

Transition challenges for alternative fuel vehicle and transportation systems

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Figure 1 shows the main model structure as discussed in the paper. Variables are numbered according to the section where they are treated (1. Vehicle adoption; 2. Familiarity; 3. Learning about attribute performance; 4. Endogenous attribute improvement; 5. Infrastructure).

1. Notes on vehicle adoption

a. Vehicle Fleet Aging Chain

For simplicity, the age structure of the fleet is not treated in the paper. Below we lay out how this is incorporated in the full model.

The total number of vehicles for each platform $j, j=\{1, \dots, J\}$, of each age cohort $m, V_{j,m}$, accumulates net vehicle replacements and aging (see Figure 2):

$$\frac{dV_{j,m}}{dt} = v_{j,m}^r + v_{j,m}^a \quad (\text{A-1})$$

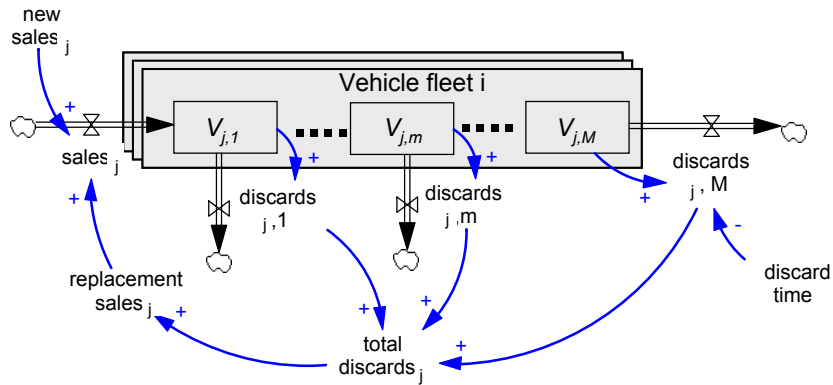


Figure 2 Vehicle replacement with aging chain

Aging captures vehicles coming from a younger cohort less those aging into the next cohort:

$$v_{j_m}^a = v_{j_m}^{a+} - v_{j_m}^{a-} \quad (\text{A-2})$$

with

$$v_{j_m}^{a+} = \begin{cases} 0 & m = 1 \\ v_{i_{m-1},m} & m > 1 \end{cases} \quad v_{j_m}^{a-} = \begin{cases} v_{i_{m,m+1}} & m \leq M \\ 0 & m = M \end{cases} \quad (\text{A-3})$$

while

$$v_{i_{m,m+1}} = f_{i_m}^s V_{i_m} / \tau^c \quad (\text{A-4})$$

Where $f_{i_m}^s$ is the survival fraction for each cohort.^{1,2}

Net vehicle replacements are new vehicle sales, s_{j_m} , less age dependent discards, d_{j_m} :

$$v_{j_m}^r = s_{j_m} - d_{j_m} \quad (\text{A-5})$$

We do not consider the used car market here. New vehicle sales enter the first age cohort, thus:

$$s_{j_m} = \begin{cases} s_j & m = 1 \\ 0 & m > 1 \end{cases} \quad (\text{A-6})$$

Total sales for platform j , s_j , consist of initial and replacement purchases:

$$s_j = s_j^n + s_j^r \quad (\text{A-7})$$

The full model allows for growth in the fleet as population and the number of vehicles per person grow. In the paper population and the number of vehicles per person are assumed constant,

¹ Annual survival (and/or scrappage) rates by model year can be derived from registration data (e.g. by L. Polk & Co, AAMA).

² In equilibrium average vehicle life λ^v is found by: $\lambda_j = \sum_{m=1}^{M-1} \left(\prod_{m'=1}^{m-1} f_{j_{m'}}^r \right) \lambda^c + \prod_{m'=1}^{M-1} f_{j_{m'}}^r \lambda^{c_M}$

implying the total fleet is in equilibrium and initial purchases are zero. Vehicles sales for platform j arise from the replacement of discards from any platform i and cohort m , $d_{i_m}^r$:

$$\sum s_j^r = \sum_{i,m'} \sigma_{i_m,j} d_{i_m}^r \quad (\text{A-8})$$

where $\sigma_{i_m,j}$ is the share of drivers of platform i cohort n replacing their vehicle with a new vehicle of platform j . The share switching from i to j depends on the expected utility of platform j as judged by the driver of vehicle i , cohort n , $u_{i_m,j}^e$, relative to that of all options $u_{i_m,j'}^e$.

