PHEV Marketplace Penetration

An Agent Based Simulation

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16. Abstract
Energy security and climate change issues have increased the call for improved energy efficiency from all sectors of the economy, especially the transportation sector. While vehicle manufacturers can in principle make their current vehicle offerings more fuel efficient, historically they have not done so for reasons of poor auto market sensitivity to fuel economy. However, recent economic events have changed the automobile marketplace. Now, despite current gasoline prices at around $2/gal, there is nonetheless a greater demand for more fuel efficient vehicles, the primary reason for which is anticipation of a return to higher ($3/gal to $4/gal) fuel prices when the recession is over. Unfortunately, simply making the existing fleet of conventional vehicle offerings more fuel efficient will not adequately address energy security and climate change issues. New advanced technology vehicles also need to be considered such as plug in hybrid electric vehicles (PHEV), which hold the promise of considerably improving fleet energy efficiency and reducing fleet carbon footprint. However, because these vehicles cost a lot more than their conventional counterparts, especially in the near term, their market viability is in question, especially if no government policy initiatives are instituted to enable successful market penetration. To address this question, UMTRI has developed an agent based simulation to characterize the penetration of new vehicle penetration into the marketplace under a variety of consumer, economic and policy conditions. Our results show that by 2015, sales could reach $2-3$ percent with fleet penetration of around 1%. By 2020, sales could reach around $4-5$ percent with fleet penetration a little more than 2%. And in 30 years, they could be around twenty percent of sales with a fleet penetration of about 16%. Without subsidies, the current policy case would result in a fleet penetration level of less than 1% in ten years. Subsidies are critical; sales tax exemptions can help if applied to scenarios where OEM subsidies are in place.

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Executive Summary

Energy security and climate change issues have increased the call for improved energy efficiency from all sectors of the economy, especially the transportation sector. While vehicle manufacturers can in principle make their current vehicle offerings more fuel efficient, historically they have not done so for reasons of poor auto market sensitivity to fuel economy. However, recent economic events have changed the automobile marketplace. Now, despite current gasoline prices at around $2/gal, there is nonetheless a greater demand for more fuel efficient vehicles, the primary reason for which is anticipation of a return to higher ($3/gal to $4/gal) fuel prices when the recession is over. Unfortunately, simply making the existing fleet of conventional vehicle offerings more fuel efficient will not adequately address energy security and climate change issues. New advanced technology vehicles such as PHEVs also need to be considered. Once having penetrated into the fleet to an adequate degree, these vehicles hold the promise of considerably improving fleet energy efficiency and reducing fleet carbon footprint. Because these vehicles cost a lot more than their conventional counterparts, especially in the near term, their market viability is in question, especially if no or inadequate government policy initiatives are instituted to enable successful market penetration. To address this question, we have developed an agent based simulation to characterize the penetration of new vehicle penetration into the marketplace under a variety of consumer, economic and policy conditions.

The agent based model presented herein is comprised of four classes of decision makers: consumers, government, fuel producers and vehicle producers/dealers. These agents, virtual decision makers in software, interact with one another and the environment (especially economic) based on their individual needs and/or organizational objectives. Briefly, ever cycle (one month) consumers review the status of their driving mileage, fuel costs, and whether or not it's time to buy another car. If it is determined that there is a need to change mileage or buy a car, they act in a way to remain at least budget neutral and meet their driving needs and model preferences. Nominally, agents can choose from twelve models of vehicles produced by three OEMs. At the end of each cycle, car dealers review sales and revenues, replenish the new car lots consistent demand and adjust the prices of used cars based on virtual market supply and demand. Government monitors system wide fuel use and carbon emissions and vehicle introductions and implements policies (fuels, vehicle tax incentives, etc.) to meet policy objectives. Finally, fuel producers provide fuels for automotive application and change prices both exogenously (petroleum induced gasoline price shock) and endogenously (competition between two fuel types).

The model was developed to address the general question of how do new technologies migrate into their appropriate marketplaces, and in particular the vehicle marketplace. Of special interest to the authors

and sponsor was the penetration of the PHEV into the U. S. auto marketplace. For this project, the model was extended from a previous version, coded, verified, validated, and then applied to the PHEV market penetration question. After coding and verification (is the model performing as intended), validation scenarios were developed and applied to the model to assure that it was sufficiently representative of a real marketplace. The validation exercises included: 1) establish and demonstrate normal system behavior under stress free conditions (no fuel price increases, no vehicle price changes, no new vehicles being added) in the marketplace, 2) consumer response under a gasoline price shock, 3) consumer response to a vehicle model price change, 4) the introduction and penetration of vans and SUVs into the U. S. marketplace, and finally 5) the introduction of HEVs to the marketplace. After completion of validation, the model was applied to the PHEV market penetration question.

The first validation exercise explored the fleet vehicle distribution as a function of time under conditions of a stress free market. It is found that the fleet vehicle distribution stays essential unchanged within a percent or two fluctuation, but never static. When it comes to consumer agent driving behavior, budget is "king"; all other considerations are secondary, though still important. The agents tend to buy vehicles that are priced consistent with vehicle owner income, which is also consistent with their neighborhoods of residence.

As a second validation exercise, we explored the response of model consumer agents to a gasoline shock. When such a shock appears during a simulation, consumer agents reduce their driving if the extra cost of gasoline takes the agent over budget. However, they like their miles and try to maintain it. If a gasoline shock takes them over budget, upon buying their next vehicle, they choose one that they can afford and allow them to drive their desired miles (commute, errand, and long trip). Hence, a rebound affect is observed in the fuel consumption history for the run. For a quantitative assessment of the impact of gasoline price on the sales of various vehicle models, elasticity coefficients were determined. They distinctly demonstrated an increasing trend with increasing metro-highway fuel economy.

The third validation exercise address market purchasing behavior when one of the potential vehicles for purchase is over or under priced. When an OEM reduces the price of one of his cars and another OEM who has a car in the same segment does follow, the market will shift to the less expensive , resulting in a much reduced market share for the OEM that did not respond appropriately to a competitor action. If both OEMs reduce their prices, thus lowering the effective price of vehicle in their segments, vehicle sales in other segments were affected. Sales elasticities were computed for these scenarios.

As another validation test, the model was applied to the case of vans and SUVs penetrating the U. S. auto marketplace starting in the mid 1980s. Using vehicle price history and fuel price history, the

VAMMP model demonstrated significant penetration of these vehicles into the market and fleet and in good qualitative agreement with the record.

The final validation exercise for VAMMP model was characterizing the vehicle fleet penetration history of HEVs. It is found that the modeled penetration curve is in good agreement with the market record for HEVs, albeit at this time rather short. This exercise was also a good calibration task for the model in that it permitted determining key consumer agent purchasing factors, such as purchasing propensities and ambient level. These penetrations curves demonstrate the classic S-shaped logistic type curve, indicating that the relative rate of penetration is dependent on those agents who are inclined to purchase a HEV but have yet to do so. This is a common process that one often sees in market penetration studies.

As a result of the validation exercises, we conclude that the VAMMP model is sufficiently representative of the U. S. auto marketplace that it can be applied to estimating the penetration of PHEVs into the U. S. auto marketplace. The results of the agent-based modeling study of PHEV penetration into the U.S. auto marketplace show that tax rebates, PHEV subsidies, and sales tax exemptions have a significant impact on PHEV penetration levels. Our simulation results show that a suitably incentivized auto marketplace can facilitate PHEV penetration levels into the U.S. automobile fleet. More specific results are as follows:

- By 2015, sales could reach 2 – 3 percent with fleet penetration of around 1%.
- By 2020, sales could reach around 4 – 5 percent with fleet penetration a little more than 2%.
- Without subsidies, the current policy case would result in a fleet penetration level of less than 1% in ten years.
- Subsidies are critical; sales tax exemptions can help if applied to scenarios where OEM subsidies are in place.

Because the individual vehicle replacement rate is a limiting factor in any market turnover scenario, it will take time to turn over the fleet even if new vehicle technologies have marketplace acceptance. A gasoline tax increase of about 5¢ per gallon would support government funding to incentivize PHEV sales. Finally, a PHEV fleet penetration of around 18% would reduce gasoline consumption by over 20% and decrease fossil carbon emissions by about the same amount.

Results from the model are very dependent on a number of factors (parameters) describing consumer behavior. We believe that good estimates of those parameters have been made. But there is one factor in the model as well as the real marketplace that critically governs the penetration rate and degree of any new technology introduced, namely, the turnover rate at which consumers replace their cars. The rate

ranges between 3 to 10 years, depending on the buyer and whether the vehicle being replaced was purchased as new or used. It is for this reason that truly significant penetration of such vehicles, even if successful, will take on the order of decades.

Finally, the VAMMP model has been demonstrated to characterize at least qualitatively the automotive marketplace. However, more calibration is needed. The model could be greatly expanded to include other dynamic factors, such as OEM competition, fuel producer competition, OEMs behaving strategically, and others. At this time, the model provides qualitative to semi-quantitative results and could be eventually upgrade to provide semi-quantitative to quantitative result.

Introduction

Automobile fuel economy pervades debates over "solving" U.S. energy problems. The debates center on the complex economic and political aspects of oil-supply and on the overarching problem of global-climate change associated with increasing atmospheric concentrations of carbon-dioxide caused by fossil-fuel combustion. In addition to vehicle fuel economy, there are parallel discussions about driving less in order to reduce carbon dioxide emissions and relieve urban congestion. Both fuel economy and driving habits devolve into problems of consumer choice—under what conditions will consumers choose fuel economy in their automobile buying decision and under what conditions will consumers drive less? Automobiles with substantially better fuel economy, such as the 50% improvement proposed in recent Federal Legislation, will need to be lighter weight and propelled by new power train technologies, for example some combination of hybrids or plug-in-hybrid electric vehicles, advanced spark-ignition or compression ignition (diesel) engines, or in some visions, battery or fuel-cell electric-only. It remains an open question how changes in vehicle technology can/would/should address urban mobility problems and the incentives for reducing vehicle miles traveled.

Obviously, new vehicle technologies must be accepted by consumers, but it is not possible to predict consumer acceptability of new vehicle technologies. Nor is it possible to predict the consumer acceptability of *any* new product. Consumer-goods manufacturers of every kind have long sought means to do such predictions, and a staggeringly large body of marketing-science literature is devoted to the subject. For automobiles, "new" can be aesthetic design, materials-use, new power train technology, etc.. Because there are no means to predict consumer acceptance of anything new, manufacturers face risky decisions. The nature of mass-manufacturing is such that products are essentially built on speculation. In a simple picture: manufacturers build production capacity for some initial volume and then face the problem of selling what they produce. Their production capacity is based on their best estimates of what they can afford to produce and sell at a price consumers are willing to pay. Clearly, the risks are lower when the "new" part of the product is incremental. When the consumers' consideration sets move away from the familiar, the risks to manufacturers increase. On the other side, when the manufacturers rationally minimize their risk and slowly and incrementally migrate to new technology, the changes sought by society necessarily come about very slowly. For the case of new vehicle technologies, slow is not good in addressing dilemmas arising from the urgency of the fossil-fuel problem in general and the oil-problem in particular. The difficulty of the dilemma is compounded when the technology embraces more than one industry, as is the case for vehicles that re-energize directly from the electric grid, such as plug-in hybrids. Here, not only the automobile industry, but the electric utility industry has to consider the problems of new consumer technology. While the electricity utilities face very different kinds of

technical problems, they are one-step removed from consumer-choice problems. Consumers may have choices about when and where to charge their PHEVs, choices that could be influenced by price, but consumers have no choices regarding the "attributes" of electricity—they are basically constrained by what is available at the wall-socket. Nevertheless the utilities have to anticipate future demand for plug-in hybrids if they are to be prepared to supply the required electricity, and that preparation may require consumer-acceptable, costly advanced metering technologies and new electricity distribution technologies, such as employer provided charging or even eventually ubiquitous charging stations that can meet consumer demand for anytime, anywhere charging.

The main tool for gaining insight into the acceptance of new products is consumer surveys of various types, including "focus-groups" to evaluate prototypes. Surveys, however, must deal with the problem of interpreting consumers' stated preferences as a reliable predictor of future revealed preferences, i.e. what customers actually pay when they buy the new product. Retrospective studies of revealed preferences, with tools such as discrete-choice models [McFadden, 1974], can give insights into why consumers made choices they did, and these models may validate the design and guide the use of survey tools. Discrete choice models are most insightful when the consumer-choice alternatives in these models are between close substitutes, but they do not easily admit treatment of "new technologies" that embody attributes with which consumers have no previous experience. Moreover, discrete choice models become increasingly difficult to apply as the consumer choice set becomes increasingly complex. For example, a plug-in hybrid is just one attribute of many that define the consideration set for a passenger car.

The central problem of interest to manufacturers when they introduce new products is prediction of market growth. The literature on market-dynamics of new technologies is dominated by retrospective "diffusion-of-innovation" models, of which the best known and most popular is the Bass model [1969]. . Studies employing these models seek to fit model functions (for example, logistic or Gompertz) to early sales data. The fit yields estimates of the parameter values, and the fitted equations are then used to forecast future sales volumes, under the assumption that the dynamics built into the models extend into the future. A more complete discussion of such models (both analytic and numerical) with numerous examples can be found elsewhere [Sterman 2000]. Diffusion-of-innovation models make no attempt to imbed the specifics of consumer behavior. Generally, the fundamental assumption underlying the models is that the fractional sales rate is a decreasing function of the total sales. In other words, the sales rate is a function of the number of those who have not yet purchased the new technology. Hence, sales volumes, initially small, grow to a maximum after which they decline because the number of available purchasers decreases as the market "saturates". The corresponding graph of sales as a function of time is "S-shaped"

and approaches an eventual saturation level. These diffusion models can be useful macro level forecasting tools, once a market is established, but they contain no mechanisms for how the sales of new products got established in the first place. In the case of the growth of HEV (hybrid electric vehicles) markets, such as the Toyota Prius or the Honda Insight, the manufacturers took a risk and essentially "seeded" the market. The "diffusion of innovation" models then give some insights for how large the market for these vehicles could eventually become, given an initial growth period. Such data do not have the built in capability of forecasting individual name-plates (e..g Toyota versus Honda); in other words all hybrids are lumped together, under the tacit assumption that the consumer choice is "hybrid". Different growth functions, such as logistic or Gompertz functions, fit to early hybrid sales data, may yield different future trajectories and different estimates of eventual (saturation) market size because of the differences in the underlying model dynamics and also because the nonlinear fitting procedures are sensitive to sparse data and to inherent fluctuations (noise) in sales data from sampling period to sampling period (typically, monthly data).

