Figure 8 b), and thus prefer a shorter distance between an underway location and the actual location of the station:

$$e_{ri}^{t,u,s} = \frac{abs\left(d^u - d^s\right)}{\alpha_f d_f} \tag{3.13}$$

where d_f, α_f are the driving range between refills (tank range) and the fraction of the range that is considered to be critical for refills.

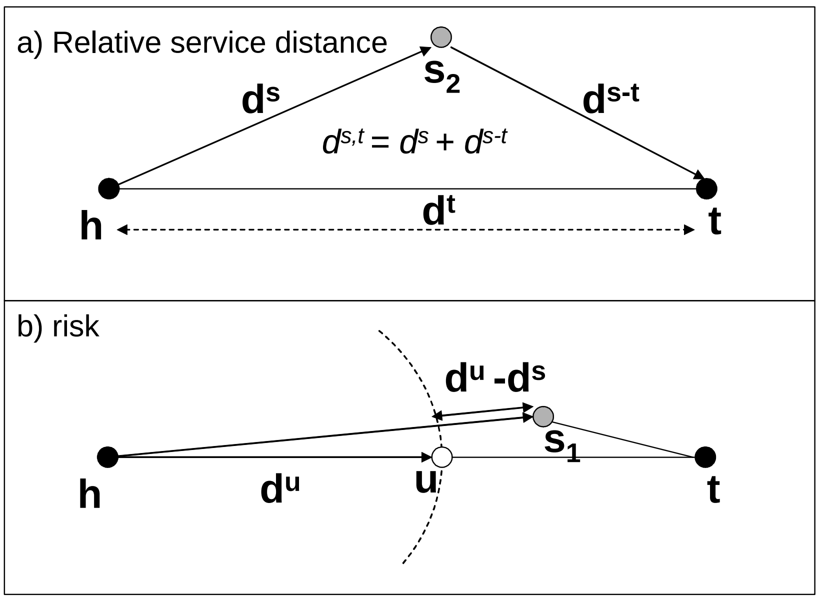


Figure 8) Endogenous determinants of trip efforts; a) service distance relative to the normal trip distance. b) out-of-fuel-risk when the station distance is further than the desired refuel distance underway. The third (refill time) is not shown here.

The final term in (3.11) represents the total relative capacity in a location:

$$e_{ft}^{s} = \max\left[1, R^s / K^s\right] \tag{3.14}$$

with R^s being the total revenues per location, $K^s = s * k_n$ is the total capacity for the patch (s are the total number of stations in the location and k_n is the normal capacity per station).

Effective trip distance and shares

Effective trip length is the sum over the normal trip trajectory (being twice the distance, or, $2d_n^t$) times the probability of not having to refill and the expected length of a trajectory through a service station times the probability of having to refill[18]:

$$d^t = \left[\left(1 - p_f^t\right) 2d_n^t + p_f^t * \left(d_f^t + d_n^t\right)\right] \tag{3.15}$$

The probability to fuel is equal to the trip distance divided by half the distance between two refills (or, tank range):

$$p_t^f = \frac{2d^t}{0.5 * d_f} \tag{3.16}$$

Where the expected length of a trajectory through a service station is the integration over trajectories, times their shares:

$$d_f^t = d_f^{t,\overline{U,S}} = \int_{u,s} d^{t,s} \sigma^{t,u,s} \tag{3.17}$$

Average effort of trips for adoption

Perceived effort of driving (see equation (2.10)) for an individual that considers adoption, is a function of the actual efforts per trip. It is assumed that the time to learn about the efforts is short relative to the adoption rate. Thus it can be approximated by a weighted averaging over the efforts of the individual trips. The weighting does not necessarily have to be a linear weighted average:

$$e^{\partial} = e^{\partial,\overline{T}} = \left[\int_t w^{\partial,t} \left(e^{\partial,t}\right)^{\varepsilon_t}\right]^{1/\varepsilon_t} \qquad \sum_t w^{\partial,t} = 1; \tag{3.18}$$

---

[18] An underlying assumption is that the probability of having to refill twice is ignored.

Where $w^{\partial,t}$ are the relative weights of the different trips and ε_t is the parameter of which the high (low) values captures the bias towards trips that require more (less) effort. In the (default) linear case ($\varepsilon_t = 1$), the linear regression characteristics are maintained (details of this functional form are explained in Appendix 3 – Constant Elasticity of Substitution function).

The relative weights represent the relative importance of each; this is proxied by a combination of trip frequency and distance:

$$w^{\partial,t} \sim \left(f_n^{\partial,t}, d^t \right) \rightarrow w^{\partial,t} = \frac{m^{\partial,t}}{\int_t m^{\partial,t}} \quad (3.19)$$

where $m^{\partial,t}$ are the total annual miles driven for one trip for a household of a particular type.