Thus:

$$\sigma_{i_m,j} = \frac{u_{i_m,j}^e}{\sum_{j'} u_{i_m,j'}^e} \quad (\text{A-9})$$

To capture a driver's consideration set we introduce the concept of familiarity among drivers of vehicle i with platform j . The model can be elaborated to include cohort-specific levels of familiarity, recognizing that drivers of, say, a 10 year old ICE vehicle have a different (presumably lower) familiarity with new ICE vehicles than the driver of a 1 year old vehicle. Such distinctions may matter when vehicle attributes change rapidly, as is likely for early AFVs as experience and technology rapidly improve. (Further disaggregation would eventually lead to an agent-based representation where each driver has an individual-specific level of familiarity with different platforms). These issues will be treated in future work. For simplicity we assume here that familiarity is equal across all cohorts of a given platform and remains F_{ij} , thus expected utility is:

$$u_{i_m,j}^e = F_{ij} * u_{i_m,j} \quad (\text{A-10})$$

b. Initial purchases and fleet growth

New car sales for fleet j are:

$$s_j^n = \sigma_j^n s_j^n \quad (\text{A-11})$$

where the share σ_j is equal to the share of replacement sales: $\sigma_j^n = s_j^r / \sum_i s_i^r$.

Total new car sales allow the total fleet $V = \sum_{j,m} V_{j_m}$ to adjust to its indicated level V^* :

$$s^n = \frac{\max[0, (V^* - V)]}{\tau^v} \quad (\text{A-12})$$

where total desired vehicles $V^* = \rho^v * H$ is product of the target or desired number of vehicles per household ρ and total households H , and τ^v is the fleet adjustment time. The max function ensures sales remain nonnegative in the case where V^* falls below V (a possibility if there is a large unfavorable shift in the utility of AFVs when the installed base is small).

Discards, d_{j_m} are found by:

$$d_{j_m} = \begin{cases} (1 - f_{j_m}^s) V_{j_m} / \lambda^c & m < M \\ V_{j_m} / \lambda^{cM} & m = M \end{cases} \quad (\text{A-13})$$

where λ^c is the cohort residence time; λ^{cM} is the residence time of the last cohort.

The number of discards people choose to replace is give by:

$$d_{j_m}^r = f^r d_{j_m} \quad (\text{A-14})$$

where f^r is the nonnegative part of the difference between total discards and the indicated contraction rate as a fraction of the total discard rate:

$$f^r = \frac{\max[0, d - v^{c*}]}{d} \quad (\text{A-15})$$

Here $d = \sum_{i,m} d_{i,m}$ is total discards, and $v^{c*} = \frac{\max[0, V - V^*]}{\tau^v}$ is the indicated fleet contraction rate. The fleet of a particular platform can contract when, for example, the perceived utility of that platform suddenly falls (say, due to unfavorable shifts in fuel costs or perceived safety, reliability, or costs) and if the existing installed base is small enough and young enough so that discards from normal aging are small.

2. Notes on Familiarity

a. Familiarity co-flows

The familiarity of drivers of platform i with platform j is updated through social exposure, as discussed in the paper. When a driver switches from platform i to k , their familiarity with platform j is transferred from F_{ij} to F_{kj} . For example, consider a model in which three platforms are portrayed, say, ICE, hybrids, and HFCVs (denoted platforms 1, 2, and 3, respectively).

When an ICE driver switches to a hybrid, the familiarity of that driver with HFCVs, previously denoted F_{13} , now becomes F_{23} . In the two platform simulations considered in the paper these dynamics do not matter since all drivers are assumed to be fully familiar with ICE, and AFV drivers are assumed fully familiar with AFVs, so the only dynamic relates to the growth of familiarity of ICE drivers with AFVs (F_{12}).

To model the transfer of familiarity as drivers switch platforms, it is convenient to consider the evolution of familiarity at the population level:

$$\frac{d(F_{ij}V_j)}{dt} = V_i \frac{dF_{ij}}{dt} + F_{ij} \frac{dV_i}{dt} = f_{ij}^u + f_{ij}^t \quad (\text{A-16})$$

where the first term, which we call f_{ij}^u , captures updating of familiarity with platform j by drivers of platform i , as discussed in the paper. The second term, denoted f_{ij}^t , captures the transfer of familiarity arising from drivers who switch platforms. When familiarity is updated much faster than fleet turnover (and therefore switching), the second term has limited impact on the dynamics of familiarity. On the other hand, when fleet turnover is very fast, the transfer of familiarity as drivers switch platforms can be important.