While the parameters that appear in diffusion models are customarily ascribed to various market and social factors, the models are explicitly functions only of time and sales. In order strengthen the intuitive connections between diffusion model parameters and social factors, Struben and Sterman [2008] have recently formulated in more detail the dependence of model parameters on consumer utility, familiarity, impact of total social exposure, and loss of social exposure. However, they point out that there is as yet little empirical evidence to support these hypothetical dependences.

Incidentally, a diffusion-of-innovation curve need not necessarily have an S-shape (Geroski 2000). If a population of potential adopters purchases a new technology as soon as they are aware of it and that awareness depends only on say advertizing (e.g. on TV or in newspapers), the fractional rate of adoption in this case is equal to a constant. Hence, the resulting adoption curve has an exponential saturation shape rather than an S-shape.

This paper summarizes another approach to understanding future markets. This approach, known as agent-based modeling (ABM), is a simulation method that creates a computer based (virtual) market built out of finite collection of heterogeneous individuals that participate in the market. These individuals are called "agents" and encompass new and used-car consumers, manufacturers, fuel-suppliers, and governments, all making decisions. Consumers' decisions are based on their individual preferences and willingness-to-pay. The model incorporates interactions between agents, such that one individual's decisions may be influenced by the decisions of her neighbors or co-workers. The model also permits exogenous "shocks", such as sudden changes in fuel supply, or government regulations. The details of

the model are described below. The approach does NOT produce forecasts of future markets; rather it produces possible outcomes given sets of assumptions of how the individual agents decide. The model works in discrete time steps. At each step the customer-agents make decisions whether to buy or not, whether to buy new or used, subject to their budgets and their preferences among the products offered by the manufacturers. In this model, manufacturers set prices—although in reality price setting is more complex; the price of used cars occurs endogenously depending on vehicle supply vs. demand. Fuel prices are set by fuel-supplier agents; government regulators can impose constraints. At each time period, agents make decisions and the outcomes influence what happens in the next time step. The model is run for many periods. The simulations yield "what-is-possible," given the individual decisions. The usefulness of the model is in its revelation of possible outcomes when the agents are presented with new choices, such as a "new technology."

There has been a growing interest in the application of agent based simulations to product development and diffusion problems. Recently, Garcia (2005) addressed the application of ABM to these types of questions and found two benefits: 1) ABMs become more effective and representative as agent heterogeneity increases, and 2) the more adaptive an ABM is the more we can learn about actual adaptive systems. ABMs have also been applied to new-technology market penetration into the transportation sector; more specifically on the growth of the hydrogen transportation infrastructure (Stephan and Sullivan 2004) and the market penetration of more sustainable vehicles (Sullivan et al 2005). The former study demonstrated successful penetration under the right subsidy and fuel availability circumstances and the latter demonstrated impact of a fuel price increase on vehicle miles travels and vehicle sales.

The purpose of this report is to detail the development of an agent-based "virtual automotive market place model" (acronym VAMMP) for use in estimating PHEV penetration into the U. S. light duty vehicle fleet. This model is a further-developed model of one introduced earlier (Sullivan et al 2005). Details are discussed pertaining to model assumptions, structure, agents, and behaviors. As a validation exercise, the model is applied to number of market stimulation scenarios and yields results that favorably correlate with data and expectations. Finally the model is applied to the question of the market penetration of PHEVs into the U. S. auto marketplace.

Model Description

Agent based models have been applied to many complex systems such as the spread of disease, the evolution of organisms, emergence of behavior in social systems, financial markets, organizational behavior, and these applications provide general conceptual foundations for our application to the automobile marketplace. Our virtual automotive marketplace (VAMMP) model is an agent based model that simulates the automobile marketplace, which is comprised of four classes of decision makers in software: consumers, government, fuel producers and vehicle producers/dealers. These agents, virtual decision makers in software, interact with one another and the environment (especially economic) based on their individual needs and/or organizational objectives. Briefly, every cycle (one month) consumers review the status of their driving distance, fuel costs, and whether or not it's time to buy another car. If it is determined that there is a need to change driving distance or buy a car, they act in a way to remain at least budget-neutral and meet their driving needs and model preferences. Nominally, agents can choose from twelve models of vehicles produced by three manufacturers (OEMs—"original equipment makers"). At the end of each cycle, car dealers review sales and revenues, replenish the new car lots consistent with demand and adjust the prices of used cars based on virtual market supply and demand. Government monitors system wide fuel-use and carbon emissions and vehicle introductions and implements policies (fuel-tax, vehicle tax incentives, etc.) to meet policy objectives. Finally, fuel producers provide fuels for automotive application and change prices both exogenously (petroleum induced gasoline price shock) and endogenously (competition between two fuel types).

Consumers (vehicle buyers) have home and work addresses, incomes, transportation budgets , vehicle preferences (size, performance, and sometimes brand and special features), driving needs (city and highway driving for errands, commuting, and discretionary trips), and preferred duration of vehicle ownership before buying another one. Consumers' incomes follow the U.S. income distribution and the transportation portions of those budgets [percent allotted to transportation] are a function of their income. The consumer agents tend to live in neighborhoods consistent with their income. Their transportation budgets are computed using an algorithm fitted to the data just cited plus or minus a 2.5% random increment. Consumer transportation budgets are comprised of fixed and variable terms as follows:

$$\text{Budget} = C_1 + C_2 + C_3, \tag{1}$$

where C_1 is the monthly vehicle payment, C_2 is the monthly fuel cost, and C_3 is the cost of insurance parking and servicing. All consumers stay within their budgets, though some are sufficiently close to their budget limit that a fuel price increase triggers a need to change their monthly driving distance. For consumers who become over budget due to a fuel price increase, options available to them to come back within budget are: 1) get rid of their vehicle (only if they are very low income), 2) take public

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transportation for commuting purposes, simultaneously reducing their commute driving, or 3) reduce their errand distance driving. Consumers' sensitivities to a fuel price increase follows the form:

$$dV/V \, / \, dP/P = \varepsilon \qquad (2)$$

where V is total monthly volume of gasoline consumed, P is the price of gasoline, and ε is a unique constant for each agent whose value ranges between -0.1 for upper income people and -0.2 for lower income consumers. Equation 2 has the form of a standard elasticity relationship. An important point to emphasize here is that not all agents are compelled to act due to a fuel price increase. Many agents have sufficient slack in their budgets that a gasoline price increase results in no action on their part. This feature is also included in the model.

In every time period (cycle) consumers not only review their transportation distance driven and associated costs but also whether or not it is time to buy another vehicle. The car buying decision hierarchy is:

➢ Screen for available cars, new and used, within budget window (eq. 1)

➢ Score potential vehicles according to size and performance preferences

➢ Rescore the revised list for brand preferences, if any.

    ✓ Select the best; eliminate all others

➢ From the remaining list, select those vehicles consistent with the agent's new or used preference

➢ In the final list, keep or remove special feature vehicles consistent with agent preference

Consumer agents may have to go back to the market for a number of months (cycles) in order to get the vehicle they prefer, but almost always consumers find a vehicle that meets their needs and preferences within a few cycles. Because there is an ample supply of new cars of all models (consistent with demand) on car lots, but many fewer on used car lots, it usually takes an agent desiring a used car longer to find a vehicle that meets his/her needs.

Upon buying a car, an agent owning a "new car" gets a trade-in value for his/her vehicle which then goes onto the used-car lot. For those owning a "used car", consumers get a scrap value for the vehicle upon purchase their next car.

When applied to the cases of the penetration of advanced vehicle technology (e.g. HEVs or PHEVs) into the marketplace, a critical component of the model is that consumer agents interact with one another. Regarding the purchase of a PHEV, which most consumers would be leery of at least initially, agents take into consideration whether any of their friends or colleagues own one or whether the population of PHEVs in the on-road fleet is high enough to reduce their hesitancy to purchase one. Agent

attitudes or propensities towards PHEVs are committed, inclined, and neutral. When replacing their old car (on schedule), committed agents (1.5% of the population) will buy one without reservation, inclined (3% of the population) will add one to his/her list of potential vehicles for consideration, and neutral agents (the rest) will buy one if the price is better than that for all other vehicles on their list. Neutral agents can be converted to inclined when enough of them (PHEVs) are around. Again, no agent buys a vehicle outside of their budget.

     Cars come in three sizes (small, medium, and large denoted 1, 2, 3) and three performance levels (low, medium, and high denoted 1, 2, 3). All vehicles have city and highway fuel economy as well as prices. Generally, large, high performance vehicles (short 0 to 60 times) are priced higher and tend to have lower fuel economy than average, whereas just the opposite is the case for small low performing vehicles. Permuting this range of vehicle attributes results in nine vehicle segments, though all are not present (e.g. no large low performing vehicles are included). As there are three OEMs (original equipment manufacturers), some segments have vehicle entries made by competing OEMs. There are a total of twelve models of vehicles in the vehicle population, though in some cases some new types of vehicles are added to the population. Table 1 shows a representative set of vehicle properties used in our simulations. For example, the introduction of HEVs or PHEVs takes the vehicle model population beyond twelve models to between 13 – 15 vehicles. All cars have two stages to their lifetime, one as a new car and one as a used car. After these two stages, the vehicle is scrapped. The price for a new car ranges between about $12k for a small, low-performance vehicle to $33k for a large high performing vehicle.

Table 1: Vehicle Characteristics and price

OEM	Size	Performance	Technology	Fuel Economy - mpg				Price $K
				City	Highway	City	Highway	
1	1	1	Conventional	27	34			12
1	2	2	"	20	28			21.8
1	3	2	"	18	24			26.1
1	1	3	"	22	29			19.2
2	1	1	"	26	35			11.9
2	2	2	"	19	27			21.6
2	3	3	"	17	21			32.8
2	1	2	"	24	32			15.5
3	2	1	"	23	30			18.7
3	2	3	"	18	24			24.4
3	3	3	"	17	22			32.8
3	1	3	"	22	28			19.2
1	2	2	HEV	48	45			25
2	3	2	"	38	31			27.4
3	2	2	"	40	45			25

1	2	2	PHEV	70	72	237[a]	228[a]	28.7
2	3	2	"	56	62	205[a]	182[a]	36.4
3	2	2	"	61	72	251[a]	218[a]	49.7

[a] Denotes gasoline equivalent mileage for charge depleting mode of operation

The fuel economies listed in Table 1 for the PHEVs denote two modes of operation. The first set of city and highway mileages are for <u>charge sustaining mode</u> whereas the second set corresponds to <u>charge depleting mode</u>. The all (mostly) electric range for the PHEVs given in Table 1 are 10 , 20 and 40 miles corresponding to OEMs 1, 2, and 3, respectively. It is for this reason that the prices of these vehicles increase considerably over their conventional and HEV counterpart, depending on the size of the battery which influences all (mostly) electric range. Of course, for the HEVs the mode of operation is always charge sustaining. The vehicle modeling effort led by Z. Filipi et al provided the fuel economies and costs for the PHEVs shown in Table 1. The PHEV fuel economies are based on the PSAT model (developed by Argonne National Laboratory) operating through an optimization routine which minimized fuel consumption under conditions that the battery state of charge go no lower than 0.40 ±0.02, the level at which the vehicle transitions from charge depleting to charge sustaining mode of operation.

Car lots come in two varieties, new and used. Every cycle numbers of and revenues from vehicle sales are tracked. In the case of new vehicles, these numbers are used to generate demand and revenue based values for restocking new car lots with vehicles acquired from OEMs on an unlimited basis with the various models available. On the other hand, used cars arise solely from the sale of cars completing their "new car stage". Generally speaking, used cars do not remain on the used car lot much more than one cycle, which is why used car buyers take a little longer finding their preferred car.

In order to establish a value standard in the model, new car prices do not change during a simulation. However, OEMs can exogenously change the price of one of its models or respond endogenously to the change in price of a competitor's vehicle in the same segment. But OEM's do not adjust the prices of their new car models from cycle to cycle based on demand and inventory. For used cars, demand and vehicle inventories are used to adjust vehicle prices on a cycle by cycle basis. Generally, if demand or revenue for a particular model is rising or flat, the used car dealer raises its price, whereas the dealer lowers its price if demand is falling or inventory exceeds a threshold. These incremental changes in prices are: ±3% for changes in demand, -10% for excessively high inventory, and finally a 0.75% price decrease (carrying charge) each month the vehicle remains on the lot.

Government's role in the model is to monitor fuel sold, fleet vehicle fuel economy, and carbon emitted and implement policies depending on various environmental and energy security considerations.

In this study, we explore the following government policy instruments: subsidies for PHEV production, tax rebates on PHEV sales, gasoline tax increases, and sales tax exemptions. More details of this are given in the HEV and PHEV sections.

Fuel Producers: There are two fuels germane to the PHEV market penetration case addressed herein, gasoline and electricity. For conventional and HEV fleet scenarios, gasoline is the relevant fuel. Fuel prices are set exogenously and in this simulation gasoline prices range from $2/gal to $4/gal; electricity prices remain fixed at $0.095/kwh.

Results and Discussion

An ABM is intended to simulate the behavior of a complex system comprised of many interacting players. For such a simulation to work properly, many assumptions are employed to meaningfully represent the behavior of the individual agents. Because most of these assumptions are too numerous to list, one must rely on model verification to insure that the model is behaving as intended, i.e. is "the model right?". The next step is to conduct validation exercises that test if the model is representative of the real system, in this case the auto marketplace. We cover those validation exercises below in order to demonstrate that VAMMP is qualitatively if not semi quantitatively representative of the U. S. auto marketplace. These exercises show that the model demonstrates either expected behavior or behavior that can corroborated by market data. Some key assumptions to keep in mind are:

- The population is fixed and there is no systematic growth in vehicle miles traveled (vmt) or vehicle population
- Wages remain constant
- All prices are in real dollar terms
- No distinction between cars and trucks
- Agent population follows US income distribution
- No limit of PHEV vehicle or component supply – adequate supply chain assumed

To better acquaint the reader with the model, we apply and compare it to a set of circumstances where actual market outcomes are obvious. Our first exercise is the base case.

Base Case Run: Our first validation exercise is run without any particular market perturbation such as a new vehicle introduction or a gas price shock. In short, it is a run under "normal circumstances" with a fixed population of vehicles for purchase and the gasoline price fixed at $2.00/gal. For typical runs,

we used 5000 agents, 4515 of which have the incomes to support a car, either new or used. This base-case example represents a statistically equivalent cross-section of our virtual auto buying population by income. Herein, we denote low income agents as earning $25k or less, middle income agents earning between $25k and $120k, and high income agents as earning more than $120k.

