MODELING THE TRANSITION TO HYDROGEN-BASED TRANSPORTATION

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ABSTRACT

At the Agent 2004 conference, Stephan and Sullivan reported on an agent-based model running under Repast J that describes how a personal transportation system might transition from petroleum to hydrogen. In this paper, we extend the original model in several ways. First, in place of a rectilinear grid of roads, we use the road topology of a real metropolitan area, the Los Angeles basin. Second, while the earlier model added hydrogen-dispensing stations on the basis of a rather simple algorithm, in the present model, station agents attempt to plan their investments on the basis of imperfect knowledge of driver fueling behavior, the expected penetration of hydrogen, the plans of competitors, and the amount of fuel they estimate will be dispensed. In addition, the driver agents are more complex. Their incomes vary, and they live and work in areas corresponding to that income on the basis of demographic data. They have attributes such as "greenness" that affect their willingness to pay more to operate a vehicle that has desirable environmental characteristics. We take advantage of Repast Simphony's networking capabilities to set up relationships between the agents on the basis of their home neighborhoods, their places of work, and common characteristics. The agents are influenced in their purchase decisions not only by their personal experience and a general "belief space" reflecting the attitude of society in general toward hydrogen but also by interactions with their peers. We examine how a transition to hydrogen succeeds or fails as these various attributes are varied and given greater or lesser influence.

Keywords: multi-agent modeling, hydrogen transition analysis, infrastructure investment modeling, social networks

INTRODUCTION

Hydrogen holds great promise as an automotive fuel. It emits no greenhouse gases either when burned in an internal combustion engine or when used to power a fuel cell, and ideally it can be made in a way that releases no net CO_2 to the atmosphere. Fuel-cell-powered vehicles can achieve energy efficiencies two or more times those of their internal combustion engine counterparts. Nevertheless, hydrogen faces formidable obstacles in replacing petroleum as the fuel of choice for automobiles. While many technical hurdles remain to be overcome, another

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equally perplexing problem is how to induce both consumers to buy hydrogen-powered vehicles and investors to build refueling infrastructure when each depends upon the other for viability and neither exists today. This conundrum is often referred to as the "chicken and egg" problem and is especially severe for hydrogen because of the large costs involved, although the challenges are by no means confined to this problem.

At this point, it appears impractical and expensive to equip passenger vehicles with two separate powertrains, one for hydrogen and one for gasoline.[1] Thus, a transition from petroleum to hydrogen will likely have to succeed on its own through reinforcing feedbacks. We can envision a few strategically located hydrogen fueling stations (HFSs) that would induce an early adopter group to purchase hydrogen-powered vehicles (HPVs), and that those increasing numbers of vehicles would encourage more investment in infrastructure, and so forth. But how could this sustained transition be achieved, particularly in the early stages? Where should early HFSs be located, and how might investments be scheduled? What may be the range of business models and strategies employed by potential investors in the underlying infrastructure? What types of drivers, if any, should be targeted as the first customers for HPVs, and what inducements would be most effective? How does the early adopter group interact with the remaining majority of consumers, and how does that interaction affect the transition? Standard econometric models are at a disadvantage in answering these questions because a successful transition will likely depend upon a diversity of players. We use multi-agent modeling and simulation to address some of these key questions.

MULTI-AGENT HYDROGEN TRANSITION MODEL

Agent-based modeling (ABM) can be especially helpful in analyzing complex problems such as hydrogen transitioning that involve a diversity of players. Such modeling uses many "agents" which are heterogeneous autonomous actors and decision-makers. Agents can be given various and differing characteristics, and they interact with one another according to rules specified in a computer simulation. At the Agent 2004 conference and elsewhere, we reported on a Repast-based ABM of the transition from petroleum to hydrogen developed at Ford Motor Company (Stephan and Sullivan 2004a and 2004b, Stephan 2005), and similar work has been carried out by others (Schwoon 2007). This initial model gave interesting results, showing different transition behaviors depending, for example, upon what relative weights drivers put on worry and inconvenience. However, it had a number of serious limitations. For example, it did not model a "real" metropolitan area; the investor agents' criterion for investment, depending only upon weighted traffic counts, may have been overly simplistic; it did not take used car markets into account; and, finally, the driver agents, while capable of being influenced in their buying decisions by a global "belief space," did not interact individually with one another.