Familiarity updating is formulated as described in the paper: updating of total familiarity is the average update from social exposure, including familiarity decay (equation 5 of the paper), over the total number of drivers V_i :

$$f_{ij}^u = [\eta_{ij}(1 - F_{ij}) - \phi_{ij}F_{ij}]V_i \quad (A-17)$$

where η_{ij} is the total impact of total social exposure to platform j on the increase in familiarity for drivers of platform i , and ϕ_{ij} is the fractional loss of familiarity about platform j .

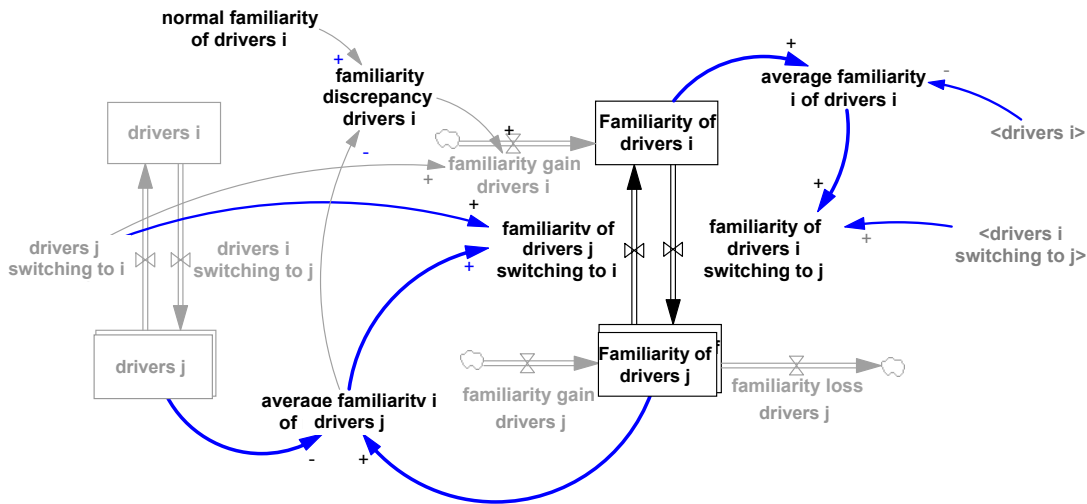


Figure 3. Familiarity change for drivers that switch between platforms

The transfer term captures two “co-flows” (Sterman 2000) that track the movement of the familiarity of a driver of platform i with platform j , one arising from vehicle sales and one arising from discards:

$$f_{ij}^t = f_{ij}^s - f_{ij}^d . \quad (\text{A-18})$$

The first term, f_{ij}^s , captures the transfer of familiarity through sales:

$$f_{ij}^s = s_i^n F_{ij} + \begin{cases} \sum_k s_{ki}^r F_{kj} & i \neq j \\ \sum_{k \neq j} s_{ki}^r & i = j \end{cases} \quad (\text{A-19})$$

This term contains the flow of new drivers purchasing platform i , and their average familiarity with platform j , assumed to equal the familiarity of current drivers of i with platform j . The second term is the transfer of familiarity associated with the flow of drivers of platform k replacing their vehicles with one of platform i . The average familiarity of these drivers with platform j is transferred as they switch. We assume drivers become fully familiar with the platform they are driving, so those who purchase a vehicle of platform j (the case $i=j$) achieve full familiarity with platform j (in a time much shorter than the other time constants).

The second term in equation (A-18) captures the transfer of familiarity with platform j associated with drivers of platform i through discards:

$$f_{ij}^d = d_i F_{ij} \quad (\text{A-20})$$

where $d_i \equiv \sum_m d_{i_m}$ is total discards .

The transfer term f_{ij}^t was used in the simulations of the paper, for the relevant cases (Figure 5 and further). The transfer of familiarity as drivers switch platforms has a small but significant

contribution to the dynamics: early alternative fuel adopters who switch back from the alternative to ICE have full familiarity with the AFV, and contribute strongly to word of mouth. Technically, a balancing loop is generated, in similar fashion as marketing effectiveness, with strength $\left[1 - u_{ij} / \sum_i u_{ji}\right] / \lambda^v$.

