THE FUTURE DEMAND FOR ALTERNATIVE FUEL PASSENGER VEHICLES: A DIFFUSION OF INNOVATION APPROACH

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1 INTRODUCTION

The United States is heavily and increasingly dependent on foreign oil. The net importation of oil accounted for 21.5% (3.16 million barrels net importation per day) of the U.S. energy use in 1970, and steadily increased to 55.5% (10.90 million barrels net importation per day) in 2001. Among all sectors, transportation constituted more than two-thirds of energy consumption in the U.S. in 2001, of which petroleum accounted for an overwhelming proportion (96.9%) of energy demand (Davis and Diegel, 2002). The continued growth in the amount of imported oil required to meet our demand for petroleum products threatens national and economic security, and is not sustainable in the long term. Accordingly, the U.S. government has been adopting a wide range of policies to reduce energy consumption in the transportation sector since the energy crisis of 1973, such as trying to reduce individuals' dependence on personal vehicles, and promoting higher average vehicle fuel economies. However, policies to change individuals' travel behavior have been of limited effectiveness mainly because of the gap between policy assumptions and individuals' actual desires and constraints (Salomon and Mokhtarian, 1997), and overall fuel economy has been declining since 1988, due to the increasing share of light-duty trucks (including minivans and pickup trucks as well as sport utility vehicles (SUVs)) in the passenger vehicle fleet (EPA, 2001).

Global warming is another major worldwide concern associated with petroleum consumption. The surface temperature of the earth has risen by 0.6 degrees Celsius since the late 19th century (IPCC, 2001). Carbon dioxide (CO_2), the main greenhouse gas (GHG), greatly contributes to the climate change. The U.S. is the largest emitter of CO_2 in the world, accounting for about 23% of the world's CO_2 emissions (compared to 4.6% of its population (Census Bureau, 2002) but 32.5% of the global total gross domestic product, or GDP (World Bank, 2002)). In 2000, the transportation sector accounted for 33% of the U.S. total CO_2 emissions from fossil energy consumption (Davis and Diegel, 2002). Replacing gasoline-based vehicles with alternative fuel vehicles (AFVs) is expected to significantly reduce CO_2 emissions from the transportation sector. Further, AFVs offer tailpipe emission benefits, especially with respect to ozone-forming pollutants such as carbon monoxide (CO) and nitrogen oxides (NO_x). Compared to a reformulated gasoline vehicle, a compressed natural gas (CNG) vehicle reduces approximately 60-90% of smog producing gases, and a liquefied petroleum gas (LPG) vehicle eliminates about 30-90% of CO (AFDC, undated-a and undated-b).

Mainly motivated by these concerns regarding petroleum consumption, climate change, and mobile source emissions, the Energy Policy Act (EPACT) was signed into law in 1992. Substituting alternative fuels for petroleum products in light-duty vehicles, encouraged by EPACT92, is promising to lower the amount of petroleum used for transportation, and thus reduce the nation's dependence on imported oil and conserve limited, non-renewable resources for future generations. Accordingly, alternative fuel vehicles (AFVs) have been appealing transportation technologies since at least 1990. The public and private sectors have invested billions of dollars into the development of AFVs. At this time, a few types of AFVs are on the road in the U.S., and some demonstration plans for AFVs are in progress. These vehicles are potential substitutes for current gasoline vehicles, and may account for a considerable share of the automobile market in the future. Conversely, it is also possible that some types of AFVs will die out since they fail to meet the requirements of potential consumers and hence do not achieve sufficient market share to be viable.

The EPACT92 established two goals: making alternative fuels replace at least 10% of petroleum fuels used in the transportation sector in 2000 and at least 30% in 2030. The act required that federal and state agencies as well as alternative fuel providers must purchase some specified proportion of AFVs in their new vehicles acquisition, establishing an innovator leadership and encouraging the public to purchase AFVs. However, "several fleet managers and representatives of the automobile industry acknowledge it is unlikely that usage of alternative fuel vehicles by these fleets will convince the general public to buy them" (GAO, 2000, p. 19). Accordingly, the amount of alternative fuel used for transportation accounted for only 0.2% of total transportation fuel consumption in 2000. That is, the goal of EPACT92 is, to date, far from being achieved. Sperling and Ogden (2004) pointed out that the market failure of AFVs is largely due to two reasons: they do not provide personal benefits to consumers and their social benefits are exaggerated. The General Accounting Office (GAO) concluded that "the goals in the act for fuel replacement are not being met principally because alternative fuel vehicles have significant economic disadvantages compared to conventional gasoline vehicles. Fundamental economic impediments — such as the relatively low price of gasoline, the lack of refueling stations for alternative fuels, and the additional cost to purchase these vehicles — explain much of why both mandated fleets and the general public are disinclined to acquire alternative fuel vehicles and use alternative fuels" (GAO, 2000, p. 4). In addition to these obstacles, the extent of AFVs' penetration in the market depends on a variety of endogenous and exogenous factors, such as their performance, their benefits and limitations, consumer acceptances, the regulatory environment, and so on (Leiby and Rubin, 2001; Schulte, et al, 2004; Spitzley, et al, 2000;). Therefore, it is not easy to forecast the market penetration of various AFVs.

Yet, the forecasts of AFVs' markets are essential to evaluating their potential contributions to the reduction of energy consumption and emissions in the transportation sector. The assumed effects of various AFV regulations on the demand for low emission light-duty passenger vehicles are incorporated into EMFAC 2001, a powerful emission-modeling tool for quantification of pollutants from on-road sources (available at http://www.arb.ca.gov/msei/on-road/previous_version.htm#EMFAC2001). As an example, EMFAC 2001 assumes that advanced technology-partial zero emission vehicles (AT-PZEVs) account for 0.9% of 2003 model year vehicles, and will increase to 12.9% in 2020. For model year 2004, the Honda Civic GX (CNG) and Hybrid and Toyota Prius were classified as AT-PZEVs (CARB, 2004). Other AFVs have the potential to be AT-PZEVs. It is important that these assumed implementation schedules be accurate since they directly affect the outcomes of the emission model. Thus, building models that forecast the demand for AFVs can be useful in evaluating and/or updating these assumed implementation schedules.

The transitional alternative fuel vehicle (TAFV) model proposed by Leiby and Rubin (2001) simulates market outcomes for the use and cost of alternative fuels and vehicles over the timeline of 1996-2010. The model corrected one of the major assumptions of previous studies — that the demand for AFVs is based on mature markets. Specifically, they incorporated transitional impediments such as limited refueling infrastructures and production scale in the model. In addition, they considered prices and choices for fuels and vehicles to be endogenous variables. The TAFV model accounts for dynamic linkages between investments and vehicle and fuel production capacity, tracks vehicle stock evolution, and represents the effects of increasing scale and expanding retail fuel availability on the effective costs to consumers. Various policy alternatives are evaluated, including fleet vehicle purchase mandates, fuel subsidies, and tax incentives for low greenhouse gas emitting fuels. They concluded that it may be difficult for the alternative vehicle and fuel markets to get started in the absence of any policy initiatives, and EPACT 2010 replacement goals are unlikely to be achieved or approached without major new government support.

The research conducted by Leiby and Rubin is valuable since it incorporates various AFV-specific variables in their models and demonstrates the complex picture of AFV market development. The limited scope of the present study necessitates a more primitive approach, but one which we also believe to be valuable for its relative simplicity and reduced input requirements compared to those of the TAFV model. The approach taken by this study is to apply diffusion models to estimate the aggregate demand for AFVs under different scenarios based on current and assumed conditions for the factors listed above, and to evaluate the influence of various factors and policies on the demand. In this study, we focus on forecasting the U.S. demand for alternative fuel passenger vehicles, including light-duty automobiles and light-duty trucks, with a timeframe from 2005 to 2025.

The organization of this report is as follows. The next section reviews the literature on automobile demand models and diffusion models, which are employed to forecast the demand for AFVs. Section 3 provides a brief overview of the current status (including limitations) of the main AFV technologies, and the future outlook. Section 4 describes the data and variables used in this study. Section 5 presents modeling procedures and model results. Section 6 analyzes several scenarios based on the model outcomes and assumed conditions. The final section draws some conclusions about the development of AFVs.

2 LITERATURE REVIEW

In this chapter, we present a review of the literature on two main topics: automobile demand models and diffusion models. The first topic focuses on the factors found to be important in forecasting the demand for automobiles, and thus will suggest the factors we need to consider for the models developed in this study. The second topic reviews the fundamental concepts, development, and application of diffusion models, which is the type of model employed in this study.

2.1 Automobile Demand Models

Many studies focusing on automobile demand or ownership have been conducted since 1940. The models used in these studies can be classified into two categories: disaggregate and aggregate. Generally, disaggregate models consider the household the analysis unit and utilize random utility theory to predict household vehicle choice, while aggregate models are used to forecast a regional or national automobile demand or ownership rate. In the next section, we review some disaggregate studies of conventional vehicle choice and AFV choice; aggregate studies are reviewed in the following section.

2.1.1 Disaggregate Studies

Most published disaggregate studies of conventional vehicle choice concentrate on vehicle attributes, household and primary driver characteristics, and brand loyalty. On the other hand, most studies of AFV choice not only focus on vehicle attributes and household characteristics, but also include some variables that are not applicable for conventional vehicles but which could greatly affect AFV choice, such as availability of fuel stations, refueling time, maintenance cost, and so on. Further, most AFV choice models are based on stated preference surveys since some AFVs (or some of their attributes) analyzed in these models were not available on the retail market, at least at the time that the surveys were conducted. This review of the disaggregate demand models for conventional vehicles and AFVs provides insight into the relationship between household vehicle choice and various explanatory variables.