Derivation of this aggregate variable, and various others, is mechanistic and can be found in (Appendix 2 - Tables)

Supply dynamics

Profits

A service firm's profits, given presence in a particular location are revenues r minus fixed costs co_f :[19]

$$\pi = r - co_f \tag{4.1}$$

Given the foregoing discussion, derivation of profits is purely mechanical (that is, no parametric assumptions are required). Firm's revenues are the product of share σ_s among stations of the total location revenues R^l,

$$r = \sigma_s R^l \tag{4.2}$$

With shares being evenly distributed among firms $\sigma_s = 1/S$ (conditional upon $S > 0$) that are assumed to have equal capacity. Further, local revenues integrate the shares $\sigma_s^{l',\partial}$ of purchases $Pu^{l',\partial}$ from all households per type ∂

$$R^l = \int_{l',\partial} \sigma_s^{l',\partial} * Pu^{l',\partial} \tag{4.3}$$

where purchases equal the product of price and vehicle miles divided by the efficiency mpg [20]:

$$Pu^{l,\partial} = p * \frac{M^{l,\partial}}{mpg} \tag{4.4}$$

Finally, the share of household type ∂ in location l' that reaches station s is the integration over all her/his shares per trip times the relative frequency of trip:

$$\sigma_s^{l',\partial} = \frac{\int_{t,u} f^{\partial,t} * \sigma_u^{\partial,t} * \sigma_s^{\partial,t,u}}{\int_{t,u} f^{\partial,t}} \tag{4.5}$$

---

[19] Costs could be location dependent

[20] Hydrogen fuel parameters are expressed into gasoline gallon equivalent

Firm entrance and exit

Local entrance rates en are determined by two factors (Figure 9); first, potential entrants decide to enter or not (resulting in an aggregate entrance rate EN), second, they make a strategic choice on where to locate. That is, entrance strategies result in a relative distribution σ_{en} over the whole area:

$$en = \sigma_{en} * EN \tag{4.6}$$

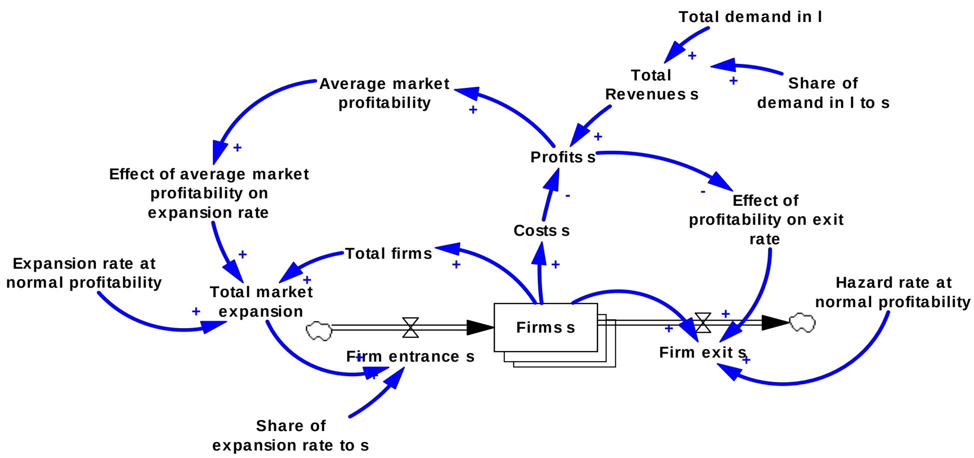


Figure 9 - Firm entrance and exit

Market expansion is driven by market profitability and a entrance rate λ_n at normal profitability:

$$\begin{aligned} EN &= \lambda_{en} S \\ \lambda_{en} &= \lambda_n * f\left(\overline{\pi}\right); \qquad f' > 0 \end{aligned} \tag{4.7}$$

Reference profits are determined by opportunity cost and are assumed to be fixed, based on the same utility as for entrance:

$$f\left(\overline{\pi}\right) = \exp\left[\beta_{en} \frac{\overline{\pi}}{\pi_n} - 1\right]; \beta_{en} > 0 \tag{4.8}$$

Exits are mediated by firm profitability, following the standard hazard formulation.

$$\begin{aligned} ex &= \lambda_{ex} s; \\ \lambda_{ex} &= \lambda_n * f\left(\pi\right); \qquad f' < 0 \end{aligned} \tag{4.9}$$

The functional form and reference profit is identical to that of (4.8), while $\beta_{ex} < 0$.

Note that when profits equal normal profits, net market growth is zero.

Entrance share

The entrance share depends positively on relative attractiveness to enter, which is a function of expected profitability:

$$\sigma_{en} = f\left(\pi^{E}\right) / \int f\left(\pi^{E}\right) \tag{4.10}$$

The functional form and reference profit is identical to that of (4.8), while $\beta_{en,s} > 0$.

Expected profits are the net of expected revenues and cost:

$$\pi^{E} = \sigma_{s}^{E} * R^{E,l} - co_{f} \tag{4.11}$$

With the expected share being the unit station capacity (of one entrant) divided by the total effective competition for that location:

$$\sigma_{s}^{E} = \frac{k_{n}}{k_{eff} + k_{n}} \tag{4.12}$$

with effective competition being the integral over station competition effect that decays over typical distance d_{n}^{s} :

$$\begin{aligned} k_{eff} &= k_{eff}^{\bar{S}} = k_{n} \int_{s'} S' * f\left(d^{s'}\right) \\ f\left(d^{s'}\right) &= \exp\left[\beta_{c} * \left(\frac{d^{s'}}{d_{n}^{s}} - 1\right)\right]; \beta_{c} < 0 \end{aligned} \tag{4.13}$$

Similarly, an entrant in l expects that a fraction of regional demand $R_{eff}^{l,l'}$ is available:

$$R^{E,l} = \int_{l'} R_{eff}^{l,l'} \tag{4.14}$$

Effective demand consists of a share of the flow of revenues available locally that decreases with distance and an adjustment of demand $R_{g}^{l'}$ that involves expected new revenues that result from adoption and vehicle miles. distance:

$$R_{eff}^{l,l'} = f\left(d^{l'}\right) * R^{l'}\left(1 + g_{r}^{l'}\right) \tag{4.15}$$