Under a U.S. Department of Energy (DOE)-sponsored project, a team drawn from Argonne National Laboratory, RCF Economic and Financial Consulting, Inc., Ford Motor Co., and other organizations is building a new analysis tool and continually expanding and enhancing it. The results reported here are from supplementary experiments that focus only on specific parts of the core model. In particular, the paper concentrates on the sensitivity of hydrogen vehicle

[1] Other schemes have been tried. On-board fuel reformers capable of producing hydrogen from gasoline were attempted in the 1990s but abandoned as impractical. BMW is currently testing a "dual-fuel" hydrogen/gasoline vehicle with a conventional internal combustion engine that can be switched to run on either fuel.

market penetration to differences in preferences and learning behaviors among drivers of hydrogen automobiles under simplified assumptions about infrastructure investors. The driver utility function considered here is a modified version of the one used in the core model, so that the experiments reported here should be viewed with these limitations in mind.

Agent Environment and Agents

In the present simulation, we choose as our model region a 100-by-50-mile rectangular area centered on the Los Angeles, California metropolitan area and divided into 5,000 square cells (Figure 1). In addition, there is a 25-mile-wide buffer zone surrounding this region in which agents do not live but into which they may travel. The roads on which agents travel include actual interstate expressways and "ubiquitous" local roads passing through every cell except where there are natural barriers. Driver agents are given a number of characteristics: income, "greenness," degree of concern about running out of fuel, and buyer-type "personalities." High-, middle-, and low-income driver agents are randomly located predominantly, but not exclusively, in neighborhoods of the same type on the basis of demographic data and are distributed such that the overall agent population density scales to the real population density (Figure 2). Similarly, agents are randomly but preferentially assigned to "jobs" in locations chosen to be relatively near their homes and the average salary levels of which preferentially match their incomes.

FIGURE 1 Los Angeles, California metropolitan area showing modeling grid structure (not including "buffer zone") and major expressways as laid out in the grid format