We first review nine studies, spanning two decades, involving conventional vehicle choice models. All these papers utilized discrete choice models such as multinomial logit and nested logit to analyze conventional vehicle choice. Table 1 summarizes the significant results of these models. As indicated in Table 1, conventional vehicle choice models can be further classified into two groups: vehicle-purchasing models (four of the nine studies reviewed) or vehicle-holding models, depending on whether the model relates only to recently-purchased or to any owned vehicles, respectively. Leased vehicles are sometimes included in both models. Different from vehicle-purchasing models, vehicle-holding models often contain additional variables relating to used vehicles such as vehicle age, scrappage rate, and transaction cost (Choo and Mokhtarian, 2004). Both the results of vehicle-purchasing models and those of vehicle-holding models can increase our insight into vehicle choice.

The overview of these models suggests several common effects on vehicle choice. First, not surprisingly, a higher purchase price decreases the probability of choosing a vehicle in eight of the nine models studied. Second, operating cost is significantly negative in five models (Kitamura, et al. (2002) did not include this variable). Third, brand-loyalty-related variables are significant in all five models (Berkovec, 1985; Brownstone, et al., 2000; Hocherman, et al., 1983; Mannering and Winston, 1985; Mannering, et al., 2002) that included them as explanatory variables. Finally, number of seats, luggage space, engine size and horsepower frequently appear in these models, meaning that people prefer capacious and powerful vehicles. However, it is difficult to make general conclusions on vehicle type choice from these models because different vehicle type categories were used in each model.

Table 1. Significant Results of Conventional Vehicle Choice Models

Reference	Lave and Train (1979)	Manski and Sherman (1980)	Hocherman, et al. (1983)
Model Type	Multinomial logit model of vehicle type purchased	Multinomial logit model of vehicle holdings	Two-stage nested logit model of vehicle type purchased, conditional on a purchase being made
Dependent Variables	- subsubcompact - sports - subcompact-A - subcompact-B - compact-A - compact-B - intermediate - standard-A - standard-B - luxury	Chosen alternative plus 25 alternative makes/models/ vintage (randomly selected from 600 vehicle types)	Upper level: Buying a first car or replacing an existing car Lower level: Chosen alternative plus 19 alternative makes/models/ vintages (randomly selected from 950 vehicle types
Significant Explanatory Variables	- purchase price /income (–) - auto weight*age of respondent (+) - no. of household members (+, for subsubcompact and subcompact A) - when no. of household vehicles >2 (+, for smaller cars)	- purchase price (–) - higher operating cost and low income HH (–) - no. of seats (+) - vehicle weight and HH age (+) - acceleration time (+) - luggage space (+) - scrappage rate (–) - transaction-search cost (–)	- purchase price (–) - operating cost (–) - engine size (+) - vehicle age (–) - income (+) - brand loyalty (+) - no. of same make cars (+) - horsepower/weight (+) - older or high-income (+, expensive cars)
Reference	Berkovec and Rust (1985)	Berkovec (1985)	Mannering and Winston (1985)
Model Type	Nested logit model of vehicle holdings	Nested logit model of vehicle holdings	Multinomial logit model of vehicle holdings
Dependent Variables	Upper level: vehicle age groups - new (1977-78) - mid (1973-76) - old (1967-72) Lower level: 5 vehicle classes - subcompact - compact - intermediate - standard - luxury/sports	Upper level: No. of vehicles (0, 1, 2, and 3) Lower level: 131 vehicle classes and vintages - 10 years (1969-1978) - 13 vehicle classes each year: (domestic) subcompact, compact, sporty, intermediate, standard, luxury, pickup, truck, van, and utility vehicle; (foreign) subcompact, larger, sports, and luxury - all models before 1969	Chosen alternative plus 9 alternative makes/models/ vintages (randomly selected from 2,000 vehicle types)
Significant Explanatory Variables	- purchase price (–) - operating cost (–) - no. of seats (+) - vehicle age (–) - turning radius in urban (–) - horsepower/weight (+) - transaction (+)	- purchase price (–) - no. of seats (+) - proportion of makes/models in class to total make/models (+)	- purchase price/income (–) - operating cost/income (–) - lagged utilization of same vehicle or same make (+)

Note: Sign in parentheses means positive or negative effect on the choice of the associated vehicle.

(Table 1. Continued)

Reference	Kitamura, et al. (2000)	Brownstone, et al. (2000)	Mannering, et al. (2002)
Model Type	Multinomial logit model of vehicle holdings	Multinomial logit model of vehicle purchased	Nested logit model of vehicle purchased
Dependent Variables	- 4-door sedan - 2-door coupe - van/wagon - sports car - sports utility - pickup truck	A 689-level classification according to vintage, body type, import/domestic, and price level.	Upper level: Vehicle acquisition type - cash, non-cash (lease, finance) Lower level: Chosen alternative plus 9 alternative makes and models (randomly selected from 175 vehicle types)
Significant Explanatory Variables	- age of respondent (+, for 4-door, 2-door, and van/wagon) - male (– , for all but pickup) - college degree (+, for 4-door) - no. of household members (+, for van/wagon) - high income (+, for SUV) - low income (+, for Pickup and 2-door couple) - transit accessibility (+, for 4-door)	-price/ln(income) (-) -operating cost (-) -import (-) -no. of vehicles in class (+) -new (+) -pollution (+) (problematic) -small car (-) -sports car (-) -sports car with HH size >=3 (+) -minivan with HH size >=3 (+)	- purchase price/income (–) - passenger side airbag (+) - horsepower (+) - vehicle residual value (+) - consecutive purchases (+)

Note: Sign in parentheses means positive or negative effect on the choice of the associated vehicle.
Source: Choo and Mokhtarian (2004).

We now turn to the subject of AFVs, and review some disaggregate studies of AFV choice done during the past ten years. Similar to conventional vehicle choice, most studies (Brownstone, et al., 2000; Bunch, et al., 1993; Ewing and Sarigöllü, 1998; Golob, et al., 1997) introduced multinomial, conditional, or nested logit models for AFV choice. AFVs incorporated in these models include electric vehicles, LPG vehicles, hybrid electric vehicles, CNG vehicles, methanol vehicles and unspecified AFVs. Table 2 summarizes some significant results of those studies reviewed. Similar to conventional vehicle choice, purchase price and/or operating cost are significant in most AFV choice models. Specific to AFVs, vehicle performance variables often appear in these models; especially, the driving range of AFVs is a major concern for AFV choice. Compared to conventional vehicles, a lower emission rate increases an individual's probability of choosing

AFVs, suggesting that the innovative attribute of AFVs is well accepted by at least a niche market, environmentalists. Fuel availability and fuel flexibility both positively affect AFV choice.

2.1.2 Aggregate Studies

In this section, ten studies focusing on aggregate automobile demand or ownership are reviewed, as summarized in Table 3. Among these models, regression analysis was most commonly used to estimate automobile demand (Button, et al., 1993; Dargay and Gately, 1999; Dyckman, 1965; Tanner, 1979; Khan and Willumsen, 1986; Madre, 1990). Time series and/or cross-sectional data were employed to conduct the analyses in these models. Specifically, a linear or sigmoid curve was assumed to illustrate the relationships between aggregate automobile demand or ownership and various explanatory variables, and the ordinary least squares method was extensively applied to estimate the demand equations. Besides regression analysis, aggregating automobile demand or ownership using disaggregate discrete choice models was utilized by Manski (1980) and Train (1986). However, one common problem of most regression models and aggregated discrete choice models is that they usually develop one equation to estimate automobile demand or ownership, ignoring the interaction and simultaneity of some endogenous variables, such as the relationship between automobile demand and the driving population (Abu-Eisheh, 2001). To capture these effects, simultaneous equation models have recently been used to estimate aggregate automobile demand or ownership (Abu-Eisheh, 2001; Chung and Lee, 2002).

Table 2. Significant Results of Alternative Fuel Vehicle Choice Models

Reference	Description	Significant Results
Dagsvik, et al. (2002)	Luce model based on stated preference survey Alternatives: Gasoline vehicle (GV) LPG vehicle (LPG) Electric vehicle (EV) Hybrid Vehicle (HEV)	Given that all attributes are equal, and refueling and maintenance infrastructure are well equipped: -AFVs are competitive -Purchase price (-) -Driving range (+) -Top speed (+, only for 18-29 year old males) -Fuel consumption (-) -EV, women (+) -HEV, all age groups and gender groups (+) -LPG, almost all (except 18-29 year old males) (+)
Brownstone, et al. (2000)	Multinomial logit model based on stated preference survey Base: midsize/large gasoline vehicle Alternatives: EV CNG vehicle (CNG) Methanol vehicle	-Price/ln(income) (-) -Operating cost (-) -Range (+) -Acceleration (-) -Top speed (+) -Pollution (-) -Station availability (+) -SUV, sports car (+) -Sports car with HH size >=3 (-) -Station Wagon, truck and van (-) -Minivan with HH size >=3 (+) -College * EV (+) -Electric truck, electric sports car (-) -CNG and Methanol constant (+) -EV constant (-, insignificant)
Ewing and Sarigöllü (1998)	Multinomial logit model based on stated preference survey Base: GV Alternatives: EV More fuel-efficient gasoline and alternative-fuel vehicle (FEV)	-Price (-), maintenance cost (-), refueling time (-) -Emission rate (-) -Acceleration (+), range (+) -Commuting cost (-), commuting time (-) -Older people (-) -FEV*Renter (dummy) (-) -FEV*owning more than 1-vehicle (dummy) (-) -EV*Amount extra willing to pay for a ZEV, if given access to express lane (+) -Female and older are less sensitive to acceleration and range -Acceleration (+, for share-ride commuting (dummy), and for next car would be a sports car (dummy)) -Commuting cost (-, for female, and for next car would be a van (dummy); + for the older) -FEV constant and EV constant (+)
Golob, et al. (1997)	Conditional logit model based on stated preference survey Base: GV Alternative: EV CNG vehicle (CNG) Methanol vehicle	-Emission (-, for government and school) -Capital cost (-) -Operating cost (-) -Range (+) -Station density (+) -CNG duel fuel (+) -Gasoline on-site refueling available (+) -CNG station time (-) -EV, CNG, and Methanol constant (-)

Note: Sign in parentheses means positive or negative effect on the choice of the associated vehicle.