The adjustment entails closing a fraction of the maximum potential demand, that decreases with distance in similar fashion:

$$R_{g}^{l'} = g_{r,n} * f\left(d^{l'}\right)\left[\frac{R_{\max}^{l'} - R^{l'}}{R^{l'}}\right]; \qquad R_{\max} = f\left(\overline{H * M^{l,\partial}}\right) \tag{4.16}$$

where the incapacitated maximum growth fraction $g_{r,n}$ captures both the effect of miles and adoption increase and:

$$f\left(d^{l'}\right) = \exp\left[\beta_r * \left(\frac{d^{l'}}{d_n} - 1\right)\right]; \qquad \beta_r < 0 \tag{4.17}$$

Analysis

This analysis studies characteristic behavioral implications of the SBD model. As computational capacity is a constraint, a reduced model version is used that minimizes calculations, while preserving its fundamental characteristics. Several simplifications were carried out. First I emulated continuous space by a finite element modeling (FEM) approach, e.g. (Reddy 2004). Further, spatial degrees of freedom are limited to one dimensional "strip". To avoid boundary effects first and last patch were connected to yield a circle.[21] Second, time steps are blown up to the maximum feasible. In fact, the limited degrees of freedom simplify the identification of characteristic behavior modes and are justified as a higher degree turn out to reinforce those.

Model parameterization

For the purpose of parameterization I distinguish between two types: "observable parameters" (those that can be estimated heuristically with comfort), and the remainder, "unobservable parameters", of which there are only 8. All are provided in Appendix 4 – Parameters), but the most critical parameters are discussed here. For those relevant, the state of California serves as a reality check, but some are adjusted to permit a proper collapse into the one-dimensional representation.

The circular strip has a perimeter of 256 miles, with patches being 4 by 4 miles. Households have identical socio-economic conditions (vectors $\overrightarrow{E_a^i}, \overrightarrow{E_d^i}$ are held at 1). Further, for the purpose of this analysis I consider only one type of drivers, which has normal vehicle miles, average trip length and distribution of an average household. Data for this can be derived from trip-tables (e.g (Domencich, McFadden et al. 1975)) that suggest that can be derived from a two-parameter lognormal distribution:

$$f_n^t = 2\, f_{med}\, \frac{d^t}{d_n} \exp\left[-\left(\frac{\ln\left[2d^t / d_n \right]}{\sqrt{2}\sigma_t} \right)^2 \right] \tag{4.18}$$

[21] A disadvantage of this is that the effective length is reduced by two, as the maximum distance is half the perimeter.

with σ_t being the sensitivity of visiting frequency to distance (here the standard deviation) and f_{med} the frequency of the median. Further, the normal frequency is defined such that the integration over the populations corresponds with average annual miles m :

$$(1/H)\int_{l,\partial,(r,\theta)} h_a^{l,\partial} 2d^t f_n^{\partial,t} = m \tag{4.19}$$

Average population density and average trip length of 32 miles (25% of the maximum distance that can be traveled) remain constant throughout. Figure 10 shows the circular configuration, similar to the one used in other economic problems in product space (Hotelling 1929; Salop 1979) and geographic space (see (Krugman 1996)).

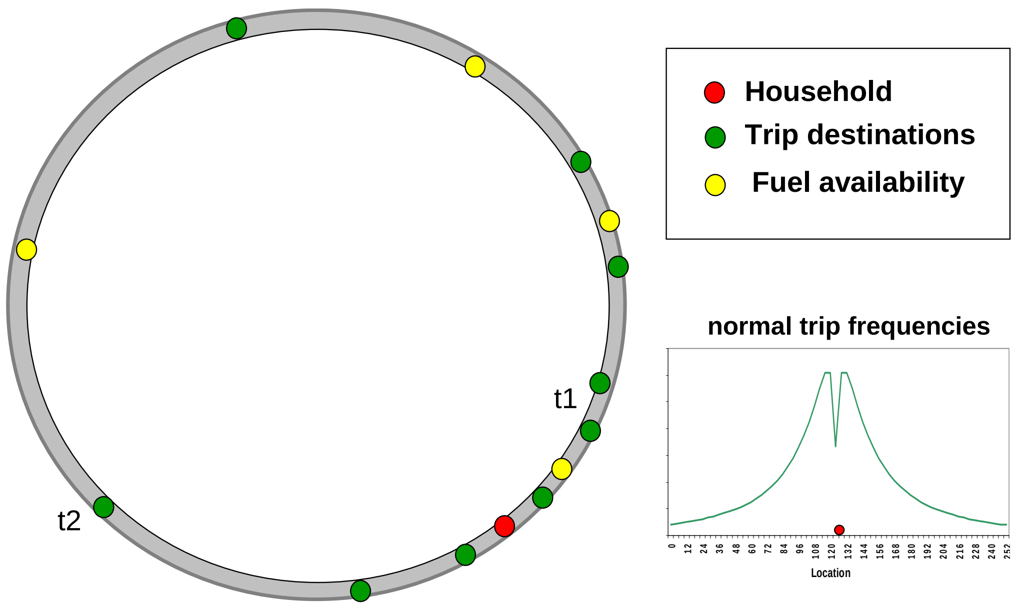


Figure 10 - "highway five", circular configuration shows a subset of trips for one household and 4 fuel stations. Right bottom shows a typical distribution of normal trips.

Shown are one household and a subset of its normal destinations, with frequency as function of distance shown in the bottom right.[22] Each household has an identical distribution. For illustrative purpose, ignoring potential effects of crowding, trip effort for t1 seems to be reasonably low, while t2 is poorly covered.