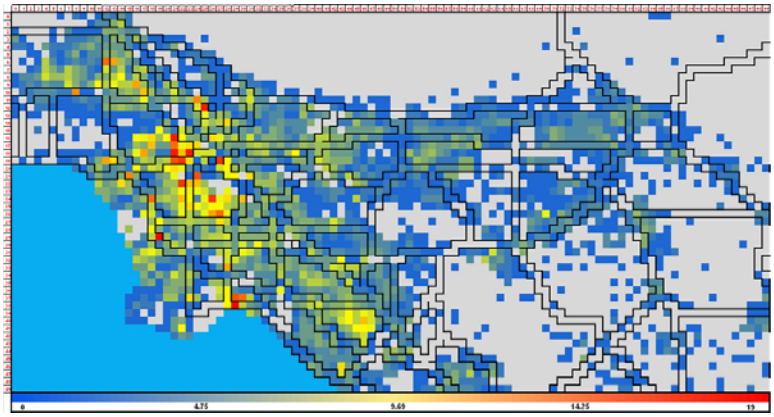

FIGURE 2 Population densities (households per square mile) in the model area

In addition to the driver agents, there are investor agents who build hydrogen refueling stations at strategic locations where anticipated fuel sales will be sufficient to make a profit. The results presented here are based on an investment decision strategy that is more simplistic, that is, investors place or remove HFSs on the basis of suitably weighted traffic counts and sales as opposed to exogenously supplied thresholds. We are currently testing more sophisticated investment algorithms. Our more advanced agents make their investment decisions with imperfect knowledge of driver vehicle purchase and fueling behaviors, the expected penetration of hydrogen, the plans of competitors, and the total demand for fuel. Given the uncertainties they face, the investor agents try to do the best they can, possibly make non-optimal decisions, and learn from their experience. Our advanced investor agents work with limited knowledge about what has happened in the past (such as fuel sales in particular locations) and have some crude assumptions on what might happen in the future. With this limited knowledge, they develop demand expectations for use in making their investment decisions. As the driver agents respond to the roll-out of the supply infrastructure by purchasing HPVs and hydrogen fuel, the investor agents receive feedback on the actual demand realization. They use this information in an ex-post analysis to revise their expectations and adjust their future investment plans by using a simple form of Bayesian learning. Rather than having single-value expectations, our investor agents have subjective probability density functions of sales. The investors use rules of thumb to determine whether and where to locate fueling stations. Similar to our driver agents, investor agents have a utility function they try to maximize. This approach allows us to distinguish between different types of investor agents with different attitudes toward risk, ranging from risk-prone to risk-averse.

Agent Decision Rules

For brevity, we will concentrate our discussion of agent decision rules in this section on the model's driver agents. In the course of a simulation, driver agents drive to and from work and to various destinations in the model region and the buffer zone. Drivers note the presence or absence of HFSs (whether or not they actually own an HPV). They accumulate either real (when driving an HPV) or potential (when driving a conventional vehicle [CV]) inconvenience and worry. On the basis of the increasing prevalence of vehicle-based global positioning system (GPS) units, we expect that drivers will have access to real-time data on the locations of HFSs and automated route planners that will show in advance whether it is possible to make a trip using an HPV and where to stop for fuel. Thus, drivers need not be concerned about the distance to the next HFS but nevertheless will suffer some worry if the distance between two HFSs takes their fuel below an agent-dependent "comfort level" for refueling. Drivers suffer inconvenience if there is no HFS in either their home or their work cells and also if they have to make a special trip to refuel before starting on a planned trip. Finally, agents are inconvenienced if their refueling habits must be altered as a result of owning an HPV. Serious inconvenience is suffered if the agent cannot make a desired trip with his or her HPV because of a lack of HFSs en route. An agent suffers inconvenience to a lesser extent if he/she must make a special trip to refuel or must refuel before he/she would otherwise want to in order to be able to reach a more distant HFS.

When it comes time to purchase a car, the agent weighs the pluses and minuses he/she sees of owning hydrogen versus conventional technology.[2] All factors are cast in terms of

[2] In order to engender the maximum number of purchases from a limited number of agents, our driver agents own fleets of 1,000 "millicars" (millicar = 1/1000 car) and buy/sell a specific number of these millicars every quarter

present-value dollars and summed up in the driver agent's personal "utility function." These factors include the difference in capital cost of the two types of vehicle as well as the difference in operating cost per mile. The latter term is converted to a present-value amount on the basis of the number of miles the agent expects to drive over the time period in which he wants to recoup any additional capital investment. The driver assigns dollar values to intangible factors. For example, he places a cost on the inconvenience of having to make a special hydrogen refueling trip based in part on the distance traveled. The agent sums up all such trips he made (or would have had to make if he had had a hydrogen car) over his driving experience, but weights recent experience more heavily. (Clearly, it is a rare driver who performs this math in the real world, but most drivers have some experience-based intuitive understanding of the inconvenience they can expect to suffer as a result of a scarcity of HFSs. It is this intuitive weighing of many different factors that we seek to simulate with a utility function.)

An important new feature is the ability of the driver agents to interact with one another and influence each other's buying decisions. Drivers are assigned personality types characterizing their buying behavior, as shown in Figure 3. An Early Adopter, for example, considers it a plus to be one of the first to buy a new technology; a Fast Follower also likes new technology but wants others to try it out first, etc. Thus, any agent's purchase of an HPV influences other agents' buying decisions either positively or negatively. Agents can interact with one another through four spheres of influence. The first is a global influence. Agents drive around and see others driving HPVs, see HPVs on television, and hear pundits expounding upon them. As more and more drivers switch to hydrogen, many personality types are persuaded to buy such vehicles themselves. Many, but not all, types want the new and uncommon: for example, if everyone has adopted a particular technology, "Techno-freaks" feel it is time to move on to something new.