However, a more complicated result emerges when learning about performance through social exposure is introduced (see section 3), as early adopters might learn about mediocre performance. Hence, their word of mouth results in lower perceived attractiveness of alternatives among others.

3. Notes on attribute learning

In the paper perceived vehicle performance is treated as a scalar that aggregates the effects of all vehicle performance attributes, P_l , including price, operating cost, power, driving range, fuel and service availability, and ecological impact, $l = \{1, \dots, L\}$. In the full model each performance attribute can be represented separately. Then perceived utility combines the perceived individual attributes, yielding a multinomial logit formulation:

$$u_{ij} = u^* \exp\left(\sum_l \beta_l P_{jl} / P_l^*\right) \quad (\text{A-21})$$

Here u^* is the utility derived from any platform when all the attributes l have a performance level equal to their respective reference values P_l^* ; β_l is the sensitivity of utility to performance for attribute l .

Each performance attribute follows a standard learning curve, improving as relevant knowledge of related to each performance attribute, K_{jl} , improves,

$$P_{jl} = P_{jl}^0 \left(K_{jl} / K_l^0 \right)^{\gamma_l} \quad (\text{A-22})$$

P_{jl}^0 is the performance level for attribute l when the knowledge for its attribute equals a reference knowledge K_l^0 . The strength of the learning curve, γ_l , can differ for different vehicle attributes, reflecting their different complexity and technical potential. For example, the cost of electric vehicles may fall faster (through better design and scale effects) than battery performance might improve.

Effective knowledge K_{jl} can differ per attribute. Effective knowledge at the attribute level is tightly related to the technological capabilities that produce the various modules of the vehicle (drive train, body, brake system, fuel system,...). However, relations between modules are complex. Organizations improve performance for each attribute by gaining knowledge at the level of modules, and improving those. However, module performance is linked (weight reductions improve power and range for a given drive system; greater energy density in fuel cells or batteries improves cost, weight, power, and/or range. Hence the strength and impact of knowledge spillovers might differ for each attribute. The dynamics of performance improvement and spillovers at this level of specificity are discussed elsewhere (Struben 2006).

Further, the process of learning about a perceived attribute state l of platform j , as perceived by a driver of platform i , for cohort m , $P_{i,m,jl}$ is similar to that of familiarity: people learn about the state of the different attributes through various channels such as marketing, advertising and media reports, direct exposure (drivers of platform i learn about platform j from those driving it), and word of mouth exposure through drivers of platforms k (or through non-drivers, $k \neq j$).

However, people also learn gradually about vehicle attributes by direct experience with the platform. Total learning sums the contributions of all these channels. Capturing these processes, rather than assuming direct perception of the real performance, is important due to the long life of vehicles. These dynamics are also discussed in (Struben 2006).

4. Running the model

The model used to generate the simulations in the paper is available at web.mit.edu/jjrs/www/AFV_Files/AFV_Transition_Model1.vmf. The model is built in the Vensim simulation environment <<http://vensim.com>>. To run the model, users can download a free model reader from <http://www.vensim.com/reader.html>.

Navigate through the model by selecting different views (by clicking on the view names below left, or through page up/down buttons). Vensim Reader provides a quick tutorial for how to perform a run and change parameters. To replicate the simulations of Figures 4-7 in the paper, use the settings as indicated below (use the defaults of the model unless another value is listed). All indicated variables can be selected and changed in the “control view”.

Figure 4

Paper	Model	unit	value
-	INITIAL TIME	dmnl	0
-	SW Endogeneous Drivers (Switch)	dmnl	0
-	Initial Installed Base Fraction 2	dmnl	0.05
-	Initial Familiarity12	dmnl	[0, 1]

The “Phase Plots and Diagrams” view provides phase plots (left top and bottom) that show the results in a similar format as Figure 4 in the paper. We have generated the results for the figure by emulating this first order structure in an Excel spreadsheet and were crosschecked with the model. One can replicate the results as follows: after other variables are set properly, go to the “Phase Plots and Diagrams” view and vary “Initial Familiarity12” for subsequent runs (use values between 0 and 1 and small intervals; this variable can also be changed in the “Phase Plots and Diagrams” view), and interpret the results on screen. One can also use the “SyntheSim” feature (see help) and follow the same procedure.