Figure 1 is a map of agents by home address who own vehicles in different segments. The map shows an urban center surrounded by a suburban ring and a pair of nearby satellite towns. Each of these regions is divided into low (yellow green), middle (blue or grey), and upper (dark green) income neighborhoods. Results in Fig. 1 show who owns (by income level) the most and least expensive cars, either used or new. To keep the figure as simple as possible, only two vehicle segments are shown: "segment 1" represents small, low performing vehicles at the bottom end of the price scale and "segment 9" corresponds to large high performing expensive vehicles. From the clustering of red dots shown in the figure, it is clear that the more expensive cars are owned by agents living in the higher income neighborhoods whereas the clustering of black and white dots shows that the least expensive cars are owned by those living in the lower income areas

Color	Segment	Vintage
Red	9	new
Yellow	9	used
White	1	new
Black	1	used
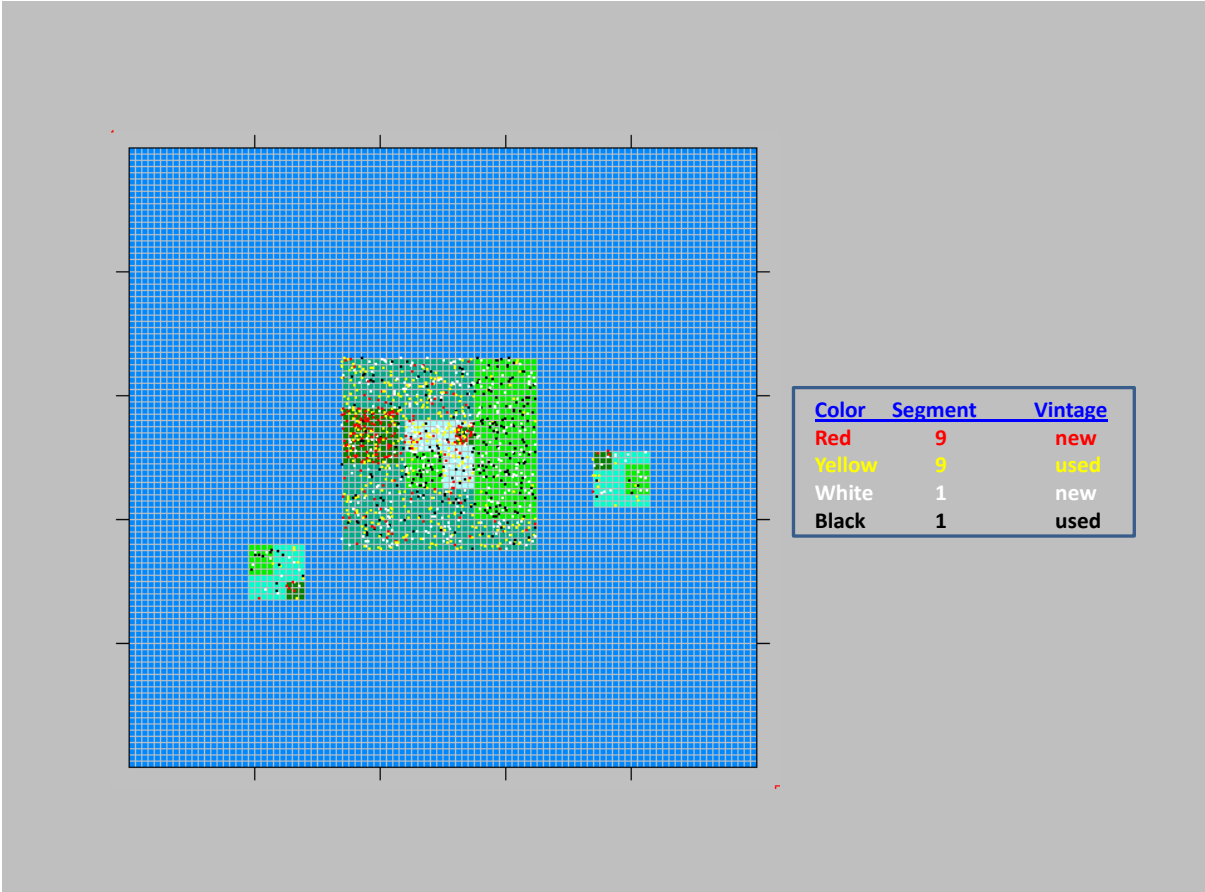
Fig. 1: Agent Population Owning Either a High Performance Large
Vehicle or a Low Performance Small Vehicle

A more quantitative assessment of the vehicle ownership pattern is given in Table 1. Though not all segments are shown, the table does show that a higher percentage of higher income agents tend to own the more expensive cars, and a higher percentage of lower income agents own lower cost cars. Middle income agents tend to own more medium priced cars. Further, as lower and middle income agents stretch to own a more expensive car, they tend to buy used cars.

Table 2: Vehicle Ownership Percentages for Select Auto Segments in the Base Case Scenario

Income	Size of Pop.	Segment 1[a]		Segment 5[b]		Segment 9[c]	
		New	Used	New	Used	New	Used
Low	977	11.6	22.7	0.4	10.7	0	1.0
Medium	3009	7.5	3.8	8.6	8.2	2.8	9.6
High	509	5.5	2.4	5.7	1.6	24.0	12.4

[a] Low performance small vehicle; [b] medium performance, medium size; [c] high performance large vehicle

These are expected results. Despite the diversity of incomes of the agent population, even within their respective income brackets, they are making car buying decisions primarily based on their transportation budgets. Though agents have vehicle size and performance preferences, they buy vehicles within their budgets. If they prefer vehicles which are outside of their budgets (if purchased new), they purchase used vehicles, which are less expensive.
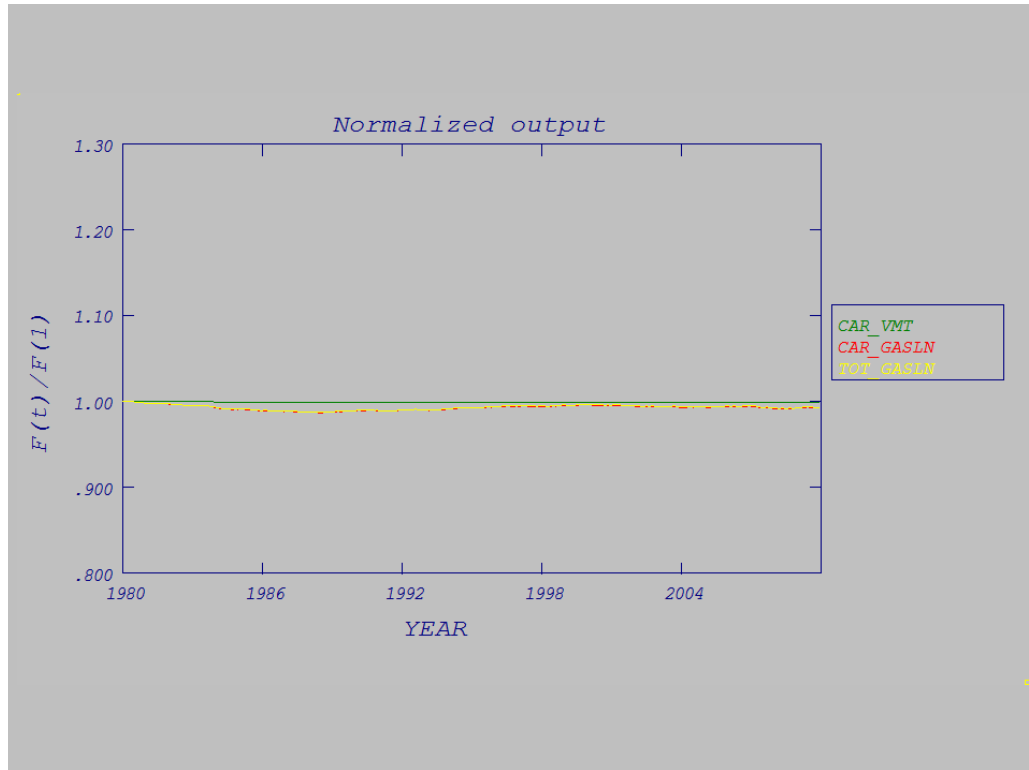
Figure 2: Fleet wide vmt, LDV gasoline and total gasoline sales results over a thirty year time frame

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Figure 2 shows fleet wide responses of vmt and gasoline consumption over the time frame of interest, in our case 30 years. The functions plotted are vmt, gasoline consumed by cars, and total gasoline consumed (by cars and buses) and they are all normalized by their respective value [F(1)] during the first iteration of a simulation run. The plot shows some variation (on the order of 1%) in these fleet metrics, though no consistent trend is observed. Given the diversity of the population in incomes, vehicle taste and ownership periods, which all can influence the supply vs. demand relationship of used prices, such variation is reasonable and expected.

Incidentally, plots shown herein unless otherwise stated represent individual runs of the model at a particular value of the random seed. In the case of Fig. 2, repeated runs with different seeds yield statistically equivalent trends shown in the figure. However, in cases where the model is representing a market under stress, considerable variation can occur. In those cases, multiple runs, typically twenty, are conducted and averages are generated for responses of interest.

Gasoline Price Change: Our second validation scenario is to illustrate the influence of a 50% increase in the price of gasoline at simulation time of 1981 (from $2.00 to $3.00 a gallon) on vehicle use and purchasing trends. An inspection of Fig. 3 reveals an overall decrease in the population of vehicles with higher to moderate gasoline consumption, i.e. for vehicles with higher performance and size. Figure 4 is a more consolidated representation of these trends. It is clear from these two figures that in the long term some consumer agents are shifting toward owning smaller fuel efficient cars.
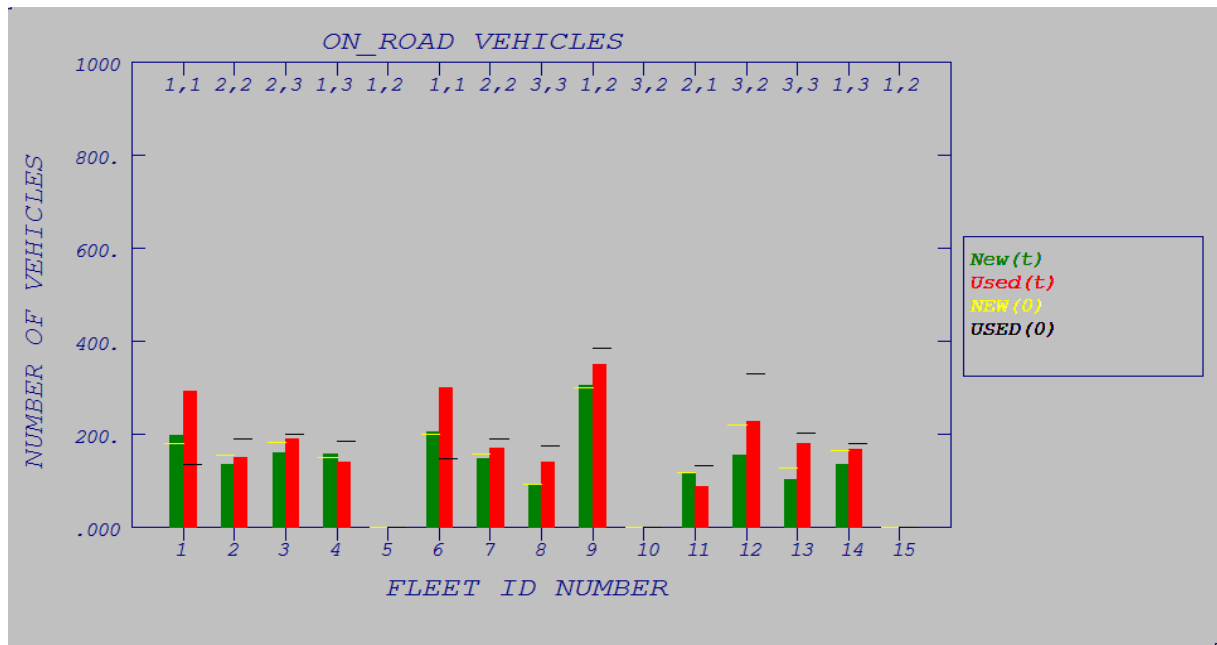

Figure 3: Fleet ownership distribution by model after a 50% increase in gasoline price at end of simulation. Size and performance for each vehicle is given at the top; dashes are population at start of run; bars for end of run.

In Figure 5, we show the effect of this price increase on vehicle miles travelled (vmt) and gasoline sales. Firstly, notice the short term elasticity response to the gasoline price increase. This is due to some agents exceeding their monthly transportation budgets, causing them to reduce their vmt. All consumer agents are sensitive to fuel prices with elasticities that range between -0.1 to -0.2, depending on income. However, agents act to change their driving behavior only if the fuel price increase takes them above their monthly transportation budget limit. Otherwise, they do not change their driving behavior.
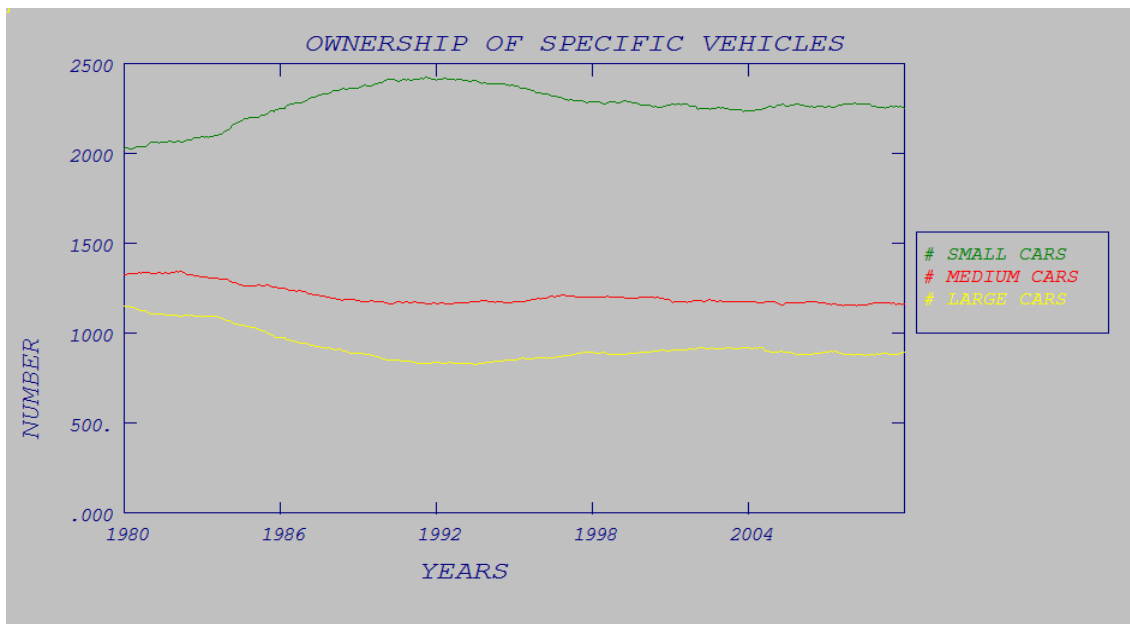
Figure 4: Trends in vehicle size distribution upon a 50% increase in gasoline price