[22] While not suggested by the graph, one location can contain both stations as well as households.

Attractiveness of *not* adopting a HFCV /*not* using the HFCV for a trajectory are fixed, and equals attractiveness that would follow from a hydrogen infrastructure of 1 station every 4 mile[23]. Thus, the maximum adoption is 50%, occurring at this “reference infrastructure”, where HFCV vehicle miles are equal to the normal vehicle miles of 15.000 miles per household per year (with one vehicle per adopted household). Further, utility parameters are set such that relative attractiveness to adopt/drive is 50% at double the average/ trip effort. Subsequently, aggregate HFCV adoption must then be 25%.

Station entry decisions are driven by the average profitability of the market. Strategic entrants’ location decisions are driven by the relative attractiveness, based on expected revenues for each entrant (equations (4.8) and (4.10) and further). The purpose of this analysis is to learn how unexpected aggregate patterns emerge out of local entrant behavior. Therefore we take the most optimistic assumptions for entrant behavior, thus parameters $\left\{\beta_r, \beta_c, g_{r,n}\right\}$ are calibrated such that probability of location corresponds with the optimal, for the same local decision rule.

[23] This equals the current gasoline situation in California

Open loop equilibrium analysis

Figure 11 and Figure 12 illustrate a basic model validation test: open loop responsiveness of driver adoption to station concentration, with uniform population distribution. The total number of stations is controlled externally by varying a station distance parameter. Figure 11 a) shows adoption for three different station distances (d_s=128, 32, 8 miles).

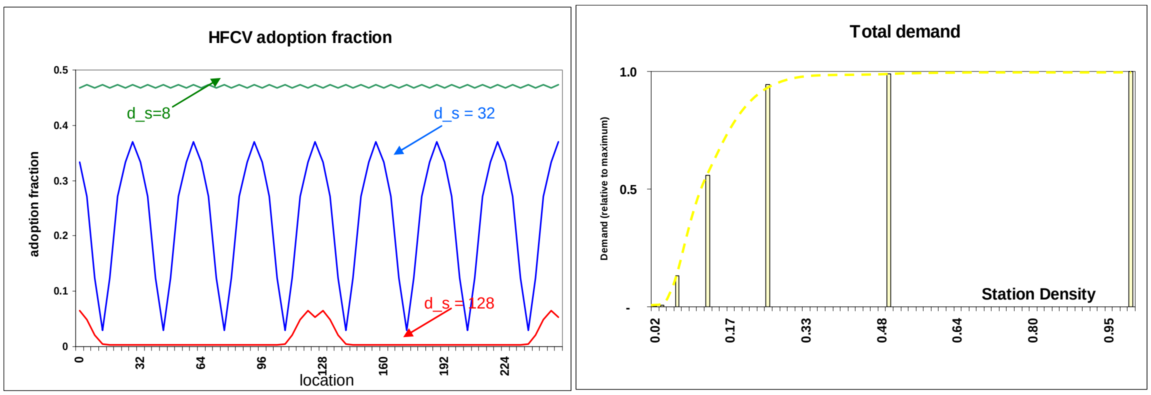


Figure 11 instantaneous adoption profiles; a) indicated adoption fraction for stations separated by 8, 32, and 128 miles, b) adoption curve for increasing station density

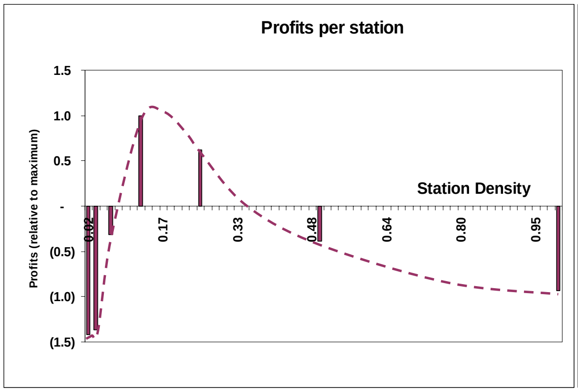
For stations separated by 128 miles (stations at 0 and 128 miles), adoption is very limited and decays very rapidly with households' distance to a nearest station increasing.[24] With station separation of 32 miles yields a dramatic (much more than proportional) increase of total adoption that is due to a non-linear drop of average trip effort. However, efforts for those households that live more than ~10 to 15 miles away from any station still turn out to be too high to yield significant adoption. When stations are separated 8 miles apart, the adoption fraction virtually equals its maximum (that is, 50% of the households). So far behavior does not differentiate from standard spatial game theoretic outcomes (e.g. Tirole (1988)).

Figure 11 b) shows demand (integration over all user demand times their vehicle miles) for increasing station density (or better, decreasing spacing between stations). Results

[24] As can be seen in this (extreme) case adopton is highest a few miles from the station, this is because, given the normal trip distribution, a larger fraction of trajectories are served better, as

are shown in for five different station spaces (d_s = 4, 8, 16, 32, 64, and 128 miles). The continuous curve yields an s-shape.

Figure 12 a) shows station profits for increasing station densities, under condition of equidistant spacing. At very low densities demand is too low, so that stations' cost always exceeds their revenues, hence station profits are negative.