Figure 5

Paper	Model Variable	unit	Value 5a	Value 5b	Value 5c
-	INITIAL TIME	dmnl	0		
α_2	AFV Marketing Effectiveness Shock	1/year	0.01	0	0.01
c_{121}	Effective Contact Rate Non Drivers	1/year	0	default	default
-	[Initial Familiarity12, Initial Installed Base Fraction 2]	dmnl	[0, 0.05], [0.20, 0], [0.05, 0.20], [0.40, 0.05], [0.80, 0.10]		

The “Phase Plots and Diagrams” view provides a phase plot (right) that can show the results trajectory by trajectory in the same format as the paper. The results can be replicated by performing the runs one by one. The results were derived through a command script (see help), which can be replicated in the full Vensim version, by using the [AFV Transition M1 Fig5.cmd](#) file (in zip format). After other parameters have been set properly, one can also use the Synthesim Feature (see help): go to the “Phase Plots and Diagrams” view and vary “Initial Familiarity12” and “Initial Installed Base Fraction 2” (these variables can also be changed in the “Phase Plots and Diagrams” view), and interpret the results on screen.

The nullclines and basin of attraction were derived through sensitivity runs (not available in Vensim Reader), by varying Initial Familiarity12 and Initial Installed Base Fraction 2 respectively between 0 and 1, and 0 and 0.5, with an interval of 0.01 (yielding 5151 starting points). Results were exported for time is 0 and time = 1000 years. For the results at time zero, points were identified as being on a nullclines, when net familiarity change rate was zero, or when net change rate for the installed base was zero. The final time (t=250 years) results were used to identify the basin of attraction: initial condition points for which the final time values tended toward the low equilibrium were assigned to the low basin of attraction.

The model also has a piecewise linear approximation for the effect of social exposure (which can be used by setting “Sw Logistic Curve Effect on Forgetting” to 0). As can be seen, simulated values of the linearized version are very close to those using logistic curve. For these runs the nullclines and attractors can be derived exactly.

Figure 6

Paper	Model Variable	unit	Value
α_2	AFV Marketing Effectiveness Shock	1/year	0.025
-	Marketing Duration	years	[10,50]

In this figure we have used the sensitivity run feature, varying “Marketing Duration” between 10 to 50 years, with intervals of 0.5 years. This feature is not available with Vensim Reader. To replicate Figure 6, vary the marketing duration for subsequent runs (from 10 to 50 years, with intervals of 0.5 years), or use the “SyntheSim” feature (see help) to gradually increase the “Marketing Duration”, with real time view.

Figure 7

Paper	Model Variable	unit	Value
c_{122}	Strength of word of mouth about AFVs for contacts between AFV and ICE drivers	1/year	0.25 [0-1]
c_{121}	Strength of word of mouth about AFVs for contacts between ICE and other ICE drivers	1/year	0.15 [0-1]
α_2	AFV Marketing Effectiveness Shock	1/year	0.025 [0-0.1]
u_2^0	Relative Utility from AFV	-	1 [0.5-2.5]
λ	Average vehicle life	years	8 [2-12]
g	Growth rate of the total car parc	1/year	0 [-0.02-0.18]

In this figure we have used the sensitivity run feature, setting the model parameters equal to those for Figure 6, with “Marketing Duration” equal to 20 years. In each of the 6 graphs we

varied one parameter only, with the ranges as indicated in the tables. Intervals were 5% of the total range for each variable. The plots indicate the time when the installed base reached 15% and 25% of the total installed base respectively. The sensitivity feature is not available with Vensim Reader. To replicate the graphs of Figure 7, vary the relevant variable for subsequent runs, or use the “SyntheSim” feature (see help) to gradually increase the relevant variable, with real time view.

Figure 8

Paper	Model Variable	unit	Value 7-1	Value 7-2	Value 7-3	Value 7-3
c_{121}	Sw Experience Effect on	1/year	default	1	1	1
κ_2	Knowledge Share Internal Entrant	dmnl	default	default	0.5	0.5
κ_1	Knowledge Share Internal Incumbent	dmnl	default	default	default	0.5

5. References

- Sterman, J. (2000). *Business dynamics : systems thinking and modeling for a complex world*. Boston, Irwin/McGraw-Hill.
- Struben, J. (2006). "Transitions towards Alternative Fuel Vehicles: Learning and Technology Spillover Trade-offs." Under Preparation.