There are some other features in figure 5 that merit comment. Notice that shortly after the fuel price increase and an initial drop in vmt, the latter begins to rise again. This is due to some agents purchasing more fuel efficient vehicles, thus reducing their monthly gasoline costs, which permits them to reclaim some of the miles they gave up just after the fuel price increase. Finally, the long slow decline in vmt and gasoline consumption is due to two factors: 1) some consumer agents migrating to more fuel efficient vehicles, and 2) some agents seeking another mode of transportation (bus) instead of their cars for commuting purposes. Some vmt reduction is also due to some consumers agents being forced out of the car ownership population. The reason that car gasoline and total gasoline decline at different rates is due to the increase use of the bus alternative for commuting.
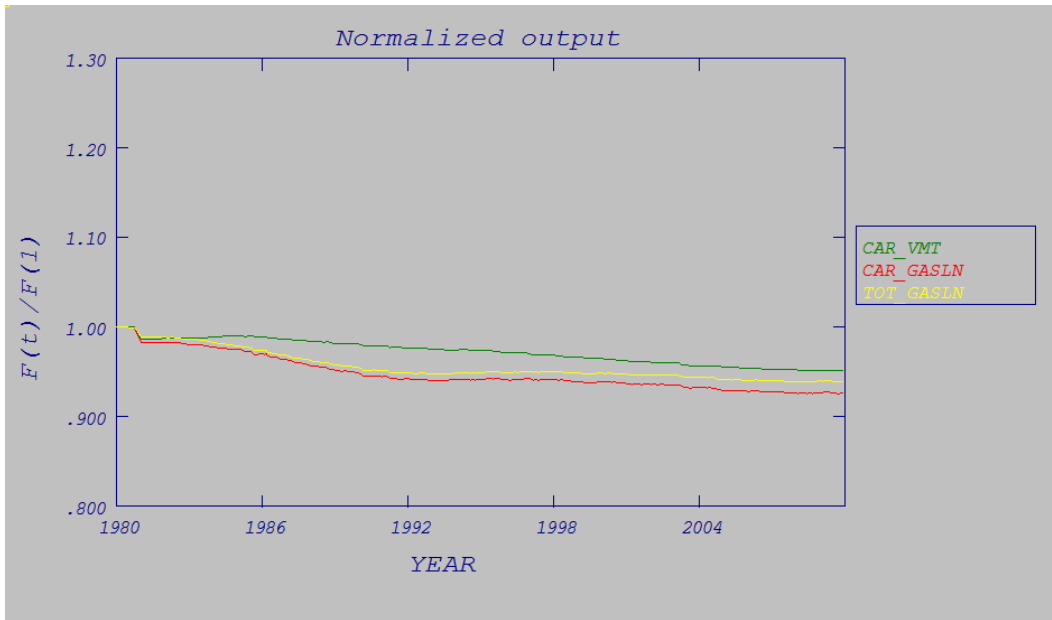
Figure 5: Fleet metrics upon a 50% increase in gasoline price.

As was pointed out in Fig. 4, a fuel price increase does lead to long term shift in vehicle purchases in favor of smaller cars vs. larger ones. A more quantitative assessment of this trend is given Fig. 6, which represents long term vehicle sales vs. metro-highway fuel economy (MPG). These results, which represent average elasticities taken from 7 runs, confirm the trend shown in Fig.4. In short, a fuel price increase causes increased sales of the most fuel efficient vehicles, decreased sales of the least fuel efficient, and is sensibly neutral for vehicles with intermediate fuel economies.
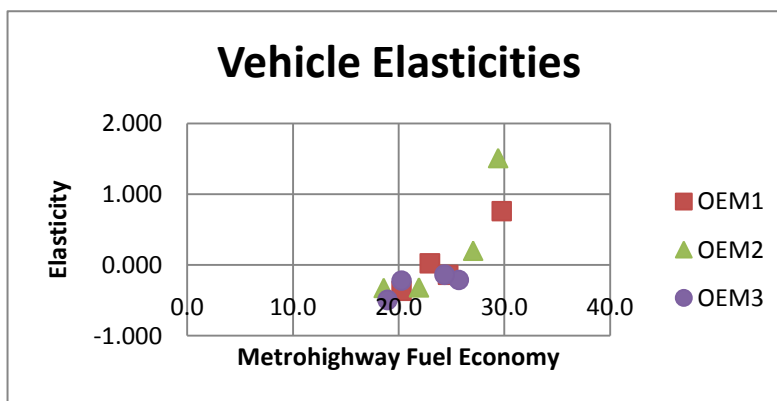
Figure 6: Vehicle sales/ fuel price elasticities as a function of metro-highway fuel economy.

Long term fuel consumption price elasticity (taken from Fig. 5) is around -0.14, which is in reasonable accord with results recently published results [Small et al. 2007]. However, recent studies suggest that the magnitude of the rebound effect is declining [Small et al. 2007; Hughes et al. 2006],

indicating that consumers are altering their driving behaviors less upon a fuel price increase than they did previously, particularly during the 1970's.

Vehicle Price Change within and outside of Segment: Once a vehicle market segment (herein taken as defined by size and performance) has been established the influence of price of one of the vehicles in that segment critically determines its continuing market success. For example, if an OEM reduces the price of one of its models in a given segment, common sense suggests that a competing OEM should do the same or suffer a sales consequence. An example of this is shown in Fig. 7, which depicts the distribution of vehicle models in the on road fleet. Notice that when OEM 2 reduces the price of model 7 by $2k (approximately 10%) for the duration of the simulation and the competing OEM 1, who makes model 2 in the same segment, does nothing, the population of model 7 in the fleet goes up appreciably and that for model 2 decreases. As indicated by the black and yellow dashes, prior to the unilateral price decrease, the populations of models 2 and 7 (segment 5; medium size; medium performance) are sensibly the same. Of course, OEM 1 would not sit idly by and watch its market share erode. Instead, OEM 1 (producer of model 2) would respond in kind, though perhaps not immediately, to a price decrease initiative implemented by OEM 2 (producer of model 7) by offering a comparable incentive.
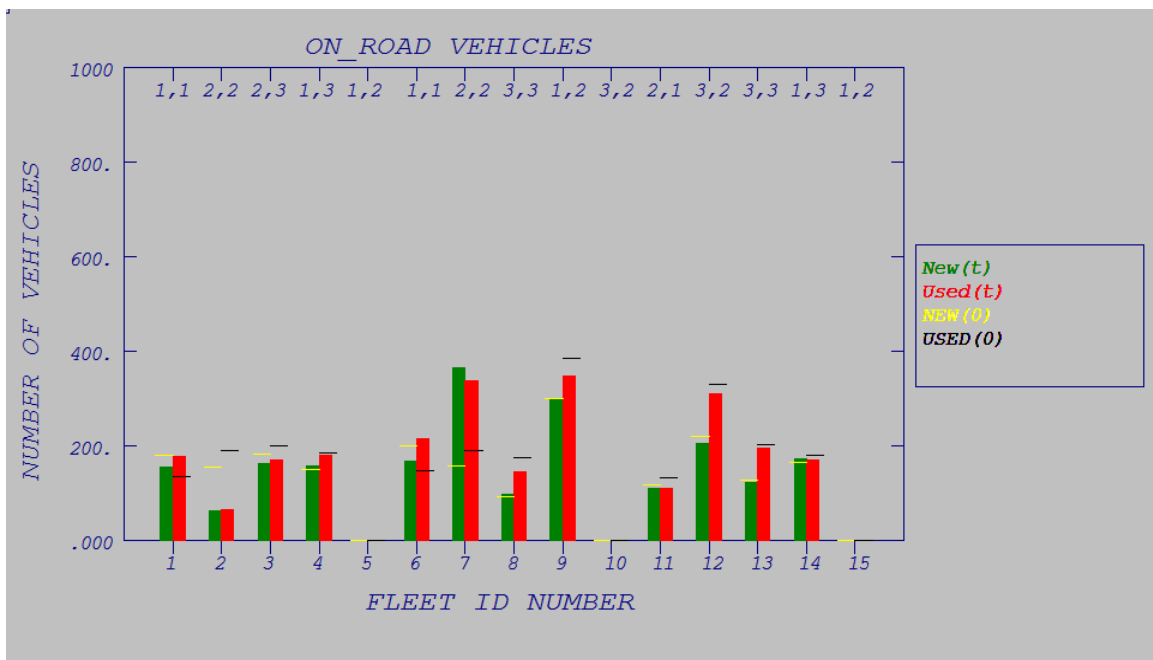

Figure 7: Vehicle fleet distribution by model at the end of the simulation for the case where model #7 has a $2k price reduction. (Yellow and black dashes denote values at simulation start; paired numbers at top denote size and performance of each model)

A different view of this effect in terms of vehicle sales is shown in Fig. 8. There it is clearly evident that from the sign and magnitude of the elasticities that the impact of a 10% decrease in the price of model 7 results in a large negative elasticity for model 7 indicating a significant increase in sales and no discernable impact on the other models with the exception of model 2. Model 2, a member of the same segment, has a large positive elasticity indicating a major drop in sales. Incidentally, the runs shown in Fig. 7 are done for larger agent populations, 10,000 and 12,000 vs. the usual 5,000. However, the results show no detectable influence of the size of the agent populations.

It is expected that if both OEMs producing models 2 and 7 reduce the price of their cars in a particular segment that this reduction would not only increase sales of those vehicles but it also would decrease the sales of the other vehicles. Indeed, this is what is observed as demonstrated by sales elasticity results presented in Fig. 9. There it is seen that sales have indeed increased for models 2 and 7, each having an elasticity of around -4. The sales of the other vehicle have also been affected. The lower priced ones show a decline in sales and higher priced vehicles show either a slight or no increase in sales. The decline in lower priced vehicles is as expected. After all, the agent population is fixed, and if they depart from their usual habit and start buying different cars especially ones traditionally priced higher that have just become affordable, then a decline in their customary choices of lower priced cars should be observed. One might have expected a greater loss in sales for those vehicles priced nearer to models 2 and 7, but the trends in the figure appear to show that all sales of new vehicles priced lower have decreased.
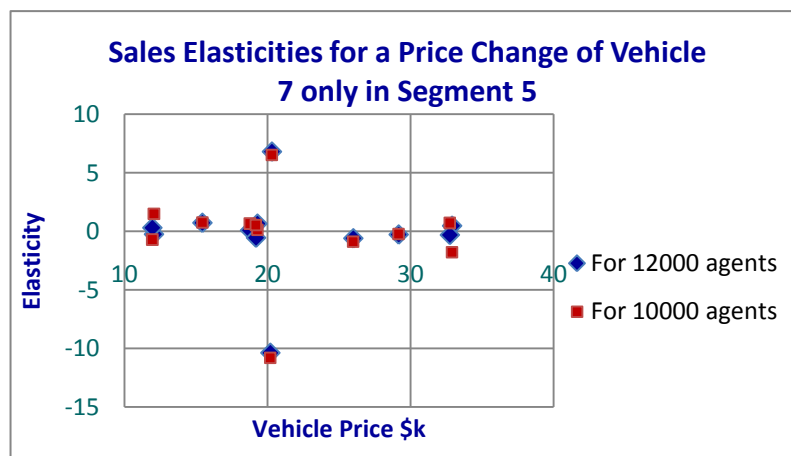

Figure 8: Elasticities for all vehicles when the price of vehicle 7 is decreased but no change in price for vehicle 2. Both vehicles are in segment 5. (Based on a average of 10 simulations)

On the other hand, for new vehicles priced higher than models 7 and 2, there appears on balance to be either no or a slight increase in sales, again considering the noise in the results. The elasticities shown in the figure are based on a 10 run average using different random seed for each.
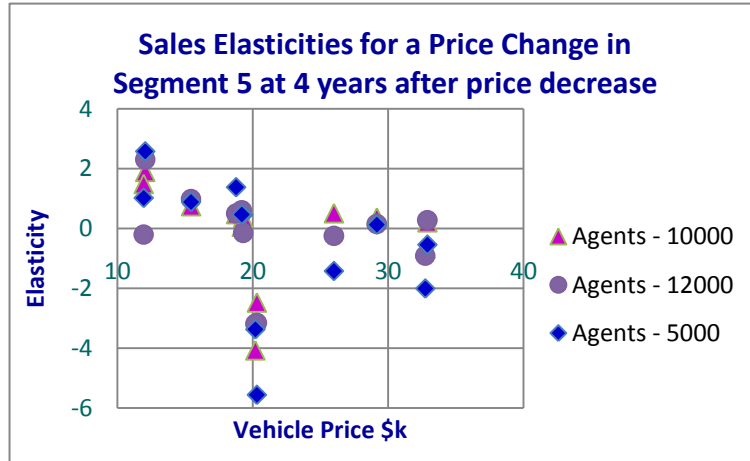

Figure 9: Elasticities for all vehicles when the price of segment 5 vehicles have been reduced. (Based on a average of 10 simulations)

Penetration of vans and SUVs: Our next validation example is the case of the penetration of SUVs and vans into the U. S. auto marketplace. Unlike the above examples which demonstrate virtual marketplace behavior consistent with common sense expectations of the real market, this example demonstrates a virtual market penetration behavior contrasted with the historical record.

Vans and SUVs penetrated the U. S. auto marketplace starting in the mid 1980s and continued their penetration at an increasing rate through the 1990s. In order to model the penetration of vans and SUVs over that time period using the VAMMP model, actual market conditions must be considered. Fig. 10 shows the price of gasoline in real dollar terms from 1970 to 2000. Between around 1975 and the mid 1980s, the gasoline price was quite high, after which it decreased to pre-1975 levels for about a decade.