(Table 2. Continued)

Reference	Description	Significant Results
Kurani, et al. (1996)	Descriptive analysis of EV demand in multi-vehicle households, based on stated preference survey	Purchases of battery-EV by multi-vehicle HHs would account for 7-18% of annual light-duty vehicle sales in CA
Bunch, et al. (1993)	Nested multinomial logit model based on stated preference survey Base: GV Alternative: EV HEV Unspecified (methanol, ethanol, CNG or propane) liquid and gaseous fuel vehicle (AFV)	-Purchase price (-) -Fuel cost (-) -Range (100 mi) (+), Range^2 (-) (maximum at 300 miles) -Emission level (-), emission level ^2 (+) (minimum at 1.5 times as much as current) -Fuel availability (+), fuel availability ^2 (-) (maximum at 90% of stations) -Multiple fuel (+) -EV low performance (-) -EV low performance with hybrid (fuel flexibility) (+) -Range*female dummy (-) → less sensitive to range -Range *HH workers per vehicle (+) -GV constant *income (+) -EV constant*college dummy (+) -EV constant*age 55+ dummy (-) -EV constant*1-veh HH dummy (-) Next purchase -Range* Full size Pickup or Van dummy (+)→ more sensitive to range -Range * Compact Pickup dummy (-) → less sensitive to range -Range* Sports car dummy (-) →less sensitive to range -EV constant * SUV dummy (-) →lower preference

Note: Sign in parentheses means positive or negative effect on the choice of the associated vehicle.

Another econometric approach to model aggregate automobile demand is the stock adjustment concept proposed by Nerlove (1957). This approach was initially used to model the demand for divisible, homogeneous, and perishable goods. The concept assumes that the desired aggregate automobile stocks in a specific year are a function of prices, incomes, and other variables. The model includes a scrappage equation expressing actual used vehicle stocks as a function of actual new and used vehicle stocks in the previous year, and an equation indicating new vehicle purchases (Manski, 1980). However, both the theory and the application of this approach were questioned by Manski (1980). First, the distinctive nature of the automobile market makes it implausible to use this concept to estimate automobile demand. For example, consumers choose a vehicle from a variety of *heterogeneous* makes and models. Second, the model assumes that new and used vehicle prices are predetermined; however, used vehicle prices cannot be predetermined due to the competitive market. Finally, differentiating automobiles by specifying only a small set of automobile classes does not satisfy the within-group homogeneity requirements of the stock adjustment concept; but if automobiles are divided into a large number of classes, we lose simplicity, a major advantage of the stock adjustment concept (Manski, 1980). Presumably for these reasons, this approach is seldom undertaken today.

Finally, diffusion models have also been used to predict automobile ownership; those applications are presented in the next section.

Through these studies, a variety of variables were found to significantly affect aggregate automobile demand or ownership, in expected ways. These variables include income-related ones (income or discretionary income, income index, gross national product, per-capita income, and household income), cost-related ones (price, cost index of motoring, transportation consumer price index, and personal transportation expenditure), land use-related ones (urbanized area and population density or percentage of population in urbanized area), demographic characteristics (number of workers, household size, percentage of population within a specific age range, and economically active population) and other variables (automobile stocks, annual transit trips per capita in the area, and so on).

Table 3. Summary of Previous Aggregate Automobile Demand Models

Reference	Dyckman (1965)	Tanner (1979)
Scope	The United States	Great Britain
Data Period	1929-1962 time series	1953-1974 time series
Model	Log-linear regression	Semi-logarithmic regression
Dependent Variable	-Demand for new cars per capita	-Cars per person
Explanatory Variables ("0": tested but not significant)	-New-car sales (0) -Income or discretionary income (+) -Prices (-) -Automobile stocks (-) -Credit (+) -Liquid assets (0)	-Income index (+) -Cost index of motoring (-)
Reference	Khan and Willumsen (1986)	Button, et al. (1993)
Scope	Developing countries	Low income countries
Data Period	1970-1975 cross-section	1968-1987 cross-section time series
Model	Log-linear regression	Log-linear and quasi-logistic
Dependent Variable	-Cars per thousand population	-Aggregate ratio of total registered vehicles to population
Explanatory Variables ("0": tested but not significant)	-Gross national product per head (+) -Purchase and registration tax per vehicle (0) -Ownership tax per vehicle (0) -Import duty per vehicle (0) -Population density (0)	-Time trend (+) -Gross national product (+) -Country specific dummy (+ or -)
Reference	Dargay and Gately (1999)	Madre (1990)
Scope	OECD countries as well as China, India, and Pakistan	France
Data Period	1960-1992 cross-section time series	1972-1987 time series
Model	Gompertz	Cramer (probit)
Dependent Variable	-Vehicle ownership ratio	-Household vehicle ownership
Explanatory Variables	- Per-capita income (+)	-Real income (+) -Time (+)
Reference	Manski (1980)[1]	Train (1986)
Scope	N/A	The United States
Data Period	N/A	1978 National Transportation Survey
Model	Aggregate discrete choice	Multinomial logit
Dependent Variables	-Used car price -Annual used car scrappage -Aggregate auto demand -Annual new car purchases	-Vehicle quantity
Explanatory Variables ("0": tested but not significant)	-New car price -Used car scrap value -The "quality" of new and used cars. -Population size -Aggregate auto ownership at beginning of year -Average abnormal maintenance costs -Consumer's rate of time discount	-Household income (+) -Number of workers (+) -Number of members (0) -Annual transit trips per capita in area (-) -Average utility in class/vintage choice (+)

1. There is no empirical analysis in Manski (1980).

Note: Sign in parentheses means positive or negative effect on the dependent variable(s).

(Table 3. Continued)

Reference	Abu-Eisheh (2001)	Chung and Lee (2002)
Scope	Palestinian Territories	South Korea
Data Period	1971-1998 time series	1970-1998 time series
Model	Simultaneous equations	Simultaneous equations
Dependent Variables	-Total number of automobiles -Number of drivers per household	-Number of automobiles -Driving population -Road length
Explanatory Variables[1] ("0": tested but not significant)	-Total number of automobiles -Number of drivers per household -Gross domestic product -Transportation consumer price index -Average number of persons per household -Palestinian National Authority indicator -Percentage of population living in urban areas -Percentage of population age 15-64	-Number of automobiles -Driving population -Road length -Household size -Economically active population -Personal transportation expenditure -Urbanized area -Population density in urbanized area -Gross national income (0)

1. All variables except gross national income in these two studies are significant in one or more equations.

2.2 Diffusion Models

Compared to conventional vehicles, AFVs can be considered new transportation technologies, which are launched to substitute for conventional vehicles. Therefore, we can apply diffusion models to predict the future of the AFV market. Diffusion theory has been widely used in the prelaunch, launch, and postlaunch strategic decisions for various innovations (Mahajan, et al., 2000). Generally, the natural cumulative adoption of many innovations follows a sigmoid curve, with adoption growing slowly in the initial year, growing steeply as it reaches the half-way point, and growing slowly again as the saturation level (maximum penetration) is approached. However, the specific spread of the curve is dependent on various factors, such as cost and performance of the innovation. The goal of a diffusion model is to determine the speed and shape of the adoption curve for an innovation, among a given set of potential adopters over time (Mahajan and Muller, 1979).

2.2.1 The Basic First-purchase Diffusion Model

In his classic work, Rogers (1983, p5) defined the diffusion of an innovation as the process by which the innovation is "communicated through certain channels over time among the members of a social system". He identified four fundamental elements in the diffusion process: the innovation, communication channel, time, and the social system. Among these elements, the communication channel is a main focus of diffusion theory. The communication channel is the means by which the information about an innovation spreads to or within the social system. According to Bass (1969), mass media (external influence) and word of mouth (internal influence) represent two basic types of communication channels affecting the adoption of an innovation. Specifically, synthesizing the models proposed by Fourt and Woodlock (1960) and Mansfield (1961), the basic first-purchase Bass model is expressed as the following continuous (1a) or discrete (1b) form:

$$f(t) = [p + qF(t)][1 - F(t)] \tag{1a}$$

or

$$S(t) = N(t) - N(t-1) = p[m - N(t-1)] + q\frac{N(t-1)}{m}[m - N(t-1)], \tag{1b}$$

where

f(t) is the density function of purchase at time t;

F(t) is the cumulative fraction of adopters at time t;

m is the number of ultimate adopters, or market potential;

S(t) is the incremental sales or number adopting during time period t;

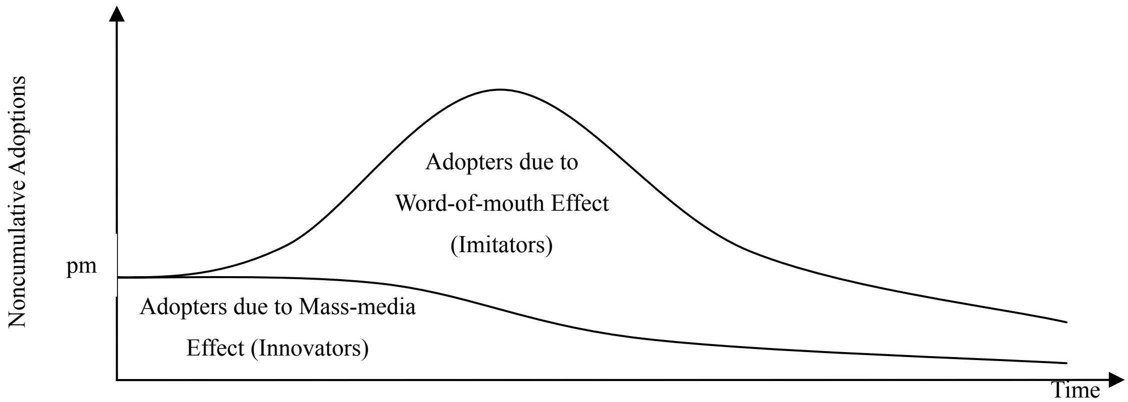
N(t) is the cumulative sales or cumulative number of adopters through time period t;

p is the coefficient of innovation; and

q is the coefficient of imitation.