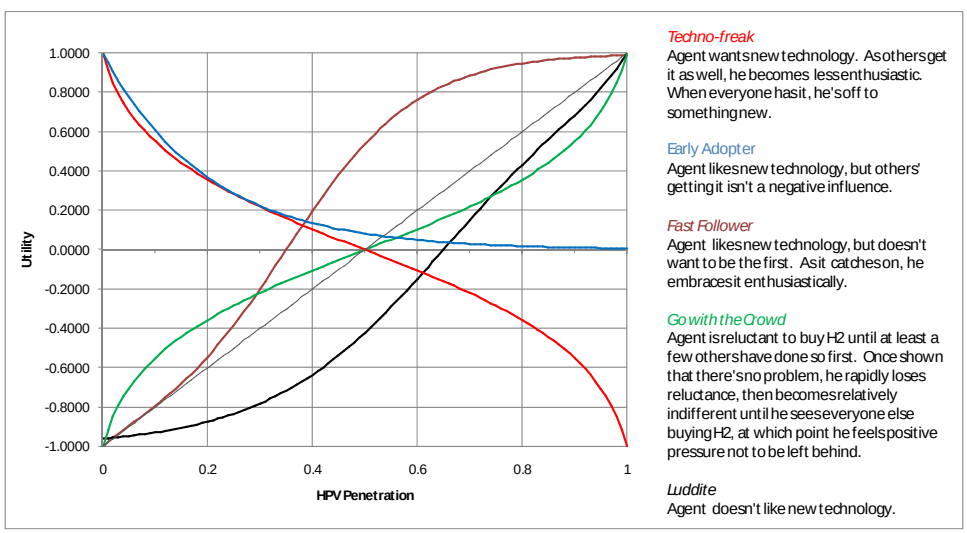

FIGURE 3 Driver agent "buyer personality types"

A second sphere of influence is the neighborhood. Talking with neighbors, seeing HPVs parked in front of their houses, and passing them on neighborhood streets likewise influences

on a schedule such that 1,000 millicars are replaced over a time period corresponding to the time that the agent would own a single car.

prospective buyers. In our model, the radius of such influence can be set exogenously. The third sphere is work. A driver talks with colleagues or sees them driving HPVs and is influenced by their choices. The fourth sphere is through social networks, where an agent is connected with friends or family not necessarily living in his neighborhood or working at his place of work. Some agents will be "opinion makers," having extensive networking connections and having high influence on others. This last sphere, however, is still being implemented and is not reflected in our current results. All these parameters are summarized in the agent's utility function as follows:

$$Utility_n(t) = d \cdot Utility_n(t-1) + (1-d) \cdot \left\{ \Delta CapCost - \sum_i w1_{n,i} \cdot InconvDI_{n,i} + \sum_s w2_{n,s} \cdot DrPers_n(fH_s) \right.$$
$$\left. + PVMultiplier \cdot \left[DistDriven_n \cdot \Delta OpCost - \sum_i w3_{n,i} \cdot InconvDD_{n,i} - w4_n \cdot Worry_n \right] \right\} \qquad (1)$$