The price of vehicles also changed over that period. Figure 11 shows that the price (weeks of median family earnings to buy a new car) for vehicles from 1970 to 2000 remained essentially flat and then dropped off in the late 1990s. Modeling runs for this validation scenario set vehicle prices over the time frame of the simulation based on year 2000 vehicle prices and scaled by the appropriate ratio of weeks worked to buy a new car.
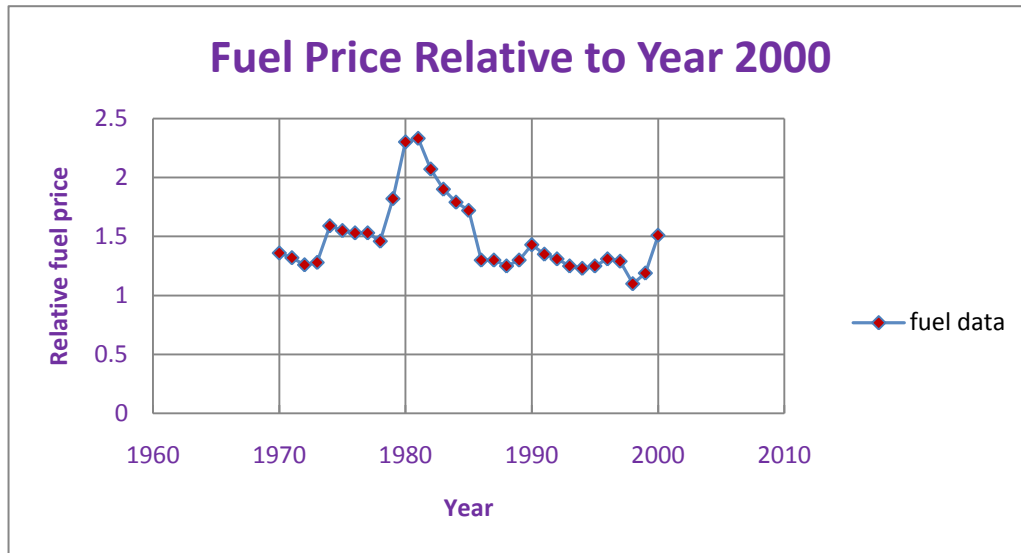
24

Fig. 10: Relative Fuel price data from 1970 to 2000. All prices in year 2000 dollars

When considering purchasing another vehicle, the consumer agents in the model respond to their budgets, fuel prices, vehicle prices, vehicle preferences size and performance relative to their preferences, and vehicles vintage (used or new). Hence, it was necessary to introduce a new vehicle purchasing decision criteria to model the penetration of a new vehicle technology (regarding SUVs and vans as "new"vehicle technologies) into the auto marketplace. Toward that end, we introduced the concept of "special feature". This is a generic term used to distinguish a new vehicle technology entering the market relative to its predecessors. To facilitate this in the model all vehicles have a technology attribute; it is either a special feature vehicle or not. Henceforth, we denote SUVs and vans as SFVs (special feature vehicles). The SFV flag (attribute) is used in a number of contexts in our research. In this section, it denotes vans and SUVs; in the next section it denotes hybrid vehicles.
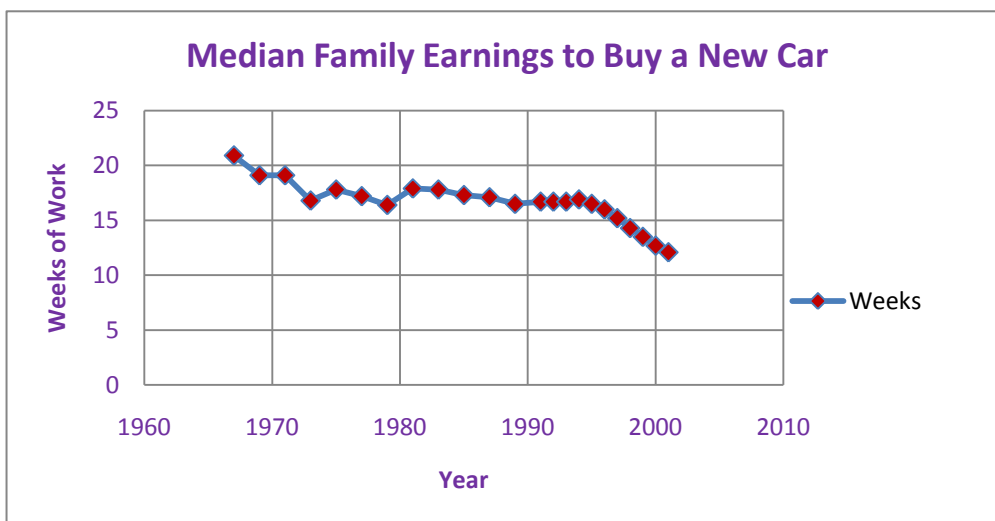

Fig. 11: Weeks of median family earning required to buy a new car.

While the special feature flag denotes a new vehicle technology, consumer agent response to it is variable. As stated above, consumer agents have three levels of propensity to buy a new vehicle technology: committed, inclined, and neutral. In the model these are treated as consumer-personality attributes and are assigned to consumer agents at model startup. This is an essential feature of the model. Otherwise, because special feature vehicles come in the same size and performance range as conventional vehicles but they cost more, special feature vehicles would not penetrate the market as agents would view them as just expensive conventional technology and avoid purchasing them.

Committed agents are "must–have" buyers of a new technology. Inclined agents are not committed to it, but they will buy it if they can afford it and see enough of them around or know someone who has one. Neutral consumer agents have no inclination to buy one at all; they will buy one if the price is right and there are many of them around. If neutral agents see enough of them around, there is a probability that some of them can be converted to an "inclined" agent. Percentages for these personality types in the consumer agent population are given above. But because those values are intended to represent buyer population attitudes toward vehicles with advanced engine technology, they are not appropriate for modeling the penetration of vans and SUVs into the light duty vehicle fleet. Vans and SUVs were introduced into the U. S. auto marketplace at a time when the baby boomers, a large fraction of the U. S. population, were beginning to have families. Market sales data indicate that consumers almost immediately "got it" regarding the utility of these vehicles, and they whole heartedly bought into them. Hence, for modeling SUV and van markets, we assumed that the committed-to-buy consumers are 50% of the population and the rest are inclined.
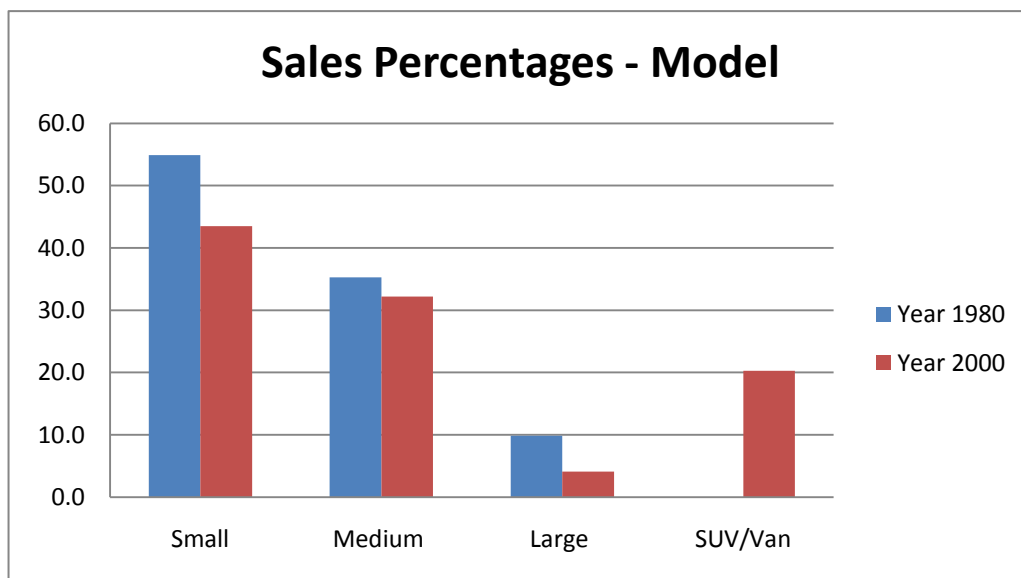

Figure 12: Model predicted sales of light duty vehicles

Using the fuel and vehicle price histories given above and the revised special feature purchasing propensities just discussed, we arrive at the vehicle sales penetrations of SUVs and vans given in Figs. 12 and 13. A comparison of the two figures reveals that model estimates of van and SUV sales penetration into the marketplace are in qualitative agreement with the sales record. While model sales penetration for vans and SUVs trend in the right direction, they do underestimate the actual penetration.
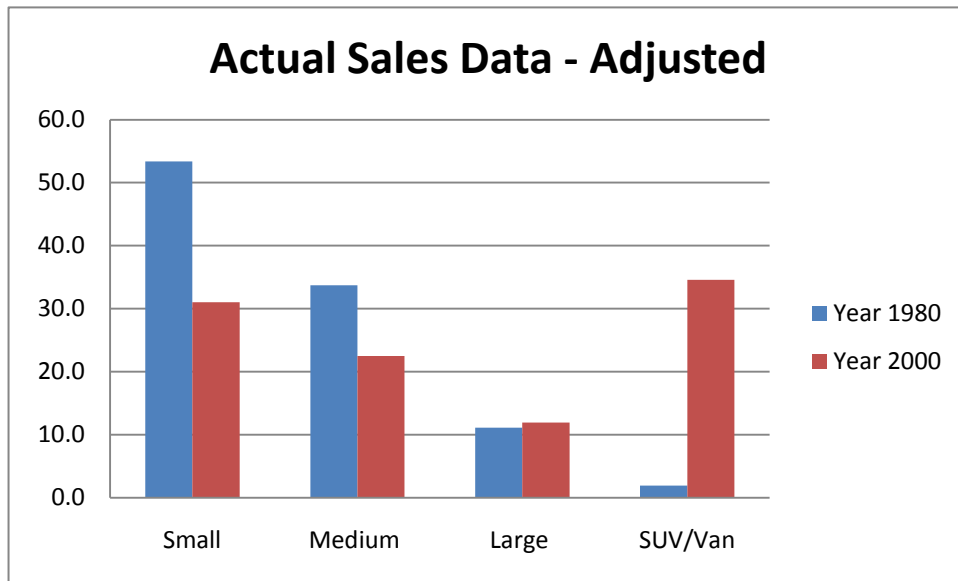

Figure 13: Actual light duty vehicle sales for the cited years; Sales percentages have been adjusted to exclude pickup trucks

There is another feature of these two figures that merits recognition. There is very good agreement between simulated and actual sales rates for the year 1980. Given that the simulation model randomly assigned vehicles to agents at model start up, during the conditioning cycles and subsequent cycle of simulation time the simulated marketplace more or less evolves to one in excellent agreement with observation. Nonetheless, because better correlation would be desirable for vans and SUVs, model revisions are underway to improve van and SUV penetration estimates.

Penetration of HEVs into the U. S. auto marketplace: The question as to whether the plug in variant of HEVs as they are currently configured can successfully penetrate the U. S. light duty auto marketplace is foremost on the minds of many policy makers. Hopefully, some insight into how PHEV marketplace penetration might transpire can be gained from the sales penetration record for HEVs and the application of the VAMMP model to that vehicle technology. What distinguishes both HEVs and PHEVs from others is that they are costly and, because they represent a new vehicle technology, they are

unknown to consumers. However, they do realize considerably better fuel economy than their conventional counterparts, and as such they can be perceived as a comparative better value than conventional vehicles. Nevertheless, consumers will be wary of rushing in to own one, at least in the near term. Though more familiar to consumers now, HEVs have not made a major headway into the auto marketplace, despite their presence in it for about a decade. Other than fuel economy, HEVs and PHEVs offer consumers less utility than vans and SUVs. It is well accepted that the early adopters of HEVs and PHEVs are motivated by either being one of the first to own such a technology or being environmentally oriented and as such wanting to use less petroleum.

A set of twenty runs of the VAMMP model shown in Fig. 14 represent an HEV scenario for penetration into the auto marketplace. The HEVs assumed for this set of runs are given in Table 1. All penetration curves represent the total HEV population in the fleet, including both new and used cars.
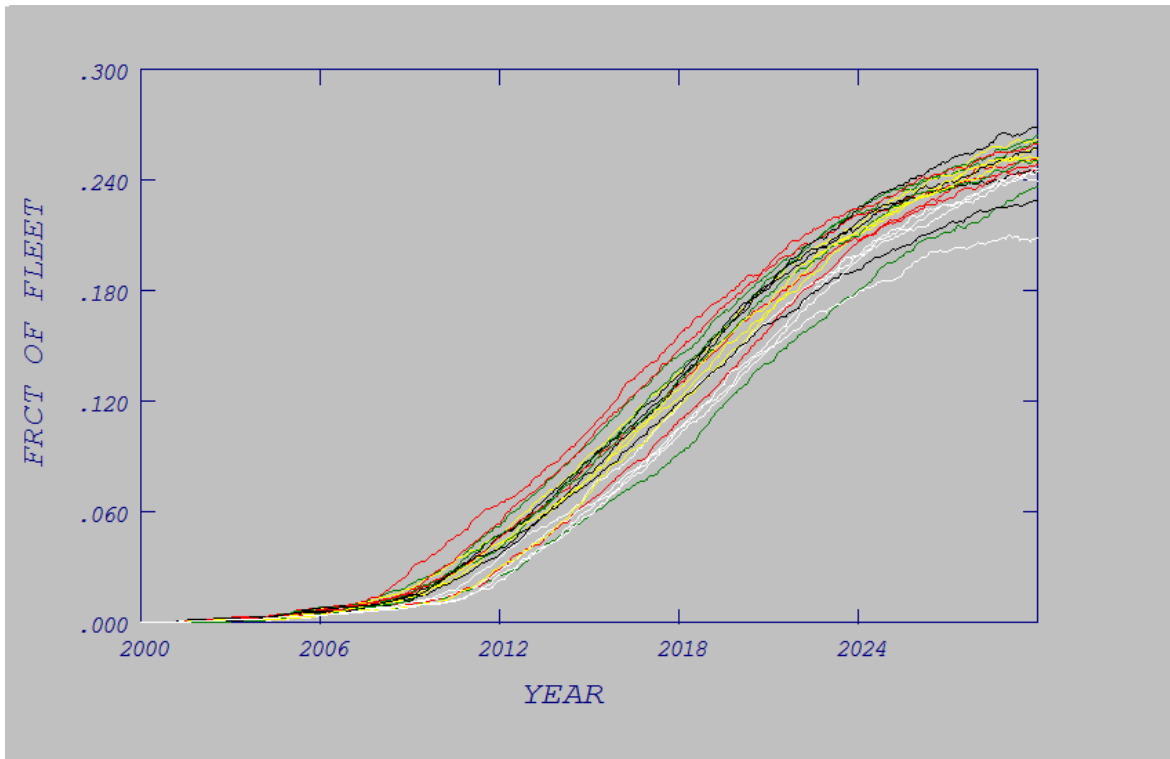

Figure 14: HEV penetration curve based on twenty runs of the simulation model

The figure shows considerable run to run variation, which is due to consumer agent diversity. The results from every run of an ABM represent the response of a specific instantiation of the system, which in our case is one of many distinct but similar automobile marketplaces. However, the modeler is simply not informed enough to know whether or not the modeled marketplace is sufficiently representative of the real one. Hence, it is customary in setting up such models to employ random numbers that are used to meaningfully represent the diversity of attributes and behaviors characteristic of most real systems and to run such models numerous times to establish a distribution of results. We typically use 20 runs for each

scenario and from them generate suitable statistics. For the example Fig. 14, the penetration level is 24.8% ±1.4%.