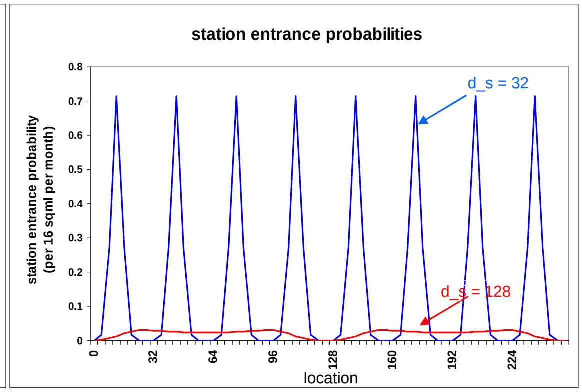


Figure 12 - a) expected entrance for stations (d=32 miles, 128 miles; last line not to scale); b) profits for increasing station density and instantaneous adoption.

Profits increase dramatically with station density, as market (adoption and vehicle miles) grows with decrease of trip efforts, and are positive for intermediate densities. For higher densities the market is already saturated and the effect of a higher entrant concentration just increases the market. Figure 12 b) shows the probability to enter per location, for strategic entrants, for stations d_s is 32 and 128 miles.[25] As expected, at low concentration, prospective entrants tend to locate away from, but nearby an existing station – as this yields the maximum growth of market and profits, more than compensating the burden of sharing the demand (see b,c). For higher concentration (d_s = 32 miles), prospective entrants prefer to locate exactly in between two existing. The insight is that location dependent entrance strategies are driven by the trade-off between two endogenous effects: market generation and competition. The first dominates in small markets (yielding co-location), the latter in more dense markets (yielding dispersion). Further, in this case, total entrance probability is much higher. [26]

[25] For strategic behavior, see discussion in the introduction of the analysis.

[26] In fact, the entrance probability for the 128 mile case is not to scale, but blown-up by a factor 10 for the benefit of the discerning the location dependent entrance probabilities.

Closed loop dynamics

It is suggestive that precise individual adoption depends on spatial factors as driver's trip distribution, and station entrance sensitivities to location. This idea is supported by Figure 13 that shows a typical distribution of stations (bars) and demand (continuous) for a uniform population and in initial state of adoption. Strategic stations tend to co-locate (though not too close). Thus, as past activity matters differently for different trip distributions/local strategies, we can expect to find different spatial diffusion patterns.

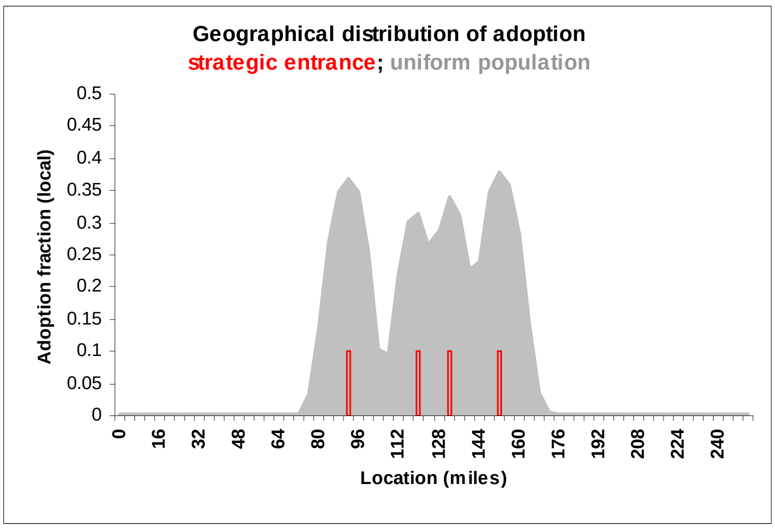


Figure 13 typical distribution of stations (bars) and adoption fraction (continuous) for an emerging market with entrants with location dependent entrance decisions.

However, much more important, is to ask whether *aggregate* adoption patterns and ultimate equilibria are sensitive to this as well, even when the averages for these factors are identical.

To test this more formally, four scenarios are compared in which demand and stations co-evolve: first, a uniform-type population distribution is considered, with and without entrants' location strategies (called I and II).[27] Two other scenarios, both with entrant location strategies have a heterogeneous population distributions that represent different

[27] That is, sensitivity to expected profits $\beta_{en,s}$ equation (4.10) is equal to 0 respectively 1.

urban/rural configurations. The distance between urban kernels is 128 miles and 64 miles respectively, or the distance relative to the typical driving distance, $d_{u/t} = 4, 2$ (III and IV). As Figure 11b) suggests that for very low station densities zero-profit thresholds are not exceeded. To overcome this, for each scenario an entrance subsidy is simulated by inducing an entrance rate of one station per quarter for the first two years (while allowing for strategic location).[28] Figure 14 shows the results in terms of average and standard deviation of demand, for 15 runs each.[29]