In this equation, $Utility_n(t)$ is the utility of an HPV for agent n at timestep t. It is normalized to range from -1 (strong desire for a CV) to +1 (strong desire for an HPV) by a normalization factor omitted for clarity. It is based on the agent's previous hydrogen utility multiplied by an exponential time-decay factor d plus his utility during the current timestep multiplied by $(1 - d)$. In this way, older experience is discounted more heavily. $\Delta CapCost$ is the difference in capital cost between a CV and an HPV, and $InconvDI_{n,i}$ represents the various types of distance-independent inconvenience agent n has experienced. $DrPers_n$ is a function based on Figure 3 giving the influence agent n receives when a fraction, fH_s, of the agents in influence sphere s have HPVs. The terms in square brackets are distance-dependent parameters: $DistDriven_n$ is the distance agent n has driven in the last timestep; $\Delta OpCost$ is the difference in operating cost per mile between a CV and an HPV; $InconvDD_n$ are the various types of distance-dependent inconvenience the agent has encountered in his driving; and *Worry* is the worry he has experienced. The weights that the agent puts on the intangibles inconvenience, influence, and worry are represented by the terms *w1-w4*. (While the w_n's can vary from agent to agent, all results shown in this paper are based on common values for all agents). Finally, all the distance-dependent terms are multiplied by a factor *PVMultiplier* to convert the experience over the quarter to a present value on the basis of a given discount rate and the agent's anticipated driving over his desired payback time period.

As mentioned, agents have different levels of income. Income designation determines not only where they live and work (and consequently who their peer groups are) but also fixes the schedule on which they buy cars and whether those cars are purchased new or used. In the current model implementation, we assign agents to one of three income groups: high (20%), middle (60%), or low (20%). High-income drivers buy only new cars and then scrap or resell them as used cars on a regular schedule (where the age distribution has a median car age of ~4 years); middle-income agents also buy only new cars, but keep them until they are scrapped (median age ~9 years); low-income agents buy only used cars (those sold by high-income agents) and keep them until they are scrapped (median age ~14 years). The buy/sell/scrap distribution schedules were adjusted to match U.S. data for overall car ownership and scrappage

(Davis and Diegel 2007).[3] Annual driving distances for older vehicle are discounted to reflect the fact that older cars are driven less (*ibid.*). In the results that follow, we typically simulate about 7,000 driver agents (representing about 0.1% of the driving population of the area), although we have made runs with as many as 70,000 agents.

MODEL RESULTS

The model results presented here are based on agent-assigned characteristics that are not necessarily meant to be realistic but rather are held relatively simple to show how the model works. We choose values for model parameters such that a significant percentage of our agents switch over to HPVs during the 20-year simulation.

Base Case – No Social Interaction (i.e., No Influence)

Figure 4 shows the penetration of HPVs into the existing fleet of CVs over a 20-year period. At the end, 64% of the vehicles on the road are hydrogen-powered. However, this figure varies dramatically by driver income level. While 81% of the vehicles owned by high-income agents are HPVs, they account for only 45% of low-income agents' vehicles. This result emerges from the fact that in our model, low-income drivers buy only used cars and buy them only from high-income drivers. Thus, for a period of some years before high-income drivers have first purchased and then sold HPVs, low-income drivers are restricted by the used car market to CVs only. As HPVs enter the used car market, they buy them whether they want the technology or not, since they are restricted in their choice by market availability.

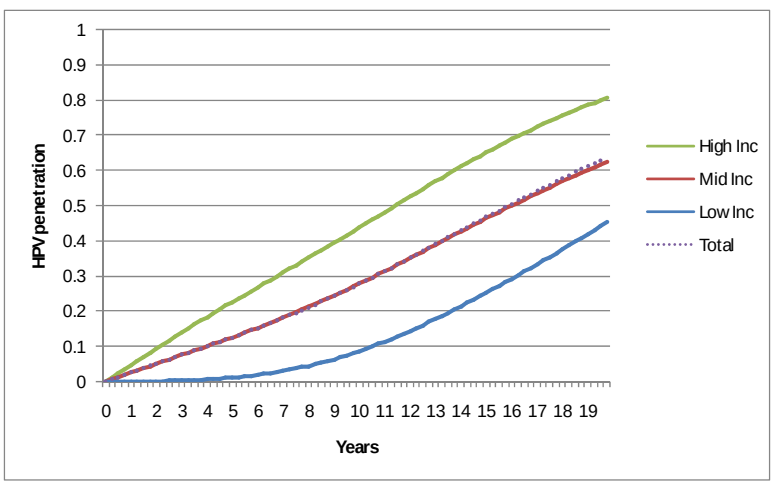

FIGURE 4 Fraction of HPVs owned by income group – agents have no influence on one another

[3] The schedules used are a compromise between a close approximation to reality and programming complexity. A possible future enhancement is to create a used car market in which all agents can participate and where prices are market-determined.