There are two sets of model parameters that influence vehicle penetration rates and levels: 1) ambient levels and 2) purchasing propensities. The purchasing propensities discussed in the Model Description section were used for the results shown in Fig. 14. We will explore this choice in a little more detail below.

The ambient level parameter set is comprised of two parameters. They are Level_1 and Level_2, which represent penetration fractions into the on-road vehicle fleet. Level_1 is the threshold level of a new technology into the fleet, after which an inclined consumer agent will add an HEV to his/her list of potential vehicles for purchase. Level_2 is the level where neutral agents see enough such vehicles around that they become converted to an inclined consumer agent. Finally, consumer agents can influence one another. For example, when it comes time to buy a car, they notice who among their friends and colleagues own a special feature vehicle. They could influence them to purchase an HEV. For Fig. 14, level_1 and level_2 were set to 1% (one in a hundred vehicles) and 2% (one in fifty), respectively. If we change these percentages to 2% and 5%, respectively, Fig. 15 results. The average and standard deviation for that set shown are: 17.4% penetration ± 3.5%. Clearly, lower ambient levels of penetration necessary to stimulate HEV uptake in the market lead to somewhat higher penetration levels sooner, with less variance and range of penetration at simulation conclusion.

There is a significantly different level of variance between the two sets of results shown in Figs. 14 and 15. Understanding the cause of the difference is of value. For example, a lower level of variance or uncertainty in a market penetration scenario would be useful to policy makers. The reason for the comparatively large variance shown in Fig. 15 is that the level of penetration required for inclined and neutral agents to change their behavior is too high. Regarding HEV penetration, this results in the marketplace being on the edge of success or failure and any statistical variation within the set of hypothetical communities can lead to widely varying results. On the other hand, when the threshold levels are lower, as is the case for the set in Fig. 14, successful penetration gets a stronger start at intermediate times resulting in a tighter distribution of penetration levels at the end of the simulation.
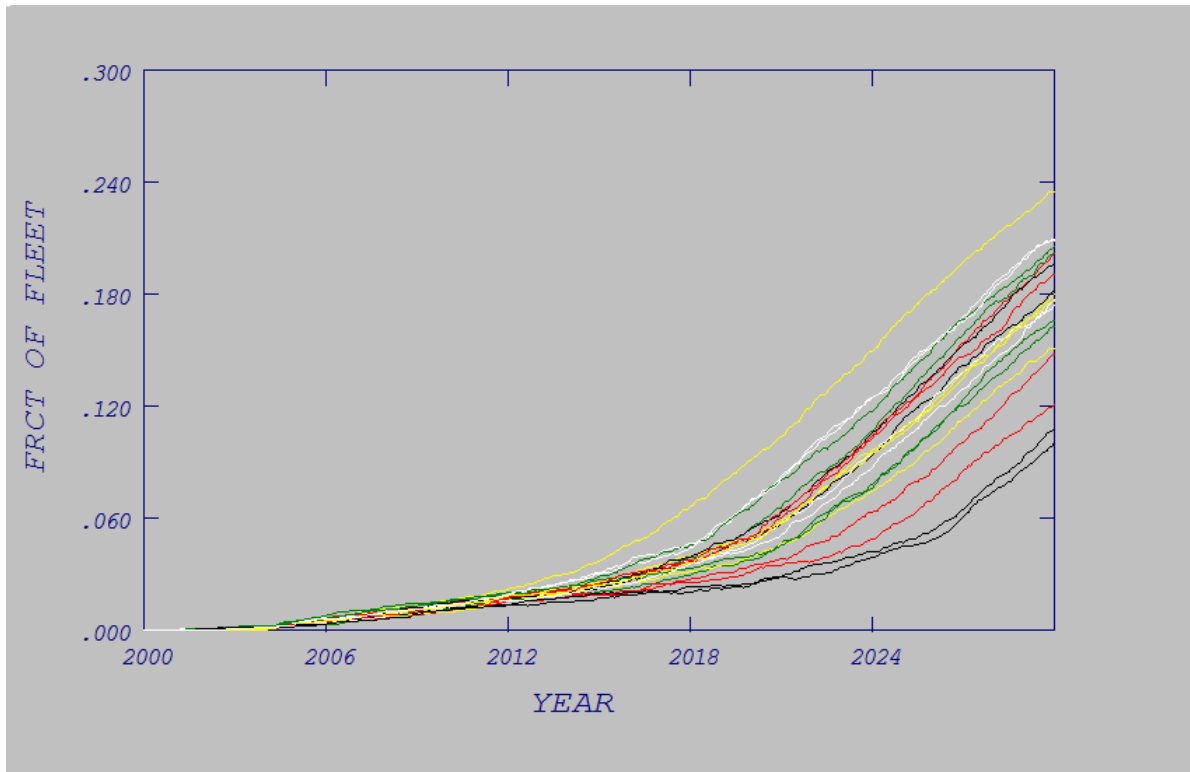
Figure 15: HEV fleet penetration for higher levels of penetration required to agents actions

When introduced into a closed system, a new technology introduced into the automobile marketplace is expected to displace some of the conventional vehicle fleet. This is shown in Fig. 16. When compared to the fleet model distribution at simulation start time (indicated by the dash marks), the introduction of HEVs (models 5, 10, and 15) has clearly reduced the percentages of some of the other vehicle models in the fleet.

On balance the simulation results shown in Figs. 14 and 15 are quite similar at short simulation time. In fact, this level of fleet penetration is very similar to what is seen in the actual marketplace for HEVs. This is seen in Fig. 17, where the actual sales record (henceforth denoted as the reference curve) is compared to the average penetration level for the set of curves in Fig. 15. Notice that at short times, the average curve is in reasonable accord with the reference. The major differences between the curves shown in Figs. 14 and 15 occur at intermediate and longer simulation times and not at shorter times.

As mentioned above, we have settled for the set of purchase propensities described in the Model Description section. The reason that we selected those values is that the initial penetration curve from the model is in reasonable agreement with the reference curve, as is evident in Fig. 17. However, if we had chosen larger values, the same level of agreement would not have been realized. In fact, if we had chosen the committed/inclined purchase propensity sets of (0.04,0.08) or (0.01, 0.10), the simulated initial penetration curve (for times up to 2008) would be at least twice that as the reference curve. These

alternative purchase propensity sets are suggested by current survey work [Curtin et al.]. However, for our modeling results, the original set is in better accord with the reference curve than the alternative sets. Hence, we choose that set. As the reader will see, this choice is important in the PHEV section, where 5 and 10 year sales and penetration percentage estimates are sought under conditions of different policy instruments enacted to enable vehicle market success.

We are tempted to attribute the difference between our choice of small committed and inclined consumer populations and the larger ones suggested by survey results to the fact that stated preference, elicited from surveys, is a much less reliable quantitative indicator of market trends than revealed preference, reflected in actual market transactions. But admittedly our model in its current form is a more qualitative to semi-quantitative tool, which might when further developed be in better accord with survey recommendations.
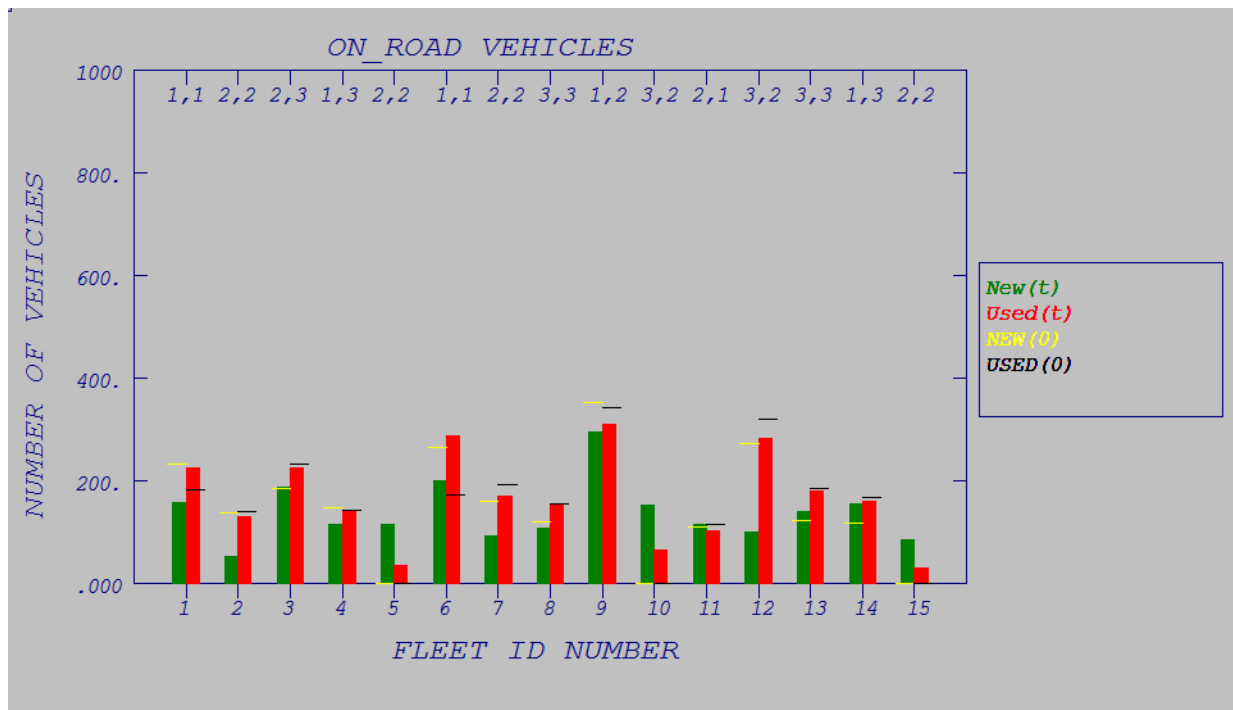

Figure 16: Changes in the vehicle model distribution in the vehicle fleet. (Yellow and black dashes denote values at simulation start; paired numbers at top denote size and performance of each model)

Another very important factor in the successful penetration of HEVs into the marketplace is tax breaks on their purchase. As seen in Table 1, the prices for HEVs are $3000 more than the prices of their conventional size and performance counterparts. The simulations shown thus far have all assumed that a $3000 dollar federal tax rebate for an HEV purchase is in place for the entire time of the simulations. If the tax rebate is rescinded, only a very small HEV fleet penetration on the order of 1% is realized and not

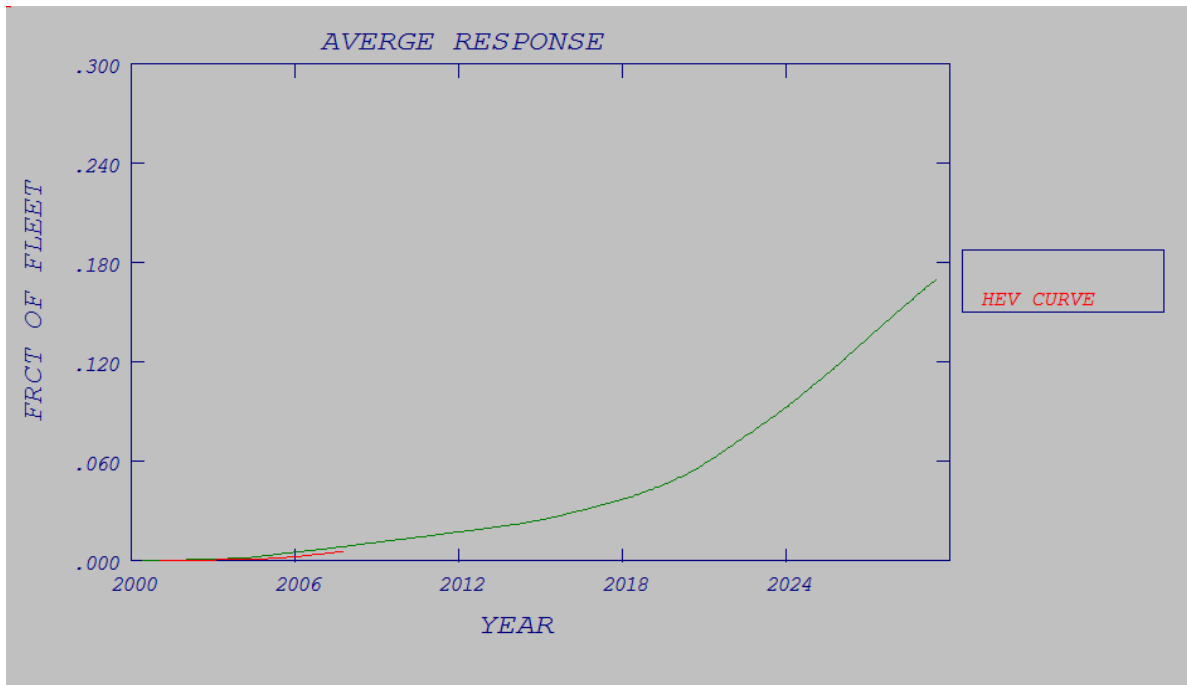the 10% to 24% as seen in Fig. 15. So the effective price of an HEV matters for success in the marketplace.

Figure 17: Comparison of an average ABM run for HEVs with actual HEV fleet penetration.

Penetration of PHEVs into the U. S. auto marketplace: As a result of the validation exercises, we conclude that the VAMMP model is sufficiently representative of the U. S. auto marketplace that it can be applied to estimating the penetration of PHEVs into the U. S. auto marketplace. This part of the study is to model specific policy initiatives and their influence on PHEV marketplace penetration. Unlike the previous section, we are also interested in near-term sales and fleet penetration behavior, more specifically at five and ten years out from the start of the simulation. Results at simulation end point are also discussed.