As shown in Figure 1, the adopters consist of two groups — innovators and imitators — in the Bass model. Thus, the sales during time period t, S(t), is modeled as the sum of purchases by innovators and purchases by imitators. The number of innovators, p[m-N(t-1)], is proportional to the remaining number of non-adopters at the beginning of period t, (m-N(t-1)), while the number of imitators is proportional both to the number of non-adopters and to the fraction who have already adopted (N(t-1)/m). When making their initial purchases, innovators are not driven by the number of previous adopters but primarily by mass media, while imitators are influenced by the number of previous buyers, a learning effect from word of mouth.

Figure 1. Conceptual Structure of the Bass Model



Source: Mahajan, et al. (1990a)

Another categorization of adopters is based on the timing of adoption by various groups. Based on the mean and standard deviation of a normal curve, Rogers (1983) classically divided adopters into five categories: innovators (the first 2.5% of the total adopters at saturation, or those about two or more standard deviations ahead of the mean time of adoption), early adopters (13.5%, or those between one and two standard deviations ahead of the mean), early majority (34%, or from the mean to one standard deviation ahead), late majority (34%, or from the mean to one standard deviation behind), and laggards (16%, or those more than one standard deviation behind the mean time of adoption). In reality, the size of each adopter category for different innovations is not identical and not derived from arbitrary time-based definitions. On the basis of the Bass model, Mahajan, et al. (1990b) defined an innovator category (pm), and four other adopter categories by examining the trends in the density function f(t) and its rate of change (df(t)/dt, e.g., when its inflection points occurred). After comparing several empirical results, they found that the sizes of adopter categories provided by the Bass model and the Rogers classification fall in similar ranges. However, they also concluded that the Bass model tends to generate a lower percentage of adopters in the early and late majorities and a higher percentage in the laggards.

2.2.2 Estimation Techniques

In the Bass model, the estimation of three parameters (p, q, and m) is required to understand the diffusion of an innovation. Accordingly, the sales data for at least three points in time are necessary to accomplish the estimation process. However, the estimates of these parameters are sensitive to the number of observations available to the estimation (Mahajan, et al., 1990a). Heeler and Hustad (1980) suggested that stable and robust parameter estimates can be obtained only if the data under consideration contain at least ten observations and include the peak of the non-cumulative adoption curve, which is supported by the results of Srinivasan and Mason (1986). However, waiting for enough observations to develop reliable models is "too late to use the estimates for forecasting purposes" (Mahajan, et al., 1990a, p9), and therefore makes the prediction useless (Hyman, 1988). Caught by this fundamental paradox, most operationally useful (as opposed to post-hoc diagnostic) diffusion models are calibrated on relatively little data and hence are not necessarily stable. However, this is a virtually inescapable feature of this modeling approach.

Three approaches are commonly used to estimate the parameters in the Bass model: ordinary least squares (OLS), maximum likelihood estimation (MLE), and non-linear least squares (NLS). Bass (1969) originally suggested using OLS to conduct the estimation. Specifically, in estimating the three parameters from discrete time series data, we rewrite Equation 1b as the following analogue:

$$
\begin{aligned}
S(t) &= pm + (q-p)N(t-1) - \frac{q}{m}N^2(t-1) + \varepsilon(t) \\
&= a + bN(t-1) + cN^2(t-1) + \varepsilon(t)\,. \qquad (2)
\end{aligned}
$$

Equation 2 is a conventional polynomial regression and the OLS procedure can be applied. As a result, the three parameters are indirectly identified in that a = pm, b = q - p, and c = - q/m. However, there are a number of shortcomings in calibrating the Bass model using the OLS technique. For example, the possible correlation between independent variables in Equation 2 may lead to unstable estimates or the wrong sign for one or more estimates; the OLS technique does not directly provide standard errors of the basic parameters p, q, and m, and thus makes their statistical assessment impossible; and the attempt to estimate a continuous model with discrete time-series data may lead to time-interval bias, which tends to overestimate adoption if cumulative adoption grows sharply, and vice versa (Schmittlein and Mahajan, 1982). Empirically, using smaller time intervals, say quarterly data instead of annual data, will reduce temporal aggregation bias (Putsis, 1996).

Alternatively, MLE and NLS techniques were proposed to estimate the parameters directly from the differential equation of the diffusion model (Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986). According to Srinivasan and Mason (1986), the model formulation of the NLS technique is as follows:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}, \text{ and}$$

$$S(t) = m[F(t) - F(t-1)] + \varepsilon(t). \tag{3}$$

The model formulation for MLE is specified in Schmittlein and Mahajan (1986). Both techniques provide standard errors of the parameters and eliminate the time-interval bias, superior to the OLS procedure. However, they have their own limitations. For both approaches, an initial value for each parameter is required to estimate the Bass model and the parameter estimates are sensitive to the initial values. The OLS estimates could be used to provide the initial values for these parameters (Srinivasan and Mason, 1986). Specifying different initial values is also highly recommended in practice (Putsis and Srinivasan, 2000). Further, model estimation may not converge in some cases, partly due to poor initial values (Judge, et al., 1985).

The NLS approach is generally better than MLE since in their MLE formulation Schmittlein and Mahajan "consider only sampling errors and ignore all other errors, such as the effects of excluded variables and the misspecification of the probability density function for adoption time", and thus are likely to underestimate the standard errors of these parameters (Srinivasan and Mason, 1986, p. 178). Mahajan, et al. (1986) compared these estimation techniques empirically and found an overall superiority of the NLS procedure. A simulation study by Srinivasan and Mason (1986) demonstrated that the biases in the parameter estimates are small, less than 7%. Recently, Van den Bulte and Lilein (1997) stated that the estimators in the NLS estimation procedure are consistent but not unbiased. Specifically, by examining both empirical and simulation data, they found that NLS tends to underestimate m and p and overestimate q to a much greater extent than Srinivasan and Mason (1986) did. They pointed out that the amount of bias depends on the amount of noise in the data, the number of observations, and the differences between the cumulative penetration of the last observation and the true saturation penetration. Thus, one possible solution to minimize the bias is to increase the number of data points, which is consistent with the findings of Putsis (1996).

Since the stability and robustness of the parameter estimates are dependent on the number of observations used to estimate them, some efforts have been made to provide time-varying parameter estimates in the presence of additional data after the initial estimation of a diffusion model. Bayesian estimation procedures and adaptive feedback filters were used to update the parameter estimates when new data become available (Mahajan, et al., 1990a).

Although the estimates for diffusion of a new product greatly rely on the time-series diffusion data, it is also possible to obtain estimates in the absence of such data. When data are not available, say, the pre-launch forecasting, managerial judgments or the diffusion history of analogous products can be used to estimate these parameters (Mahajan, et al., 1990a; Parker, 1994). Historically, several studies have suggested estimation procedures that can be used in the absence of data (e.g., Lawrence and Lawton, 1981; Mahajan and Sharma, 1986; Urban, et al., 1990).

2.2.3 Extensions of the Bass Model

The basic first-purchase Bass model offers a parsimonious representation of the diffusion process of a new product. According to the basic Bass model, the theoretical diffusion curve is symmetric and has one specified reflection point, say, 50% of market penetration. Empirically, however, the diffusion process is rather complicated. This implies that there are a few important simplifying assumptions underlying the Bass model. To make the Bass model better fit the real diffusion process, attempts have been made to relax these assumptions.

First, the Bass model assumes that the parameters remain constant over the estimation timeline. However, this may not be the case. For example, the adoption rate may grow as relative advantages of an innovation (the extent to which an innovation is perceived to be better than the one it substitutes) increase (Rogers, 1983); the influence of word of mouth on potential purchasers could increase or decrease as well as remain unchanged over time (Hernes, 1976); the price may affect the adoption rate and/or market potential of a new product (Jain and Rao, 1990; Kalish, 1985). To capture the dynamic nature of word-of-mouth impact, Easingwood, et al. (1983) proposed a nonuniform influence (NUI) innovation diffusion model as an extension of the Bass model, replacing the imitation coefficient q with q $F^a(t)$. If the constant "a" is smaller than zero, the impact of word of mouth increases over time, leading to an earlier and higher peak in the level of market penetration, and vice versa. Since the NUI model allows the impact of word of mouth to systematically vary over time, the diffusion curve may be symmetrical or nonsymmetrical, with the reflection point responding to the diffusion process.

Kalish (1985) incorporated product price and uncertainty about the product in the Bass model. Assuming full product awareness in the population, he defined the market potential as follows:

$$m(t) = m_0 \exp\left[-dP(t)\left(\frac{a+1}{a + \frac{N(t)}{m_0}} \right) \right], \qquad (4)$$

where a and d are constants, m_0 is the initial market potential, and P(t) is the product price. The empirical analysis indicated that product price affects the market potential. Theoretically, product price may play multiple roles in the diffusion process. One possibility is that price only affects market potential — a price decrease will enlarge the size of the market potential by adding households from the previously untapped market for whom the new price has become affordable. A second possibility is that price only impacts the adoption rate — the price reduction may motivate potential adopters to purchase the product sooner. Finally, it may be that product price affects the market potential and adoption rate simultaneously (Kamakura and Balasubramanian, 1988). After analyzing the best models for six products, they found (in contrast to Kalish) that product price affects the adoption rate rather than the market potential.