While this is an extreme case to a certain extent, it does reflect a real-world fact that used car buyers have to take whatever is available. When we run the model without this constraint, low-income buyers begin to buy HPVs as soon as they become available in their vintage, and in fact at the end of the 20-year period, they exceed the middle-income agents in percentage of HPVs owned. This (perhaps) counterintuitive result is explained by the fact (again, in our model) that low-income agents buy cars more frequently (and scrap them more frequently) than do middle-income buyers.

Early Adopters and Luddites

We now assign personalities to our agents and allow them to interact with one another. For purposes of illustration only, we deem all high-income agents to be Early-Adopters (hereafter referred to as HI-EAs), all middle-income agents to be Fast Followers (MI-FFs), and all low-income agents to be Luddites (LI-LUs), as illustrated in Figure 3. First we turn on Global Influence. That is, our agents our influenced by the fraction of HPVs they see on the road, regardless of where they see them or who owns them. We cut off the "population of influence" at an age of five years, so that agents ignore the technology of cars older than this age. The weight of this influence is deliberately chosen to be high. For MI-FFs and LI-LUs it ranges from -$2,000 to +$2,000 as the fraction of HPVs on the road increases from 0 to 1. That is, when only a small fraction of cars are HPVs, these agents regard an HPV as being worth $4,000 less to them than when everyone owns an HPV. For HI-EAs, the range is from +$2,000 to zero.

Figure 5 shows the results for this case. Because there are very few HPVs on the road at the start, the MI-FFs have no one to follow, so they stick with existing technology. HI-EAs start out strongly buying HPVs, but the total HPV vehicle fraction grows significantly slower than before, and this eventually pulls down their adoption rate. Finally the MI-FFs begin to adopt more rapidly as the HPV fraction rises above a critical threshold. The LI-LUs are prevented from buying HPVs early on because of their unavailability, then forced to buy them at the end when CVs are not available. When this constraint is removed, the adoption curve for this group becomes smoother.

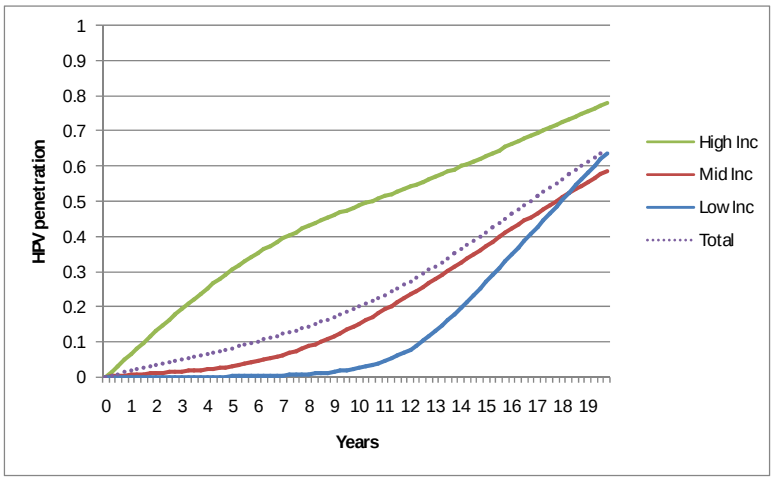

FIGURE 5 Fraction of HPVs owned by income group – agents exert global influence on one another