The VAMMP model is not intended to simulate the collective vehicle use and purchasing behaviors of a specific population of vehicle owners per se, but rather determine the distribution of collective behaviors corresponding to a distribution of vehicle owners. Such information can help establish the viability of various policy instruments intended to influence vehicle owner purchasing behavior. Examples of such information are the PHEV penetration curves shown in Fig. 18. These curves show considerable variation, especially approaching simulation termination, and are quite similar to what is reported above for HEVs (Fig. 15). We will return to this subject below. Again, all penetration curves represent the total PHEV population in the fleet, including both new and used cars. The curves displayed

either show or will ultimately show an S-shaped logistics-type form of the penetration curves, though none have to reach their asymptotic limit. This form indicates that the fractional rate of penetration is proportional to those agents who are inclined to purchase a PHEV but have yet to do so. As the remaining population of potential buyers is depleted, the rate of penetration decreases and approaches ultimately to zero.
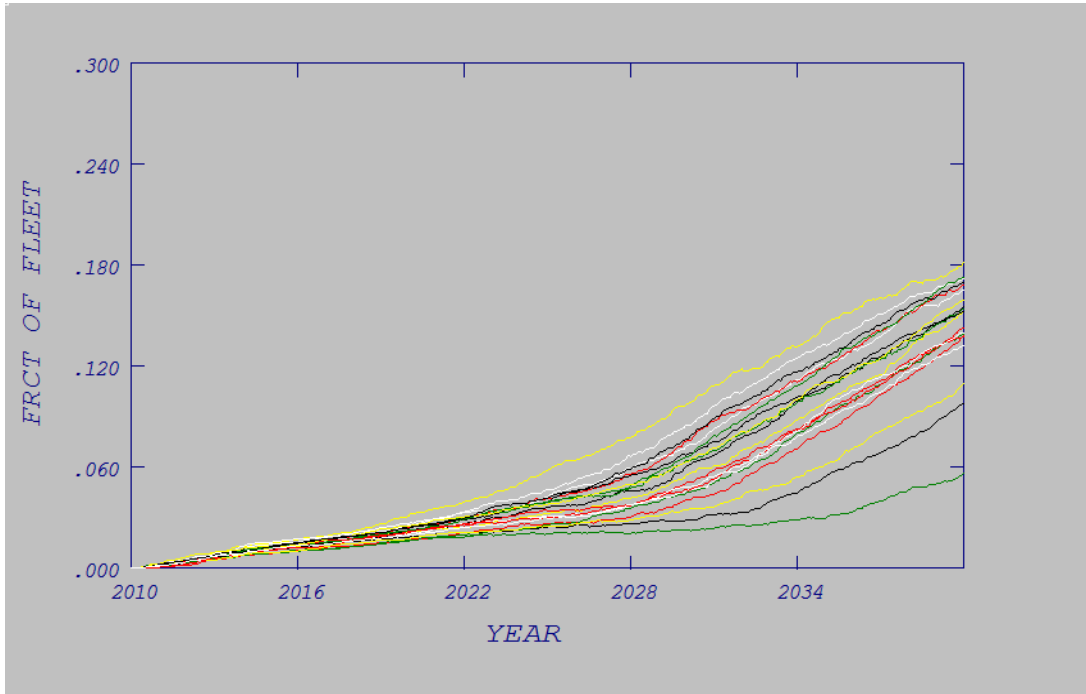

Figure 18: Penetration of PHEVs into the simulated market place; 20 runs; for full tax rebates, OEM subsidies and a tax sales tax break

All scenarios in the PHEV study start with the base case. The **base case** for the PHEV simulation study assumes that the current federal tax rebate program for PHEVs is in force. The purpose of that program is to encourage new car purchasers to buy a PHEV using a tax credit, which ranges between $2,500 and $7,500 and is computed as follows:

$$Tax\ credit\ =\ \$2,500 + 417 * (batt\_cap - 4),$$

where the units of 417 are in dollars per kilowatt-hour and the battery capacity is in kilowatt-hours. Based on this formula, the tax breaks are $2,780, $7,100, and $7,500 for PHEV-10s, PHEV-20s, and PHEV-40s, respectively. (The suffix numbers denote "all-electric range.") Of special interest are scenarios which explore the impact of additional policy options on PHEV market success when superposed on top of the base case. The two additional policy options explored are (1) government subsidies to OEMs of sufficient

magnitude to reduce vehicle sticker prices of PHEV-10s, PHEV-20s, and PHEV-40s to $1,500, $3,000 and $6,000, respectively, above their HEV counterparts and (2) sales tax exemptions.

The government vehicle subsidy schedule to cover the incremental cost of PHEVs to the consumer is:

- PHEV-10s: 100% up to 24 months, 67% up to 48 months, and 33% thereafter
- PHEV-20s: 100% up to 48 months and 67% thereafter
- PHEV-40s: 100% for all time

Sales tax is assumed to be 6%. The assumed fully accounted retail prices for the PHEVs, which include all OEM costs plus profit, are given in Table 1. The cost model used to estimate PHEV costs uses the Toyota Prius as a base case and computes incremental cost of a PHEV over its HEV counterpart based on engine power rating, battery size, and motor power rating [Filipi and Patil]. The HEV is assumed to cost $3,000 more than their conventional counterparts. The subsidies for the OEMs to price PHEV-10s, PHEV-20s, and PHEV-40s at $1,500, $3,000, and $6,000 over comparable HEVs are $2,300, $6,000 and $18,800, respectively.

In the first year of simulation time, a PHEV-10, PHEV-20, and PHEV-40 are introduced to the marketplace. The price of gasoline is $2 per gallon at the start of all simulations; for some scenarios, the price rises in steps to $4 per gallon by simulation termination. Details of those scenarios are given below. In the cases where they do vary, it is assumed that a $1 per gallon increase occurs at 20 months and 100 months after the start of the simulation. As stated above, electricity prices (9.5¢/kWh) are constant for all scenarios, and only home charging is available. All simulations run for 360 cycles or 30 years of simulation time (i.e., each cycle is one month).

Table 3: Fuel economies (mpg) for charge sustaining (CS) and charge depleting (CD) modes of operation

Vehicle	CS-cty	CS-Hwy	CD-cty	CD-Hwy	Vehicle Class
PHEV-10	69.8	72	237	228	C class
PHEV-20	55.8	61.5	205	182	Small SUV
PHEV-40	60.7	72.3	251	218	C class

Fuel economies used in the model for the PHEVs are determined as described above [Filipi and Patil] for vehicle energy consumption over three drive cycles: Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Efficiency Test (HYFET), and a "naturalistic" drive cycle. Though the latter of the three is presumably more representative of actual driving behavior, we used fuel economy values for the first two drive cycles because all vehicles on the road today have had their fuel economies evaluated using them. Those fuel economies along with vehicle class are given in Table 3. Though no fuel economy modeling was done directly for the small SUV-PHEV example, its fuel economy was estimated based on the ratio of a comparable HEV and the reference C-class vehicle. Fuel economies listed for the charge-depleting (CD) mode are gasoline equivalent values.

To facilitate clear representation of the scenarios covered, we have adopted the following three-component nomenclature: A-B-C. The first character represents the price of gasoline at simulation termination, the second represents "yes" or "no" on a manufacturer subsidy, and the third represents "yes" or "no" on a sales tax exemption. For example, 4-Y-Y denotes $4 per gallon gasoline at simulation termination, a manufacturer subsidy in place, and a sales tax exemption is operative. The curves shown in Fig. 18 represent a 4-Y-Y.
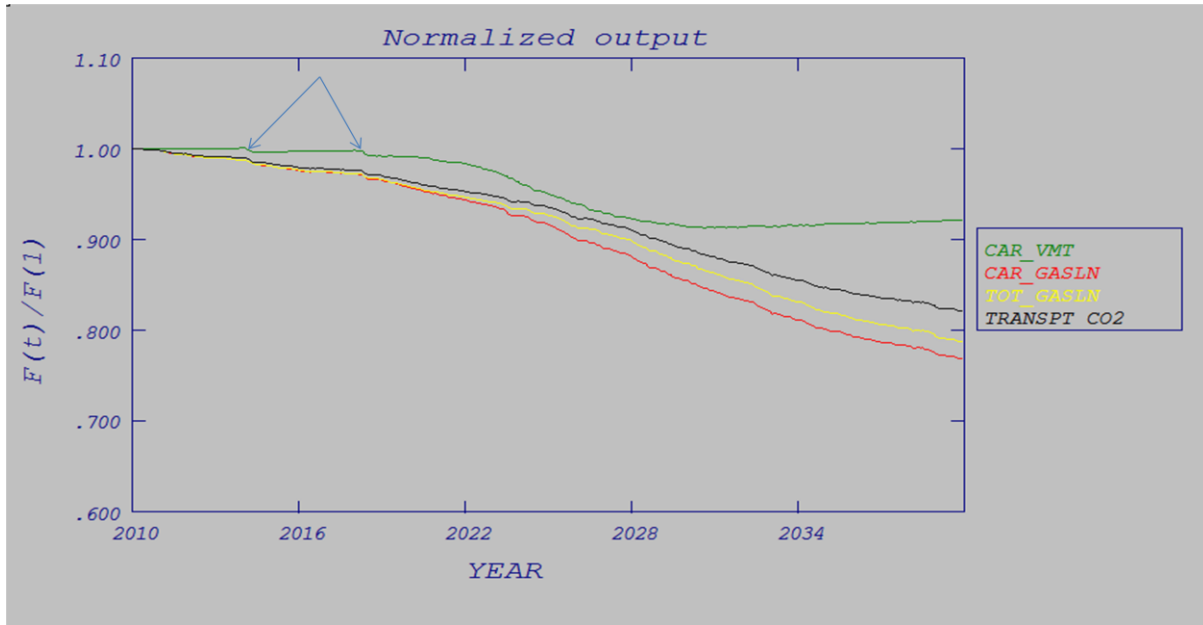

Figure 19: *Fleet parameters as a function of time; arrows denote times of gasoline price changes*

Two reasons for the government to support the penetration of PHEVs into the vehicle marketplace are to (1) reduce U.S. petroleum consumption and (2) reduce fossil carbon emissions. Figure 19 shows the response of four aggregate fleet parameters including transportation CO_2 as a function of time to the introduction of PHEVs to the marketplace under conditions of current tax rebates for consumers, subsidies to the OEMs, and gasoline price increases. This scenario is denoted 4-Y-N. Notice that "vehicle miles traveled" (VMT), car gasoline, total gasoline, and carbon dioxide (CO_2) metrics all decrease, though VMT levels out.

The primary reason for VMT reduction and leveling out is due to a limited (5%) reduction in vehicle ownership (VO). Also, consumers are moving to more fuel-efficient cars allowing them to drive their desired distances at a cost consistent with the period prior to gasoline price increases. The carbon-based metrics (car gasoline, total gasoline [cars plus buses], and transport CO_2) all decrease by about 20% due to both reduced VMT and better overall fuel economy. Clearly, the penetration of PHEVs into our

simulated marketplace demonstrates an appreciable impact on carbon emissions and petroleum consumption, though the percentages just cited apply to the year 2040.

Figure 20 presents a more detailed view of the shifts in the vehicle ownership distribution over the course of the simulation for scenario 4-Y-N. The dash marks in the figure show the ownership distribution at the simulation start; the bars represent it at simulation conclusion. It is clear that many consumers are opting for the cheapest, most fuel-efficient vehicles, namely models 1, 6, and 9 as well as the PHEV models 5, 10, and 15. Overall, ownership of larger, higher-performing, less fuel-efficient vehicles is down, relative to simulation start time.
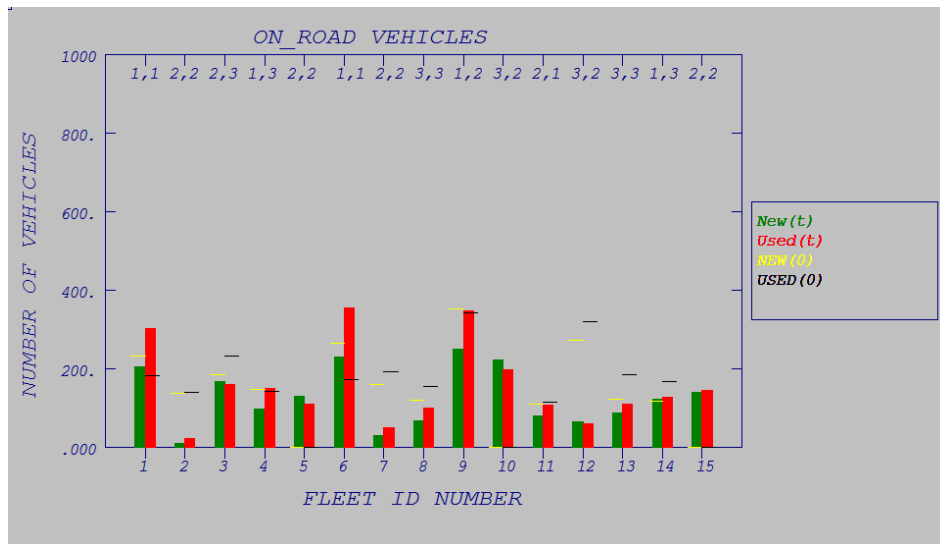

Figure 20: *Fleet vehicle model ownership by vehicle ID number; numbers at top denote size and performance; dashes (reference marks) denote ownership levels at simulation start time.*

The central focus in the PHEV section of this report is to determine the degree of PHEV fleet and sales penetration for the years of 2015 and 2020, given the various market-incentivizing scenarios being covered. It is for this reason that the purchasing propensity set discussed above is used; otherwise overestimated sales and fleet penetration results would likely be calculated for those years. This, of course, assumes that the HEV fleet penetration history is representative of the PHEV case. Because of the similarity of the two vehicle types, HEV vs. PHEV, we feel that this is a justifiable assumption. We also opt for the original set of ambient level parameters. Otherwise, we may overestimate fleet and sales penetration, especially at longer times but possibly even at intermediate times. This choice is a judgment call; we wish to be conservative in our estimates. Unfortunately, due to a lack of suitable market penetration data for advanced technology vehicles, especially HEVs, we are unable to better estimate values to key market uptake parameters.

Results from model runs and analyses of those scenarios are presented in both Table 4 and Figure 20. It is clear from the figures that both fleet penetration and sales penetration are feeble at best based solely on base case circumstances, i.e. 2-N-N and 4-N-N. Even a sales tax exemption added onto the base case has comparatively little impact. This is not surprising, as PHEVs cost considerably more than their conventional counterparts – and price is important.

Table 4: Average Fleet penetration and sales percentage results.

Scenario	% Fleet Penetration			% Sales		
	2015	2020	2040	2015	2020	2040
4-N-N	0.3	0.5	0.7	0.7	0.7	0.9
4-Y-N	1.0	1.8	10.5	1.8	2.6	15.5
4-Y-Y	1.2	2.2	12.7	2.9	3.7	16.7
4-N-Y	0.3	0.6	1.0	0.8	0.8	1.0
2-N-N	0.3	0.7	1.1	0.9	0.9	1.2
2-Y-N	0.9	1.7	10.4	2.3	2.1	16.2
2-Y-Y	1.3	2.5	19.8	3.1	5.0	24.5
2-N-Y	0.3	0.7	1.1	0.9	1.0	1.2

When an OEM subsidy is added to the base case (4-Y-N and 2-Y-N), a considerably greater market uptake of PHEVs occurs with an attendant increased penetration of those vehicles into the fleet. Fleet penetration ranges from 1% to 1.8%, depending on the year. Further, our market simulation suggests that PHEV sales could be as much as 2% of annual vehicle sales by 2015 and 3% by 2020. Though this is clearly an improvement, those vehicles do comprise 20% of vehicle offerings in our simulations and as such are still undersold at that point.