A second assumption of the Bass model is that there are no repeated adopters. In reality, however, the long-term market penetration of a new product may involve initial purchases as well as replacement and multiple purchases. In fact, replacement sales account for the majority of total sales for most mature consumer durables (Islam and Meade, 2000; Steffens, 2001). According to Equation 1a and 1b, the Bass model considers only the first purchase by a given adopter, and ignores the noise of repeated buyers. Consequently, some applications of the Bass model lead to biased estimates of diffusion processes and poor forecasts (Ratchford, et al., 2000). The nature of the existing confounded data, which do not distinguish the first purchases from subsequent purchases, is an important reason to make such an assumption in many applications. Olson and Choi (1985) made some effort to estimate the replacement demand from the confounded data. They proposed an integrated model by combining the first purchase model and a replacement purchase model, which utilizes the Rayleigh distribution to separate first purchases from replacement sales. Kamakura and Balasubramanian (1987) presented a similar model, but they relied on a survival function to estimate the replacement sales. Further, their model works both when detailed data are available on first purchases and replacement purchases and when these components are mixed in the total sales and need educated guesses. On the other hand, some studies extend the Bass model to multiple adoptions. For example, Bayus, et al. (1989) considered first purchases, replacement and multiple purchases by incorporating a hazard function in their repeated-purchase model, which is one of the few studies that integrate all three components.

Third, the Bass model assumes that the diffusion of a new product is independent of the adoption of any other existing or new products. However, in reality, multiple products may interact with each other in the market simultaneously, such as color TV and black-white TV, hardware and its associated software. Conceptually, the interactions among multiple products include technological substitution, new-product failure, enhancement, and detraction (Bayus, et al., 2000). Peterson and Mahajan (1978) were among the earliest marketing researchers to explore the interactions of multiple products. They proposed a diffusion system to capture any relationships between different products, by adding $c_iF_i(t)$ (i=1, 2) into the first term of Equation 1a for each product. The relationships between two diffusion processes can be identified according to the signs of the coefficients c_i. Thereafter, several empirical studies applied this formulation to investigate multiproduct interactions (e.g., Bucklin and Sengupta, 1993; Eliashberg and Helsen, 1994; Mahajan and Muller, 1994).

In addition to these three, there are several other assumptions underlying the Bass model. The Bass model assumes that there are no supply restrictions. However, if the demand exceeds supply capacity, some potential adopters have to be on the waiting list until manufacturers increase their production capacity and provide a larger supply. It is likely that the unavailability of a product influences its diffusion process. Jain, et al. (1989) suggested a model capturing the effect of supply constraints and applied it to the diffusion of new telephones in Israel (as cited in Mahajan, et al., 1990a). Further, the Bass model does not consider the effect of marketing strategies on the diffusion of a new product. Simon and Sebastian (1987) found that advertising had a lagged effect on the imitation coefficient in a German telephone campaign. However, they pointed out that their alternative models should not be generalized but depend on the specific situation of a product. Similarly, Mesak (1996) concluded that advertising affects the diffusion rate for cable TV. The Bass model also assumes that government policy does not impact the diffusion process. In reality, since a new product generally tends to be more expensive in its initial launch stage, a government subsidy would reduce product price and, by motivating demand, reduce production cost (Mesak and Coleman, 1992). As a result, the market penetration of the product is likely to be accelerated. While a direct government subsidy could be accommodated through the impact of purchase price on demand, other possible policies would not be so easily monetized, for example, allowing single-occupant electric vehicles to use high occupancy vehicle (HOV) lanes. Finally, most applications of the Bass model assume that both the innovation coefficient and imitation coefficient are positive. However, the cost-performance of a new product may be unbalanced at its initial launch stage, and premature market entry may lead to negative market feedback (through the imitation coefficient) and result in new-product failure (Kalish and Lilien, 1986). In practice, Mahajan, et al. (1984) developed a model for new products with both negative and positive imitation coefficients.

This discussion of assumptions underlying the Bass model is not all-inclusive. Mahajan, et al. (1990a) provide a more complete presentation of these assumptions. Although previous studies have made the Bass model more realistic and sound by properly extending its application, based on these studies, little effort has been made to relax two or more assumptions simultaneously.

2.2.4 The Application of Diffusion Models to Automobile Demand

Historically, a few studies have applied diffusion models to predict aggregate automobile ownership, either in the form of a logistic curve or using the Bass model. Tanner (1958) was among the first in the U.K. to develop a logistic model (a flexible diffusion model) to forecast automobile ownership for the long term. He assumed that automobile ownership would stabilize at a saturation level (S), and that the growth of automobile ownership in intermediate years would follow a logistic curve:

$$C_t = \frac{S}{1+be^{-ct}}, \qquad (5)$$

where C_t is the number of vehicles per person, and b and c denote initial level and growth rate respectively. Based on data from successive five-year periods, Tanner pointed out that the saturation level appeared to have stabilized at around 0.4 for Britain and 0.75 for the U.S. Forecasts on automobile ownership were made based on the extrapolatory logistic model (as cited in Tanner, 1978; Whelan, et al., 2000). However, this model was critiqued due to its inherent limitations, such as the constant saturation level (e.g., Fowkes and Button, 1977; Gallez, 1994).

Lee and Shiaw (1995) proposed a family of constrained diffusion models based on the traditional logistic curve to test the diffusion of motor vehicles (including motorcycles) in Taiwan. Income per capita, proportion of people under 18, and the prices of cars and motorcycles were incorporated in the models. Time-series data on vehicle licenses issued from 1968 to 1990 were used for model calibration, and the last three years of data were used to examine the short-term prediction ability of the calibrated models. The empirical analyses suggested that the constrained diffusion models produced promising results, and they claimed that the modeling approach is at least a useful addition to analyze the long-term trends of multi-class motor vehicle ownership.

Steffens (2003) proposed a multiple-unit ownership diffusion (MOD) model, combining the Bass model for first purchase and analogous models for subsequent multiple purchases. He assumed that a specified proportion of adopters will eventually acquire an additional unit of the product in the multiple-purchase model. Similar to the Bass model, additional-unit adoptions are motivated by mass media and word of mouth from earlier adopters of multiple units. This leads to the following model for multiple-unit adopters:

$$\frac{dM(t)}{dt} = [\pi_1 N(t) - M(t)][p_1 + q_1 M(t)], \qquad (6)$$

where π_1 denotes the proportion of earlier adopters who will become multiple-unit adopters. As an application, he used the census data on Australian household auto ownership (every five years, 1966-1996) to estimate the MOD model as well as the BHL model, an alternative multiple-purchase model. The empirical results indicated that the MOD model is superior to the BHL model in terms of better fits and forecasts. However, the application of this model depends on the availability of detailed data on first and subsequent purchases, which is scarce in practice.

3 MARKET DEVELOPMENT OF ALTERNATIVE FUEL VEHICLES

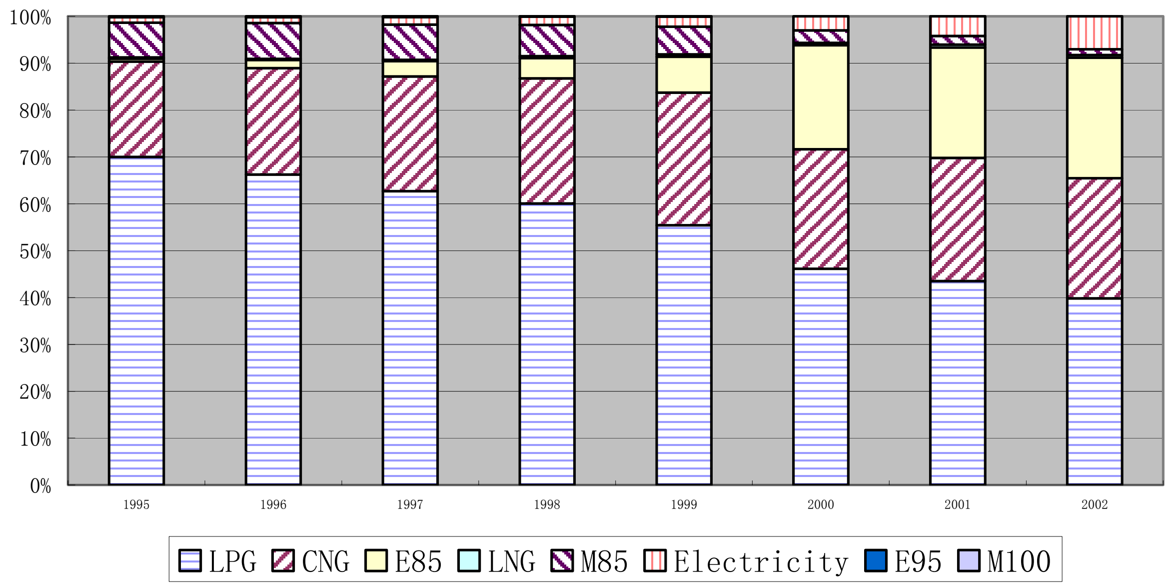
Under EPACT92, alternative fuels were defined as fuels which are not derived from petroleum, including the following: (1) methanol, ethanol, and other alcohols; (2) blends of 85% or more of alcohol with gasoline; (3) natural gas and liquid fuels domestically produced from natural gas; (4) liquefied petroleum gas; (5) coal-derived liquid fuels; and (6) hydrogen and electricity.

3.1 Supply of Alternative Fuel Vehicles

The Energy Information Administration (EIA) in the Department of Energy (DOE) reported that eight types of fuel were used to power AFVs in the U.S. during the last decade: liquefied petroleum gas, compressed natural gas, liquefied natural gas (LNG), methanol 85% (M85), methanol neat (M100), ethanol 85% (E85), ethanol 95% (E95), and electricity, respectively. According to the configurations of their on-board storage systems, these AFVs can be classified as dedicated, bi-fuel, or flexible fuel vehicles. A dedicated alternative fuel vehicle, such as the dedicated-CNG Ford Crown Victoria, is exclusively powered by one fuel. A bi-fuel vehicle, such as the bi-fuel Ford F150, has two isolated tanks and can be powered either by gasoline or by an alternative fuel, but it cannot operate on them simultaneously. A flexible fuel vehicle (FFV), such as most E85 vehicles on the road, has a single storage system and can run on gasoline, an alternative fuel, or any combination of them. On the other hand, the supply of AFVs can be divided into original equipment manufactures (OEMs) or conversions. An OEM AFV is directly assembled or manufactured by an organization while a conversion AFV is modified by a vehicle converter such that a vehicle originally powered by gasoline can operate on an alternative fuel (Joyce, 2001).