Neighborhood and Work Influence

In our final illustration of this simulation sequence, we remove Global Influence and substitute Neighborhood Influence and Work Influence. Figure 6 illustrates the Neighborhood Influence case, since the Work Influence results were very similar. Compared to the No Influence (Figure 4) and even the Global Influence (Figure 5) cases, the adoption of HPVs by MI-FF buyers is very slow, while that of HI-EA buyers has increased slightly back to the "no influence" level. Why should this be the case? Recall that, while neighborhoods are not completely income-segregated, middle-income agents, which constitute the majority of the population, are much more likely to see others like themselves as they look around their neighborhoods rather than the high-income agents needed to kick-start the MI-FFs' adoption. Consequently, adoption among middle-income agents never gets off the ground. Low-income agents are even less likely to see high-income agents in their neighborhoods, and consequently, when they are not forced to buy HPVs, these Luddites eschew the new technology almost completely.

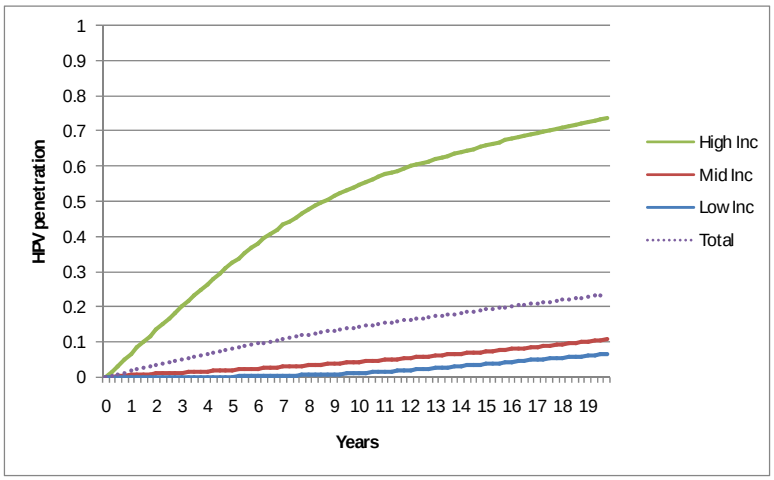

FIGURE 6 Fraction of HPVs owned by income group – agents exert neighborhood influence on one another

CONCLUSIONS

The examples illustrated above have given us confidence in the model design. As more sophistication is built into the model and driver and investor agents are given more diverse and realistic characteristics, we believe the model will allow us to gain insights into how the complex problem of interacting agents evolves in both realistic and extreme circumstances.

The purpose of the full model for the overall project is to study the development of hydrogen infrastructure. Infrastructure suppliers and purchasers of hydrogen vehicles react to one another's behavior in the chicken-or-egg interactions of the early transition to a hydrogen economy. Drivers will not purchase hydrogen vehicles unless hydrogen fuel is available conveniently, and the incentive to supply fuel depends on the existence of hydrogen vehicles to use the fuel, all occurring within a spatial context. The full model will allow the investor agent supplying infrastructure to decide whether to supply hydrogen from distributed production at fuel stations or from centralized facilities with pipeline or truck delivery to the stations. The investor

agents make their decisions on the basis of profitability, but with allowance for risk aversion in their utility functions. They are "satisficers" (imperfect maximizers) who may make mistakes in their expectations about the future. A key feature is that they learn from their mistakes by using a Bayesian approach as events unfold. The mistakes drive the system off course, while learning acts as a corrective mechanism. The full model will contain multiple investor agents who compete with one another. The full model also explores whether government interventions are needed to help speed adoption in response to energy policy goals.

As noted earlier, the experiments reported here focus on the "driver side" of the model, using simplified assumptions about investors. The utility function of driver agents in the full model differs from that used in the experiments reported here. The driver behavior in the experiments here differs by using a weighted average of current and past utilities to change behavior over time. While the experiments reported here are intriguing, it is to be emphasized that they do not reflect any conclusions from the overall project.

ACKNOWLEDGMENT

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