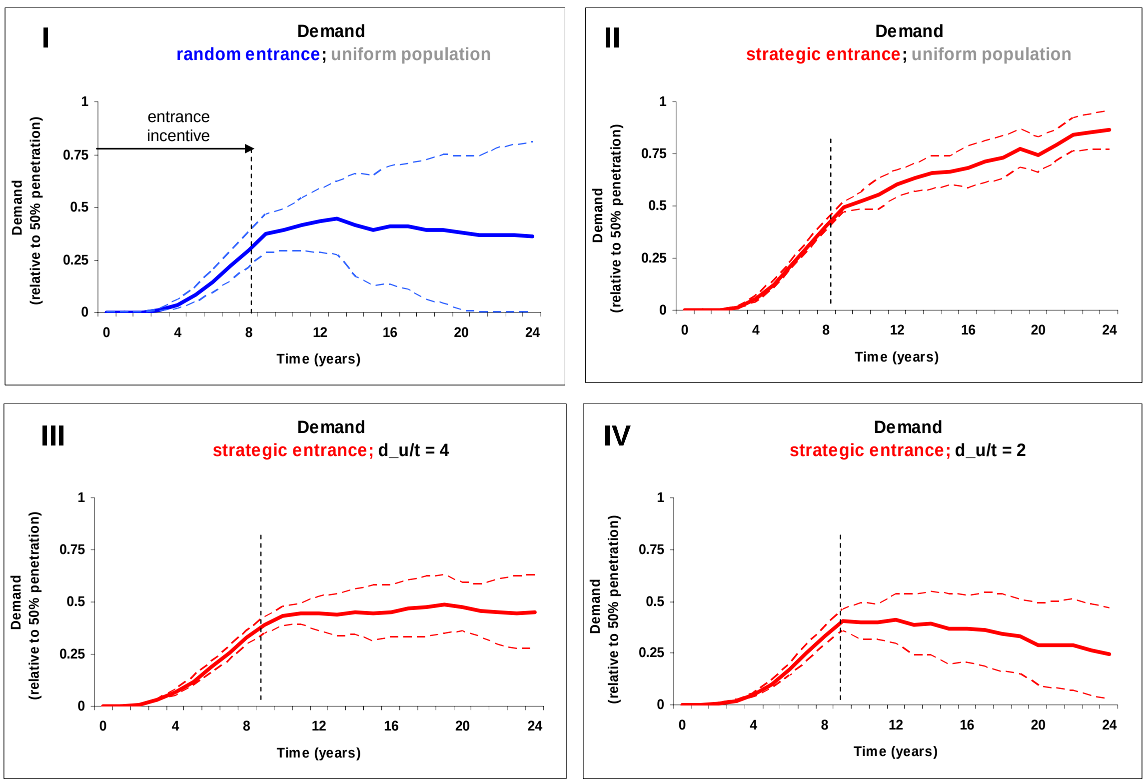


Figure 14 – demand resulting from station-adoption/vehicle miles co-evolution; top: I and II uniform population with random/strategic location decisions for entrants. Bottom: III and IV with strategic location decisions but heterogeneous population distributions (separated by 128 and 64 miles).

First, typical length for the dynamics plays out over 20 years – which makes sense as no additional loops (as word-of-mouth, learning,…) are active and the vehicle replacement

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[28] Alternatively one could simulate an subsidy, but that would yield several choices as well – key insights do not change.

[29] Noise seeds differ per run, but are the same for all four scenario's

rate is at maximum 3 years. Further, observe that for a uniform population distribution (I and II), the location strategy does much better than random entrance. This supports the sensibility of the entrant's rationality assumptions. However, strategic individual entrants do much worse in the case of heterogeneous potential demand (III, IV). While the when $d_{u/t} = 4$ saturates about 50% below its potential, $d_{u/t} = 2$ even leads to collapse of the market.[30] Further, the variance band illustrates that for all strategic scenarios the pattern of behavior is very consistent.

An explanation for the large differences in aggregate behavior modes can be found from Figure 15. It shows the distribution of stations (bars), adoption fraction (continuous), and relative population distribution (dotted lines), for all four scenarios, for one realized typical run at final time of Figure 14.[31]

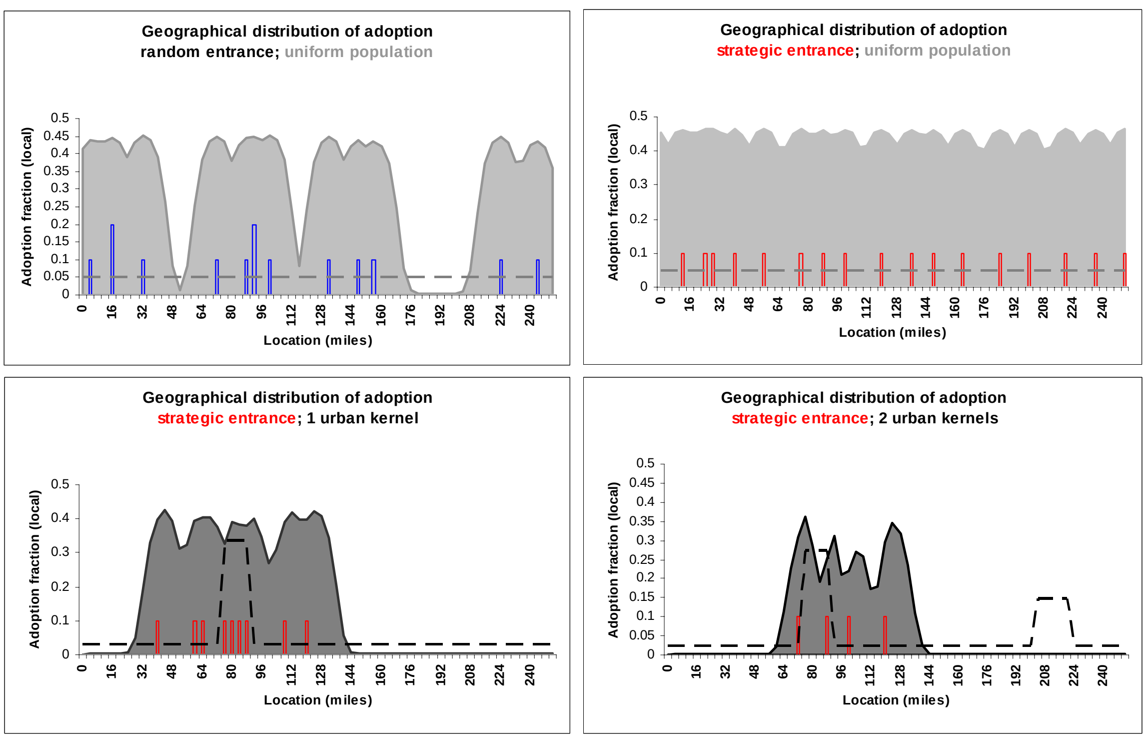

Figure 15 – adoption and station distribution after 24 years for typical runs of the four scenarios