The EIA estimated that the number of AFVs in use in the U.S. reached nearly 500,000 in 2002. Although this number only accounts for approximately 0.2 percent of the total registered on-road vehicles in the U.S., it is an important beginning to the AFV market. After more than 10 years of experimentation, some types of AFVs appear to have reached a dead end while others are experiencing a challenge to their continued existence. Still other types, such as fuel cell vehicles, have yet to break into commercial production in any significant way. Currently, LPG, CNG, and E85 vehicles account for the majority of the AFV market, as illustrated in Figure 2. However, their future is still uncertain. It is worth noting that California is leading the AFV population in the U.S., partly driven by the most severe air pollution in the U.S. and hence more stringent transportation regulations.

Figure 2. Market Shares of AFVs in Use in the U.S., 1995-2002



Source: Energy Information Administration, Office of Coal, Nuclear, Electric, and Alternate Fuels. Available at http://www.eia.doe.gov/cneaf/alternate/page/datatables/afvtable1_03.xls.

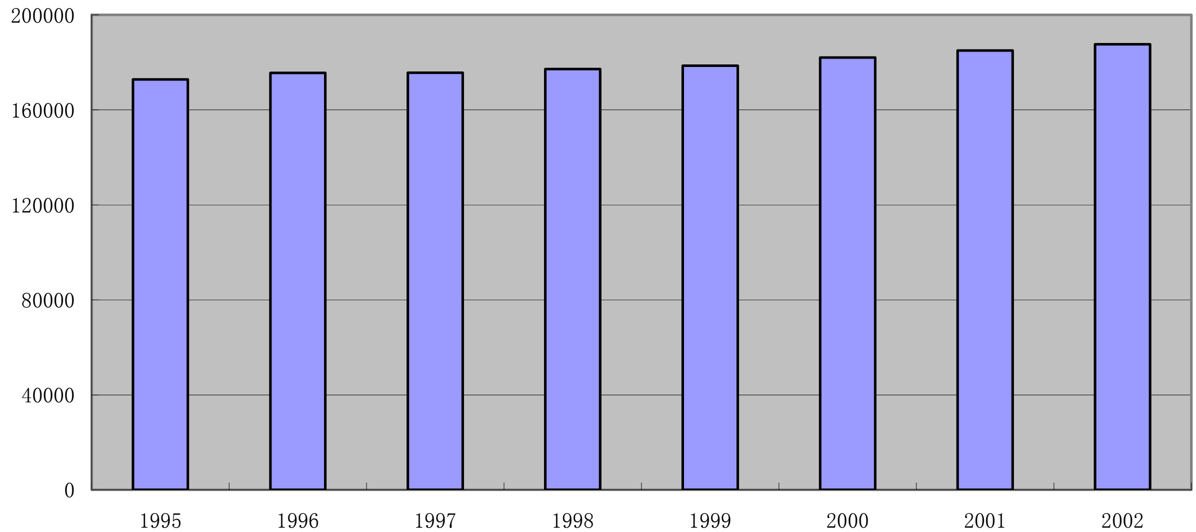
3.1.1 Liquefied Petroleum Gas Vehicles

As a transportation fuel, liquefied petroleum gas (commonly called propane) is a mixture which consists of at least 90% propane, 2.5% butane and higher hydrocarbons, and a balance of ethane and propylene. The LPG, a gas at room temperature, can be compressed to liquid and stored in special tanks under 208 psi pressure. The LPG comes from natural gas processing or petroleum refining. Domestic production of this fuel accounts for about 95-98% of the LPG used in the U.S. (AFDC, undated-c). Tests conducted by the EPA show that LPG vehicles can emit 30% to 90%

less CO and approximately half of the toxins and other smog-forming emissions, compared to gasoline vehicles (EERE, undated).

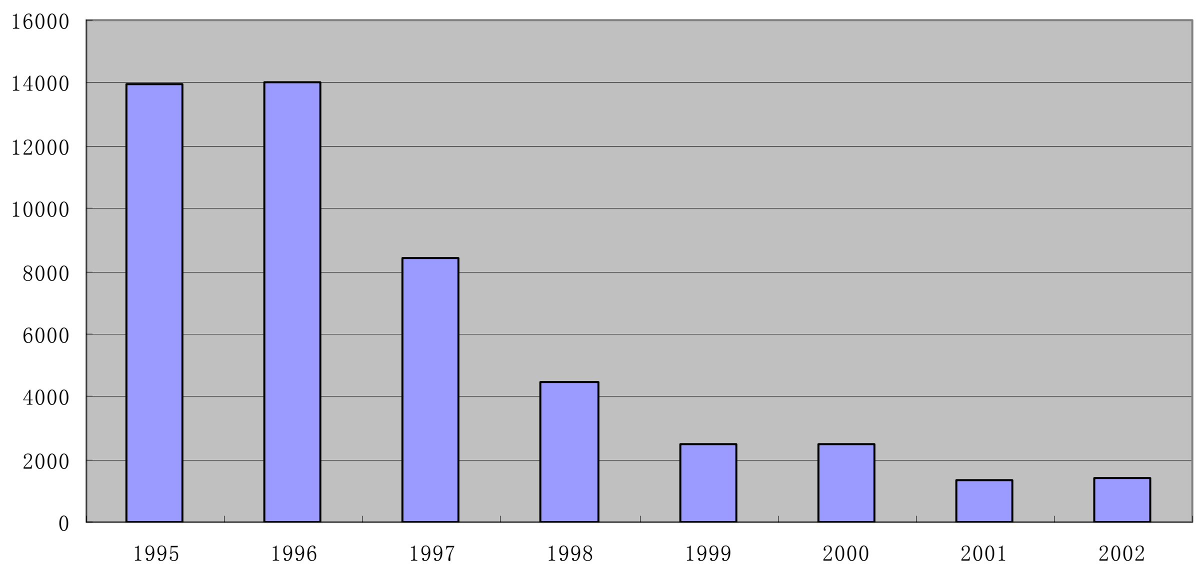
In 2002, there were an estimated 187,680 on-road LPG vehicles in use in the United States, and 42% of them were operating in California, Oklahoma, and Texas. Although that is the largest number among all alternative fuel types, LPG vehicles have experienced the slowest growth since 1995 (the annual growth rate is about 1.2%), as shown in Figure 3. Consequently, as illustrated in Figure 2, LPG vehicles have lost nearly half of their share in the AFV market since 1995, and now comprise only about 40% of the AFV market. In addition, medium-duty vehicles dominate the net growth of LPG vehicles in recent years, as illustrated in Figure 5. So the market share of light-duty LPG vehicles is getting even worse. Among other reasons, fewer conversions and limited OEM production are the main factors in the nearly flat growth of LPG vehicles. First, an Addendum to Memorandum 1A developed by EPA in 1997 greatly increased the testing requirements for alternative fuel conversions and limited the conversion kits certified for use, and thus significantly reduced the number of conversions, as shown in Figure 4. Second, the Ford F-150 bi-fuel LPG vehicle is now the only model available in the current retail market, after its introduction in 2001. On one hand, having few models available manifests lack of diversity, and greatly limits consumers' choices. On the other hand, the scarcity of models may be an effect as much as a cause of consumer rejection. The implication is that consumers are not satisfied with their overall evaluation of LPG vehicles, and uncertainty about the future of LPG vehicles remains an important concern of OEMs with respect to introducing new LPG models into the market. Recently, Ford decided to stop its production of Ford F-150 bi-fuel LPG vehicles, effective after the 2004 model year (Fleets and Fuels, 2004a and 2004b). Like most automakers, Ford is shifting its funding to promote the research and design of hybrid electric vehicles and fuel cell vehicles. Therefore, from 2005, the market penetration of LPG vehicles seems to be exclusively dependent on the limited number of conversions. Under the current regulatory and market environment, light-duty LPG vehicles will be phased out eventually as the current stock ages.

Figure 3. Estimated Number of LPG Vehicles in Use in the U.S., 1995-2002



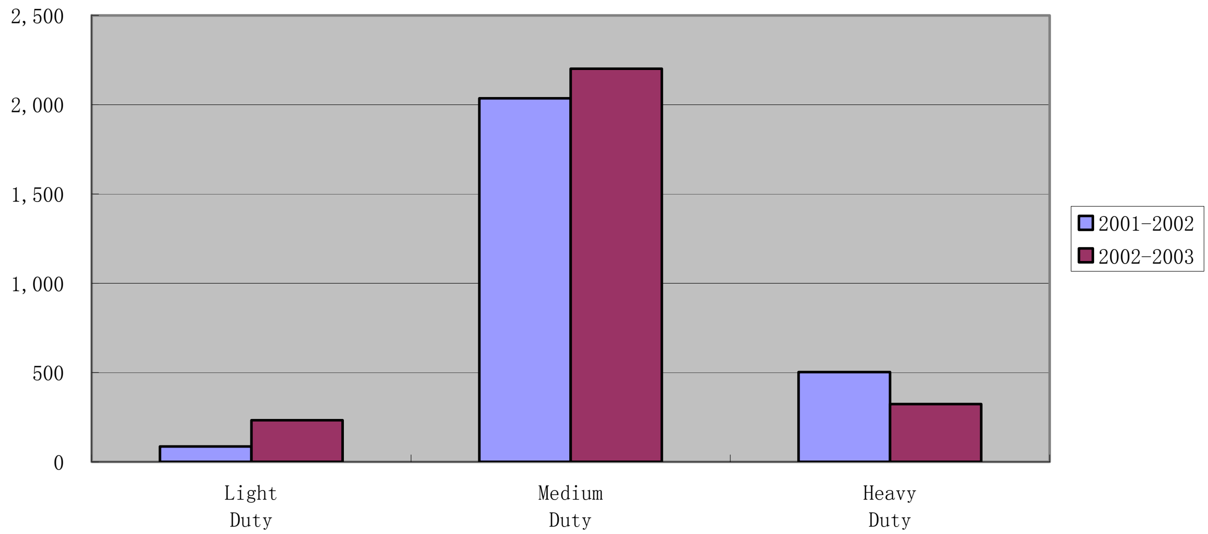
Source: same as Figure 2

Figure 4. Number of All Alternative Fuel Conversions in the U.S., 1995-2002



Source: Energy Information Administration, Office of Coal, Nuclear, Electric, and Alternate Fuels. Available at http://www.eia.doe.gov/cneaf/solar.renewables/alt_trans_fuel98/table17.html and http://www.eia.doe.gov/cneaf/alternate/page/datatables/table19a_02.xls