Another feature seen in Figure 20 is that scenarios with sales tax exemptions (4-Y-Y and 2-Y-Y) when added to the base case plus OEM subsidies demonstrate noticeably larger sales and penetration percentages. Remember, this exemption was found to have little impact when acting alone on the base case. However, for these scenarios, the added sales tax exemption makes PHEVs even more closely competitive with their conventional counterparts. As discussed earlier, our simulations show that large increases in gasoline prices, whether induced by higher taxes or higher petroleum costs, result in consumers moving toward more fuel-efficient vehicles and a few agents being forced out of vehicle ownership. However, the trend toward purchasing more fuel efficient vehicles is not observed for PHEVs. In fact, the market penetration level at 2040 is 19.8% ± 3.4% for scenario 2-Y-Y and 12.7% ± 4.5% for 4-Y-Y. The reason for this is that unlike inexpensive, fuel efficient, conventional vehicles, PHEVs range from cost parity to more expensive to own and operate than their conventional counterparts at a time when some consumer agents need to down-size to more fuel efficient vehicles. This results in PHEV sales being greater in periods of low to intermediate gasoline prices and less so at higher prices.
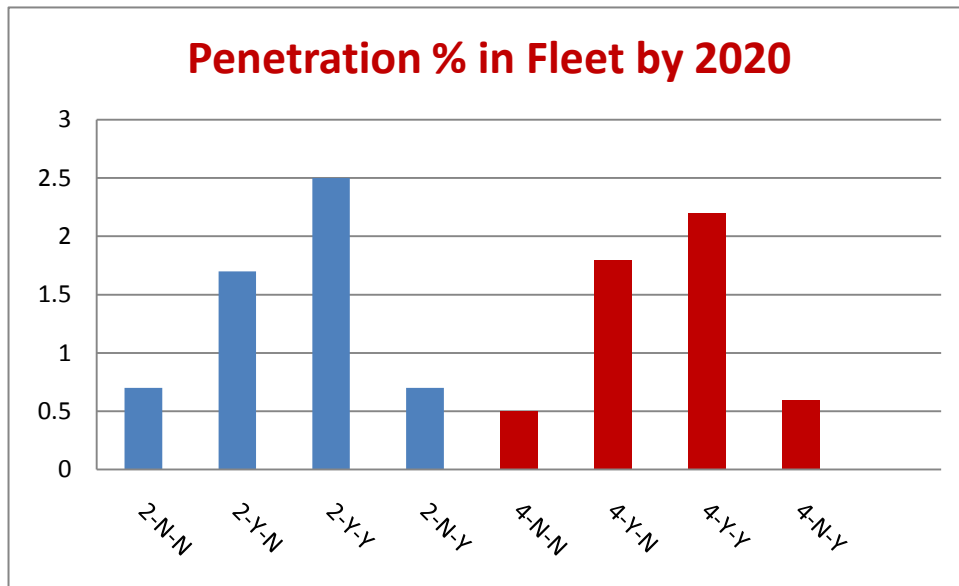
Figure 20: Fleet penetration of PHEV by 2020.

It is conceded that for successful PHEV market penetration, some series of government incentives are necessary. But how is this going to be paid for? Some suggest increasing the federal gasoline tax. We have explored this option and results are presented in Table 5. Fund balances in million dollars per thousand registered vehicles are included for the years 2015 and 2020.

Table 5: PHEV Incentives Fund including gasoline tax revenue.

Gasoline Tax Increase (per gallon)	PHEV Fund Balance per 1000 Registered Vehicles	
Year	2015	2020
4¢	$-0.01M	$0.01M
5¢	$0.02M	$0.04M
8¢	$0.16M	$0.33M

Discounting has not been included in the results of Table 5. It is clear from the table that a 4¢ to 5¢ per gallon tax increase could cover the cost of government incentives (tax rebates and subsidies) at least up to 2020.

Figure 21 shows a comparison between a simulated PHEV fleet penetration curve vs. the actual penetration curve for HEVs into the U.S. light duty fleet. Given that both PHEVs and HEVs are advanced vehicle technologies, the decade-long sales record for the latter is a reasonable basis of comparison when attempting to understand the market potential of its yet-to-be-introduced "cousins," the PHEVs. While the record thus far for HEVs is still quite limited, the two penetration curves appear to be in reasonable

accord, though not as good as seen in Fig. 17. We have no explanation for this other than our consumer agents are apparently finding PHEVs somewhat more appealing than HEVs.
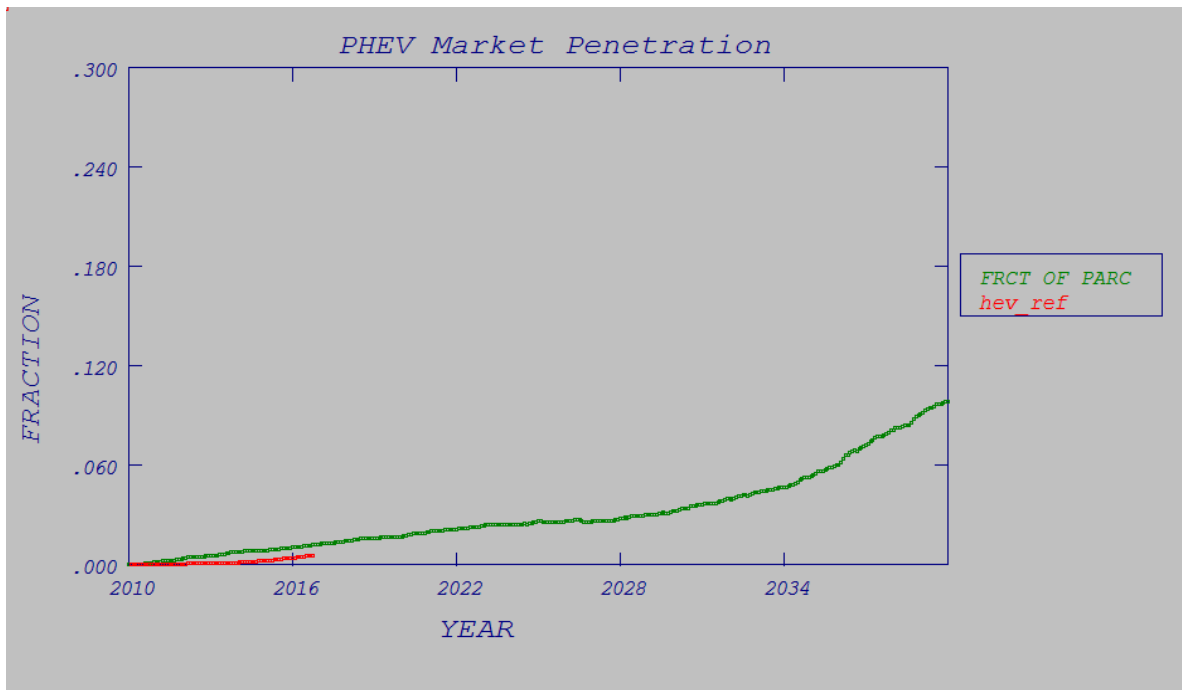

Figure 21: Penetration curves PHEV case vs. HEV history

So far in this section, we have focused on the short (2015) to intermediate (2020) term after the introduction of PHEVs to the marketplace early in the year 2010. As our runs extend for 30 years simulation time, results have been collected for 2040 (see Table 4). However, as we pointed out earlier, there is considerable variation in the results, with coefficients of variation typically ranging up to 30 to 40. One of the primary reasons for this is our choice of the ambient level parameters discussed above. If we change them from (0.02, 0.05) to (0.01, 0.02) and leave purchasing propensities the same, the penetration level at 2040 is 20.4% ± 1.2% as opposed to 12.7% ± 4.5% for the original ambient level set. A comparison of this distribution (not shown) with the one in Fig. 18 is very similar to the comparison of Figs. 14 and 15. Clearly, the new ambient level set results in a tighter distribution. Nonetheless, given the lack of good calibration data, we wish our estimates to be conservation and not overestimate sales and fleet penetration level.

The results presented above are contingent on the assumptions used in the model. One critical assumption is that the incremental price difference between HEVs and their conventional counterparts is around $3,000. A recent comparison of the prices of HEVs vs. conventional crossover SUVs published in the popular media showed incremental prices ranging from $4,000 to $9,000. However, because there is some ambiguity in comparing so-called "comparable" vehicles (especially HEVs and their conventional

counterparts) and given the latitude that car producers have in adding and subtracting various option packages, the $3,000 price differential was used in our study nonetheless. Further, at a PHEV workshop held in January 2009 in Ann Arbor, Michigan, a consensus was reached that this value is realistic and should be used. Nevertheless, if we assume a $6,000 price differential in the model, then scenario 4-Y-N shows a fleet penetration at ten years of around 0.8% instead of the 2% value cited in Table 5. Clearly, there is an effect, so financial incentives per PHEV sufficient to make them cost competitive with conventional vehicles is essential for market penetration success.

The status of the VAMMP model development is intermediate. As it is currently configured, it is consumer focused and yields qualitative to semi-quantitative results. It is structured to accommodate government, OEM, and fuel producer actions. At this time, the primary merchant feature is the "used cars dealer" using supply and demand for used cars to adjust their prices every cycle. Overall, the model is informative and yields insights into market processes. However, it is in its "adolescence" and much can be done to improve it, especially regarding its potential to provide semi-quantitative to quantitative results. A few areas for expansion include OEM agents reading the market and changing product strategy and offering. Another area is to allow supply constraints to influence OEM production over time. Permitting OEMs to alter the prices of their new cars endogenously is another useful addition. Further, energy providers (gasoline vs. electricity) should be allowed to compete with one another for sales.

Finally, there is a fundamental process that governs vehicle fleet and sales penetration; that process is vehicle turnover rate determined by consumers' vehicle purchasing activities. The rate ranges between 3 to 10 years, depending on the buyer and whether the vehicle being replaced was purchased as new or used. It is for this reason that truly significant penetration of such vehicles, even if successful, will take on the order of decades.

So policy makers and OEMs might want to see a rapid uptake of new offerings to the market, but it can't happen any faster than consumers turn their vehicles over. And it will not easy to get them to do otherwise.

Conclusions

An agent based simulation has been presented, which characterizes the penetration of new vehicle technologies into the U. S. auto marketplace. The primary focus of this study is to characterize the penetration of PHEVs into the U. S. auto marketplace. The simulation tool, named the Virtual AutoMotive MarketPlace (VAMMP) model, is a dynamic model that includes four classes of decisions makers: consumers, government, vehicle dealers (and OEMs), and energy suppliers. The four classes of

decision makers include auto providers (three vehicle manufacturers and one used car dealer), one government agent, two fuel providers (gasoline and electricity), and numerous consumer agents, typically set to five thousand but can be any arbitrary number. In the model, agents have the choice of nominally 12 different vehicle modes, new and used, though when a new technology is introduced there are 15 models. These vehicles come in three size and performance levels each, have city and highway fuel economies and cover a range of costs. Used car prices are market driven and range from 30% to 70% of new car prices. Consumer agents have incomes, work and home addresses, budgets, and vehicle preferences. They strive to stay within their transportation budgets, and to do so will adjust miles driven and the car purchased when it comes time for them to replace their existing vehicle. Gasoline price increases can influence what cars they purchase.

A series of validation exercises were described. These exercise demonstrated that the model demonstrate agent behavior consistent with actual collective consumer behavior. For example, in the absence of any market stimulations (new vehicles added, gasoline price change), the fleet vehicle distribution stays essential unchanged within a percent or two fluctuation, but never static. When it comes to consumer agent driving behavior, budget is "king"; all other considerations are secondary, though still important. The agents tend to buy vehicles that are priced consistent with vehicle owner income. Another validation exercise is the response to a gasoline shock. When such a shock appears during a simulation, consumer agents reduce their driving if the extra cost of gasoline takes the agent over budget. However, they like their miles and try to maintain it. If a gasoline shock takes them over budget, upon buying their next vehicle, they choose one that they can afford and allow them to drive their desired miles (commute, errand, and long trip). Hence, a rebound affect is observed in the fuel consumption history for the run. For a quantitative assessment of the impact of gasoline price on the sales of various vehicle models, elasticity coefficients were determined. They distinctly demonstrated an increasing trend with increasing metro-highway fuel economy.

Another validation exercise is agent vehicle choice when one of the potential vehicles for purchase is over or under priced. When an OEM reduces the price of one of his cars and another OEM who has a car in the same segment does follow, the market will shift to the less expensive , resulting in a much reduced market share for the OEM that did not respond appropriately to a competitor action. As another validation test, the model was applied to the case of vans and SUVs penetrating the U. S. auto marketplace starting in the mid 1980s. Using vehicle price history and fuel price history, the VAMMP model demonstrated significant penetration of these vehicles into the market and fleet and in good qualitative agreement with the record.

The final validation exercise for VAMMP model was characterizing the vehicle fleet penetration history of HEVs. It is found that the modeled penetration curve is in good agreement with the market record for HEVs, albeit at this time rather short. This exercise was also a good calibration task for the model in that it permitted determining key consumer agent purchasing factors, such as purchasing propensities and ambient level. These penetrations curves demonstrate the classic S-shaped logistic type curve, indicating that the relative rate of penetration is proportional to those agents who are inclined to purchase a HEV but have yet to do so. This is a common process that one often sees in market penetration studies.

Finally, the model was applied to estimating the penetration of PHEVs into the U. S. auto marketplace. The results of the agent-based modeling study of PHEV penetration into the U.S. auto marketplace show that tax rebates, PHEV subsidies, and sales tax exemptions have a significant impact on PHEV penetration levels. Our simulation results show that a suitably incentivized auto marketplace can facilitate PHEV penetration levels into the U.S. automobile fleet. More specific results are as follows:

- By 2015, sales could reach 2 – 3 percent with fleet penetration of around 1%.
- By 2020, sales could reach around 4 – 5 percent with fleet penetration a little more than 2%.
- Without subsidies, the current policy case would result in a fleet penetration level of less than 1% in ten years.
- Subsidies are critical; sales tax exemptions can help if applied to scenarios where OEM subsidies are in place.

Because the individual vehicle replacement rate is a limiting factor in any market turnover scenario, it will take time to turn over the fleet even if new vehicle technologies have marketplace acceptance. A gasoline tax increase of about 5¢ per gallon would support government funding to incentivize PHEV sales. Finally, a PHEV fleet penetration of around 18% would reduce gasoline consumption by over 20% and decrease fossil carbon emissions by about the same amount.

Finally, the VAMMP model has been demonstrated to characterize at least qualitatively the automotive marketplace. However, more calibration is needed. The model could be greatly expanded to include other dynamic factors, such as OEM competition, fuel producer competition, OEMs behaving strategically, and others. At this time, the model provides qualitative to semi-quantitative results and could be eventually upgrade to provide semi-quantitative to quantitative result.

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