[30] Not shown here, but existent, are "successful" endstate of full adoption for the heterogeneous scenarios

[31] Note that total population is equal in all scenarios

In the uniform case, station entrance starts at an arbitrary point and expands from there on gradually outward (as supported by Figure 13, which is a snapshot after 5 years for the same run as Figure 15 - II). All runs II eventually reach the full adoption equilibrium Figure 12a. In a heterogeneous case, the market grows differently: the co-evolutionary process starts, and builds, in a high potential area. After the

Table 1 - aggregate statistics for scenarios

Averages per scenario in year 30	random, D_u/D_t → 0	Strategic, D_u/D_t → 0	Strategic, D_u/D_t =4	Strategic, D_u/D_t =2
Station density	0.29	0.59	0.34	0.20
Adoption fraction	0.21	0.43	0.27	0.17
Relative vehicle miles	**0.47**	**1.01**	**0.80**	**0.58**
Average profitability	-0.43 *)	1.43	0.54	(0.89)
Mean variance ratio of effort	0.53 *)	0.38	1.23	1.07
Direction of adoption	+,-,=	+	=	-

**) averages not very meaningful because of large variability between runs*

Table 1 displays for each scenario aggregate statistics, such as station density, relative vehicle miles, and average station profits. Also shown are the mean variance ratio of effort, a useful measure of the actual distribution, of in this case the stations' service, effectively, distributed: a value equal to one corresponds with randomness, closer to zero indicates more uniform, while a larger number suggests clustering.
Of particular importance are vehicle miles, that are much lower in the strategic heterogeneous scenarios – that is, even within the urban cluster a sustainable full-scale market is not reached.

Of course more study is required before conclusions can be drawn.[32] However, a generic insight is important: locality of interactions between entrants and (potential) drivers implies that population heterogeneities do not average out in the aggregate. They can yield totally different adoption patterns with multiple equilibria. Also, while these

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[32] For instance, the effect of other important parameters must be considered as well, such as that of the shape of the trip distribution and the sensitivities to adopt relative to effort; this was tested, and indeed, they influence adoption differently for the different scenario's as well,

simulations represent stylized situations, the resulting behavior of the co-evolutionary structure cannot easily be derived from spatial game theoretic results.

As a corollary to these insights, typical curves as shown that plot indicated adoption fraction against station density (as shown in Figure 2b), are s-shaped for homogeneous/strategic entrants, and concave for heterogeneous/strategic entrants. This is already provides a usful general insight. Then, ignoring any other effects, this conclusion would suggest that in states like Kansas, or Iowa that have extremely regular road networks connecting small, proximate urban areas effectively, adoption can be expected to follow an S-shaped adoption pattern – ultimately reaching full adoption. Contrary, in California or Texas, where dense urban areas are separated by distances that are much longer than the typical driving range, adoption would be fast, but remain limited, as well as the drivers' choices of trips by HFCV.

Conclusions

Complexity of transition management

One of the critical mechanisms of adoption of HFCV's, co-evolution of vehicle fleet and infrastructure, was examined in depth. Transition challenges as those for HFCV's are often formulated in "chicken-and-egg" language, while "momentum creation", or "seeding" are prescribed policy recommendations. In line with this, Linde AG, a German company plans to build a highway ring of 30 equidistant fuel stations along the highways. Similar policies are proposed in California. Such even distributions appear in optimal high-penetration equilibria, when populations are uniform. However, it is unclear to what extend such a strategy enables a successful early transition. For instance, one out of many alternative policies could be to seed locally the high potential demand areas.

Stakes are high but so are the problems in anticipating the interactions of these dynamics (Flynn 2002). To examine this issue, a spatial-behavioral-dynamic model (SBDM) was formulated. Spatial, as the emphasis lay on local interactions. In particular the focus was on the effect of local station/driver interactions and the induced and structural heterogeneities on the co-evolutionary dynamic patterns; behavioral, because trip utilization, and adoption were explicitly modeled as function of local effort, while fuel station entrance behavior was represented as a function of local demand; dynamic, as historic interactions drive the conditions for further establishment of stations and adoption.

Analysis of a reduced version of the model underscores the strong effect of heterogeneity and local interaction strategies for relevant parameters, thus illustrating the need for such approaches. In particular, we saw that fast formation of a local niche market does not necessarily yield a successful transition. In fact the opposite can be true: the same underlying mechanisms can yield "inefficiencies", preventing large scale breakthrough. The underlying mechanism is captured in Figure 16. The problem is similar to well known trade-offs between incentives to exploiting the potential of the existing market and exploration to create a new market (here depicted as 1 and 2).

In this case, from the point of view of station entrants, in a hypothetical uniform market, these two effects are in balance implying a gradual expansion of the market potential (moving out of the center), while the short term local demand that is generated alines the incentives of the entrant with the expansion of the market.