Figure 5. Net Growth of LPG Vehicles in Use in the U.S., by Weight



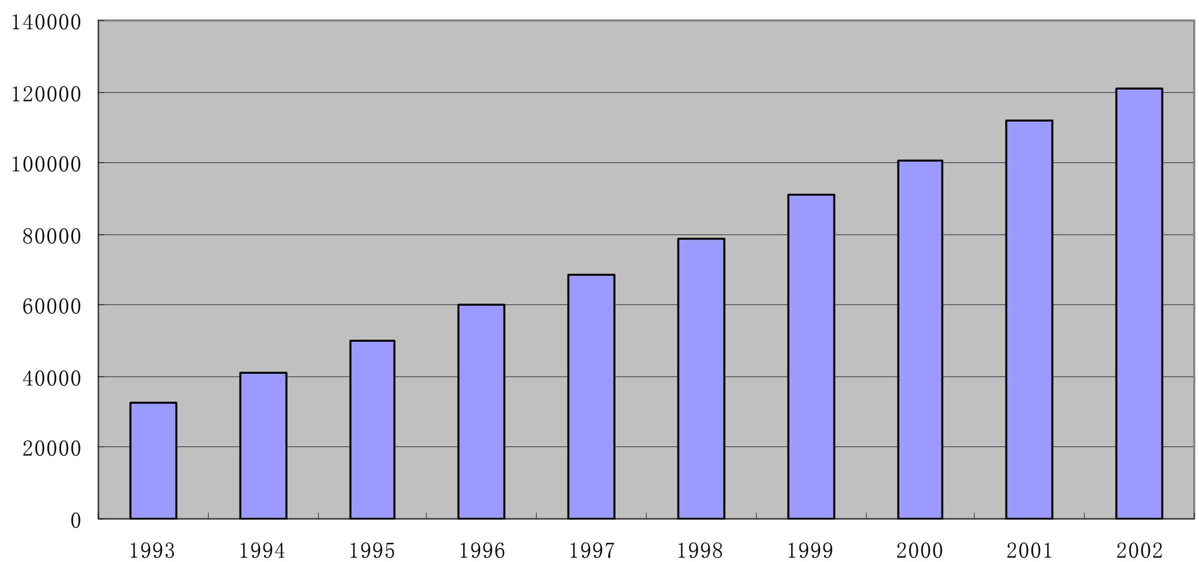
Source: Energy Information Administration, Office of Coal, Nuclear, Electric, and Alternate Fuels. Available at http://www.eia.doe.gov/cneaf/alternate/page/datatables/afvtable6_03.xls

3.1.2 Natural Gas Vehicles

Natural gas is a mixture of hydrocarbons (mainly methane), and is produced either from underground reserves or as a by-product of crude oil production. Domestic sources account for approximately 90% of natural gas consumption in the U.S. (AFDC, undated-d). As an alternative fuel for vehicular purposes, natural gas can be stored in special tanks either as CNG (compressed at the refueling station under 3000-3600 psi pressure) or LNG (cooled to a liquid at -259° F under 20-250 psi pressure). Natural gas is one of the cleanest alternative fuels available. For light-duty vehicles, natural gas produces much lower exhaust and evaporative emissions than gasoline. Specifically, CO, NO_x, and CO_2 can be reduced by up to 90%, 87%, and 20%, respectively (PPRC, 1999). For heavy-duty and medium-duty vehicles, natural gas engines produce over 90% less CO and particulate matter and over 50% less NO_x than commercial diesel engines (AFDC, undated-a). However, it is worth noting that some environmental benefits of LNG are partly offset by the energy penalty of up to 15% in the process of making and transporting LNG (SSPL, 1998).

Currently, CNG is the main alternative fuel for transit buses, taxicabs, and shuttle vans (CEC, 2003). The number of CNG vehicles in use is steadily increasing in the U.S., as shown in Figure 6. It is estimated that CNG vehicles experienced an average annual growth rate of 15.6 percent from 1993 to 2002. In 2002, CNG vehicles in use in the U.S. reached 120,839, which shoulders about 26% of the AFV market. Among these vehicles, light-duty ones account for about 72%, as illustrated in Figure 7. Thus, the current market penetration of CNG vehicles is dominated by light-duty vehicles.

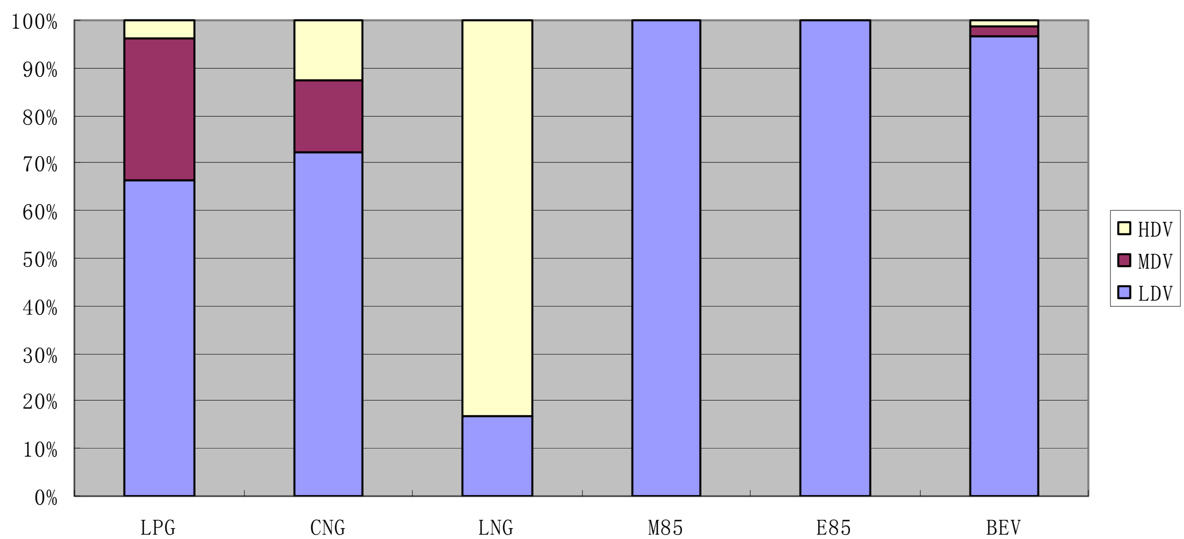
Figure 6. Estimated Number of CNG Vehicles in Use in the U.S., 1993-2002



Source: same as Figure 2

OEMs have made a great deal of effort to promote the CNG vehicle market. Since the Dodge B250 Ram Wagon was introduced in 1993, the number of CNG vehicle models increased to 9 in 2004. However, as an important manufacturer of CNG vehicles, Ford announced it would get out of natural gas vehicles in model year 2005 due to their unsatisfactory market demand. This decision will affect the dedicated CNG Crown Victoria, dedicated CNG E-250 and -350 vans and wagons, and the dedicated CNG E-450 cutaway (Fleets and Fuels, 2003a and 2004a). On the other hand, although its sales are only between 500 and 800 vehicles per year, Honda will continue to stand by the Civic GX. Honda believes that natural gas is a viable transition to hydrogen (Fleets and Fuels, 2004g). The European Commission (EC) concluded that “natural gas is the only alternative fuel with potential for significant market share well above 5% by 2020 which could potentially compete with conventional fuels in terms of the economics of supply in a mature market scenario”(EC, 2003, p. 2).

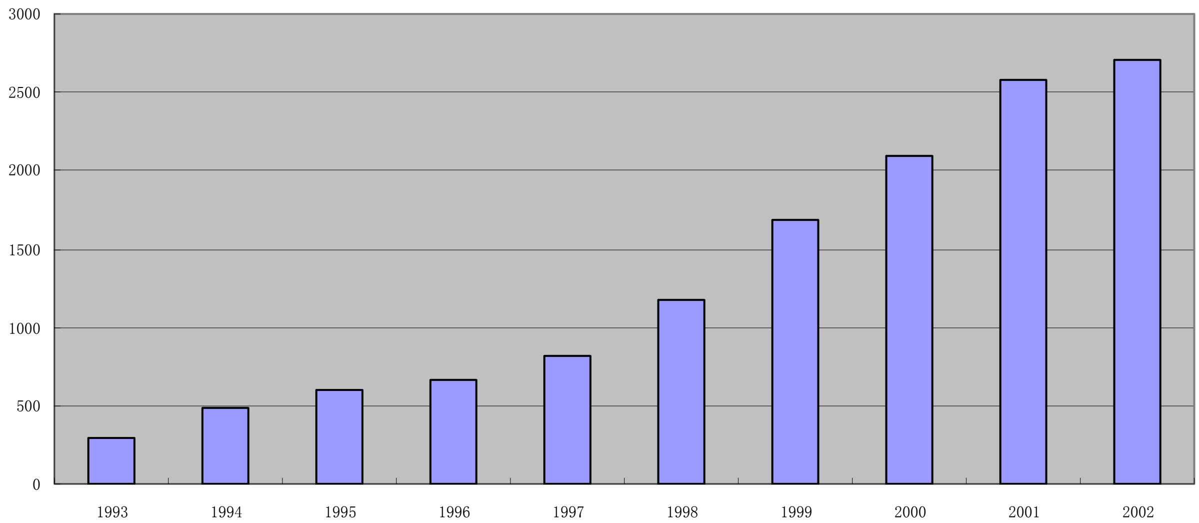
Figure 7. Percentages of AFVs in Use in the U.S., 2002, by Weight



Source: same as Figure 5.