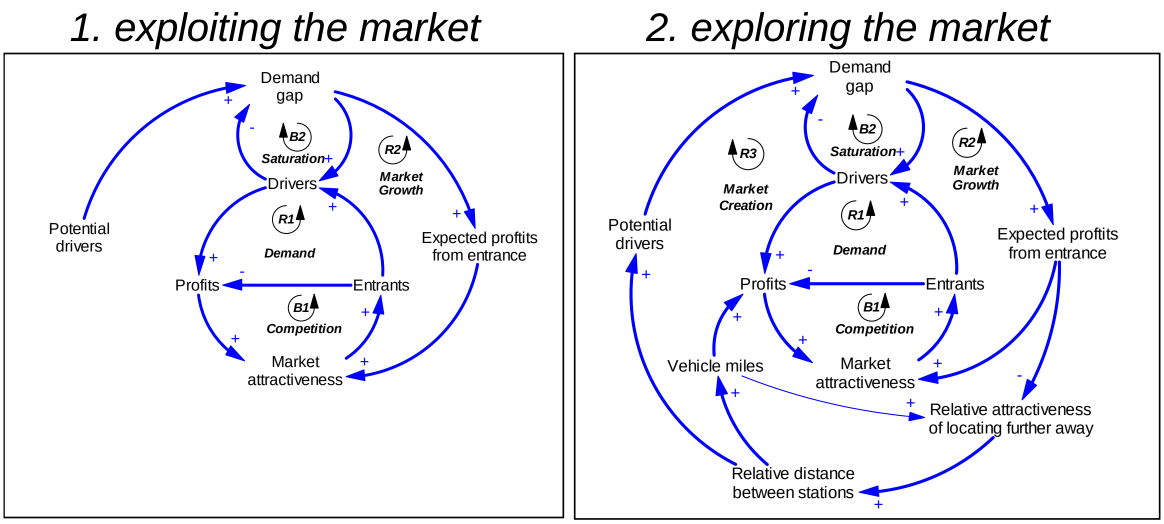

Figure 16 –1) exploiting the potential of the current market and 2) creation of a new market in more remote areas as process of exploration

However, for a heterogeneous market the cost to bridge to other potentially interesting areas/users for an individual are too high and the incentive for entrants is to exploit the existing market. Furthermore, as shifting to neighboring clusters does not occur, vehicle miles remain low, even leading to a more limited potential of the local market.

Of course, in reality, these co-evolutionary dynamics unfold within and interact with a much larger changing system. In particular, a prospective transition, such as one towards HFCV's is subject to many complexities. However, it is likely that many of these tend to reinforce the dynamics as described above. For instance, among others (Clark, Rifkin et al. 2005)) envision, in stead of classic fuel stations, the emergence of "hydrogen energy parks" that reap the benefits of complementarities between hydrogen storage for residential/business applications and vehicle applications, as well as other scale/scope economies.[33] While this might "fuel" early adopter conversion, this also yields more clustering around urban areas and initially only the largest scale operators

[33] This is also suggested by the national hydrogen association

will be successful business, reinforcing the dynamics. Furthermore, the clustering can lead to HFC's being attractive for particular vehicle user groups, such as owners of professional fleets that have a limited radius (UPS delivery, Taxi) – not providing an incentive for others to provide service elsewhere.

Additional factors as word-of-mouth / learning by using can also further reinforce these dynamics. For instance, the most probable early private buyers are urban households that purchase these vehicles as 2nd car gadget, not being dependent on the ill served infrastructure. In search of capturing large investment in alternative technologies, automotive companies are likely to adjust their portfolios to this highest potential market, in this way working themselves further in a niche market that does not need a fully covered infrastructure. A similar fate was for the early 20th century electric vehicle (EV) that within a few years was only considered for specific private/professional applications. In the 1960's the EV were promoted as "city car". Sore contemporary, this also happens for other alternative fuel vehicles, such as natural gas vehicles and infrastructure in Italy and Canada, where service, though in dense areas, allows only adopters that travel locally.

In sum, co-evolutionary transition dynamics are complex. This study draws attention to the idea that the creation of a sustainable growing market are not necessary achieved by policies that perform best in kick-starting the market. While in particular shown for the infrastructure-fleet chicken-egg problem, the problem is expected to be reinforced when other effects are also active.

Next steps

This paper hopes to contribute to the transition debate in four different ways. First, it furthers an understanding of the process of co-evolution of AFCV's with their support infrastructure. Second, general insights from the detailed analysis can be used to inform related study of the transition dynamics of HFCV's that also includes other feedbacks. In that research explicit spatial components are excluded. The results suggest that a full scale model allows evaluating real policy options – that go far beyond typical carriage. This entails, besides emergence of a support infrastructure, acceptance of the new technologies and associated practices in daily life by consumers, transformation of institutions, attributes that change as a function of cumulative sales and usage, and management of expectations. A detailed analysis also provides further insights for thinking about these transition dynamics. For policy design to effectively stimulate adoption on a large scale, a quantitative, integrative, dynamic model with a broad boundary, long time horizon, and realistic representation of decision making by individuals and other key actors is essential. Third, an extension of the current spatial model can be used as a policy tool to compare targeted entrance strategies for the hydrogen fuel supply as currently called for in the state of California; considerations could include focusing on particular adopter groups (private or professional), location (e,g, urban versus highway grids), and effects of institutional incentives (such as taxes/subsidies). For a version that includes two spatial dimensions population and road infrastructure can be uploaded using GIS data, or, alternatively, networks with similar characteristics can be grown.

Finally, this study can inform research in other areas that involves local interactions driving macro behavior. the role of space and markets is not new , both demand and supply are increasing as is shown in various socio-economic context, as labor (Fernandez and Su 2004).

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