Although the number of LNG vehicles has increased during the past decade (Figure 8), it is far behind that of CNG vehicles. Currently, LNG is used primarily as an alternative to diesel to power heavy-duty vehicles, and no new LNG light-duty vehicles have been made by OEMs in recent years. This suggests that LNG light-duty vehicles have failed to attract considerable private and commercial demand, and the future of LNG as a transportation fuel relies on heavy-duty vehicles to a great extent.

Figure 8. Estimated Number of LNG Vehicles in Use in the U.S., 1993-2002



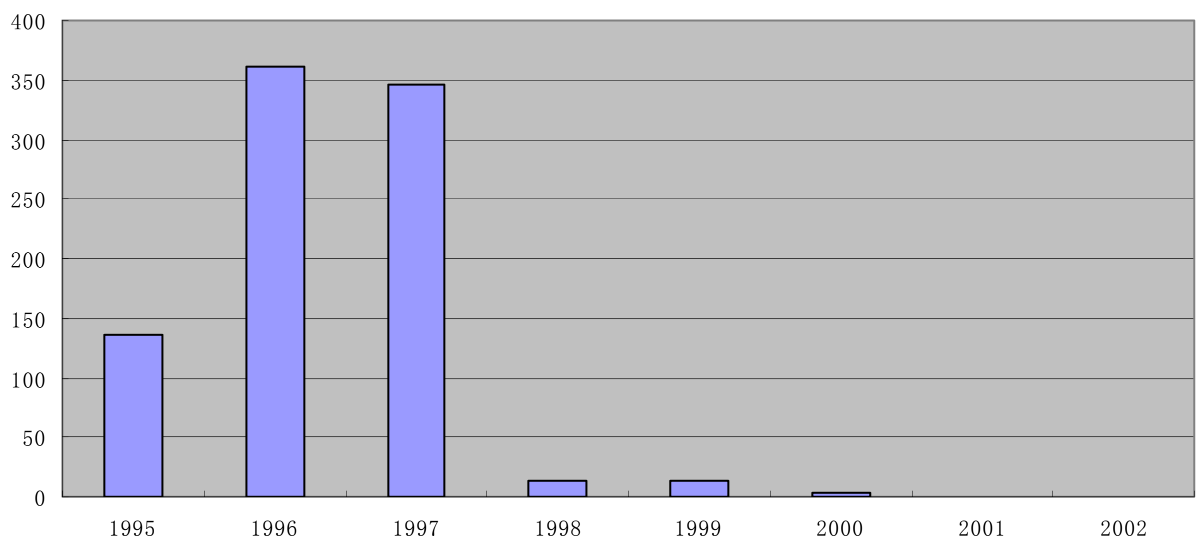
Source: same as Figure 2.

3.1.3 Ethanol Vehicles

Ethanol is an alcohol-based alternative fuel produced by fermenting and distilling starch crops that have been converted into simple sugars. Feedstocks for ethanol include corn, barley, and wheat among others. The domestic content of this fuel is about 85%-90% (AFDC, undated-e). Ethanol is most commonly used to increase octane and improve the emissions quality of gasoline. In some areas of the United States such as Illinois and Minnesota, ethanol is blended with gasoline to form an E10 blend (commonly known as gasohol) in the combination of 10% ethanol and 90% gasoline, however, this blend does not qualify as an alternative fuel. For the higher concentrations of ethanol, E85 works best in light-duty vehicles, while E95 has been used as an alternative fuel for heavy-duty vehicles. When used as a transportation fuel, ethanol achieves a reduction in smog-forming emissions of 30-50%, and toxic emissions are also reduced about 50%. In addition, ethanol significantly reduces GHG emissions, especially when it is produced from cellulose feedstocks, such as wood and agricultural wastes (PPRC, 1999).

Figure 9 illustrates that vehicles fueled by E95 were phased out by 2001. In contrast, in recent years several big automakers have introduced a few new models of FFVs that can run on E85 or any other combination of ethanol and gasoline. In 2004, there are 13 models of such vehicles available in the retail market. As a result, the number of E85 vehicles made available grew explosively. For 2002, the EIA estimated that the number of E85 vehicles that can be fueled by ethanol, gasoline, or any blend of both fuels, is about 4.1 million, but that the overwhelming proportion of these vehicles were operating on gasoline. However, these vehicles have the potential to switch to E85 when competitive conditions are met. Under this assumption, E85 vehicles would have the largest population, rather than LPG vehicles.

Figure 9. Estimated Number of E95 Vehicles in Use in the U.S., 1995-2002



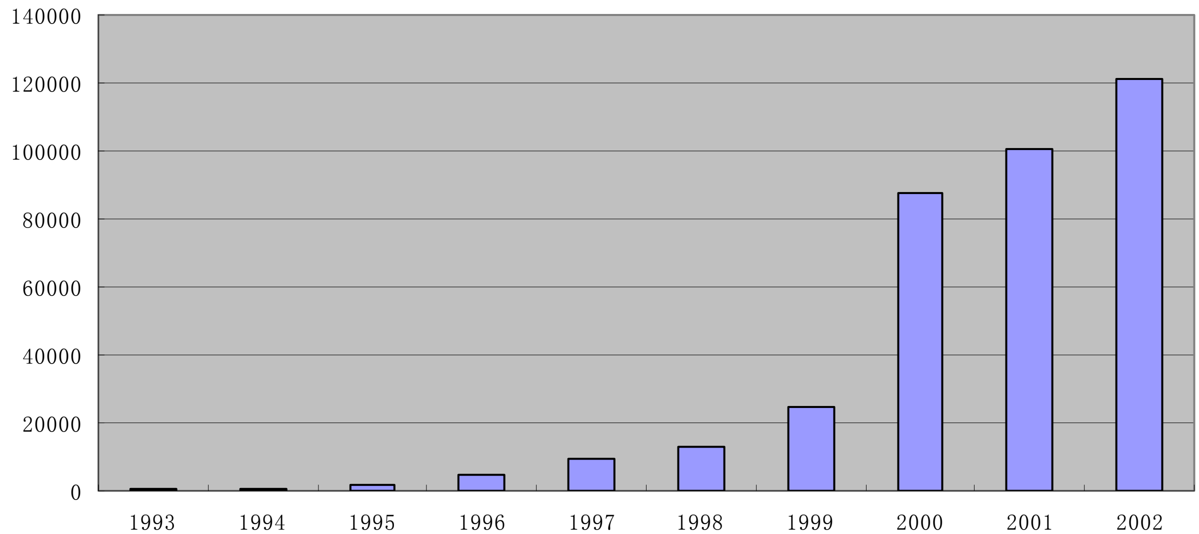
Source: same as Figure 2.

Figure 10 shows that E85 vehicles in use in the U.S. have increased dramatically in the past 10 years[1]. In 2002, the market share of vehicles powered by E85 is comparable to that of CNG vehicles, the estimated number being 120,951. These vehicles are primarily fleet-operated

[1] The DOE/GSA federal automotive statistical tool adopted in 2000 explains the jump of E85 vehicles from 1999 – 2000.

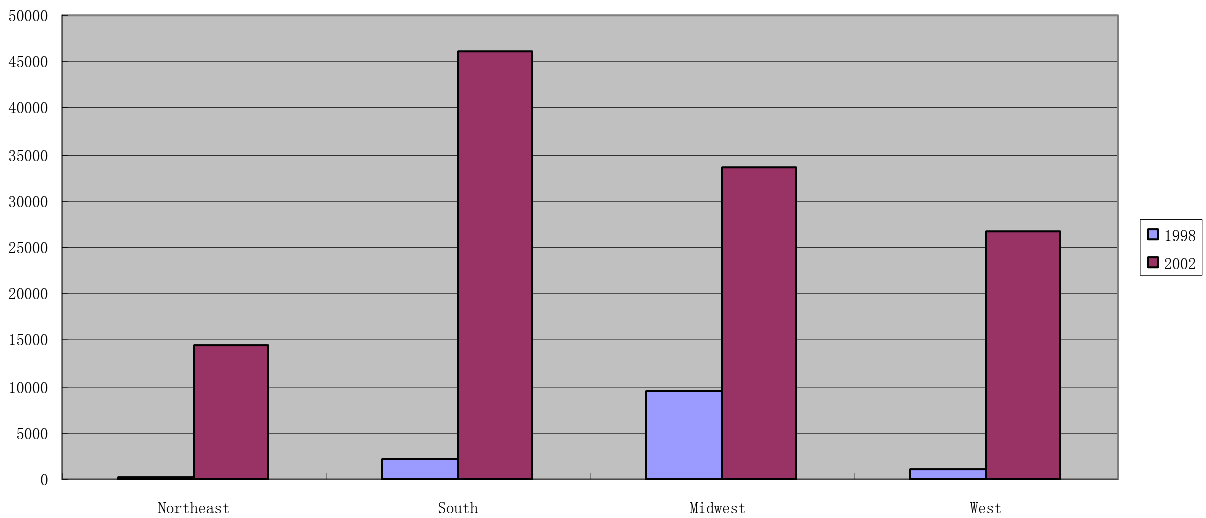
vehicles. The use of E85 vehicles exhibits a wide-spread trend nationwide. In 1998, the greatest concentrations of E85 vehicles were in the Midwest, the primary ethanol-producing region. Since 2001, while all regions have grown substantially, the South has become the region with the largest E85 vehicle population (see Figure 11). The reasons for this shift are not entirely clear.

Figure 10. Estimated Number of E85 Vehicles in Use in the U.S., 1993-2002



Source: same as Figure 2.

Figure 11. Estimated Number of E85 Vehicles in Use in the U.S., 1998 and 2002, by Census Region



Source: Energy Information Administration, Office of Coal, Nuclear, Electric, and Alternate Fuels. Available at http://www.eia.doe.gov/cneaf/alternate/page/datatables/afvtable2_03.xls http://www.eia.doe.gov/cneaf/solar.renewables/alt_trans_fuel98/table2.html

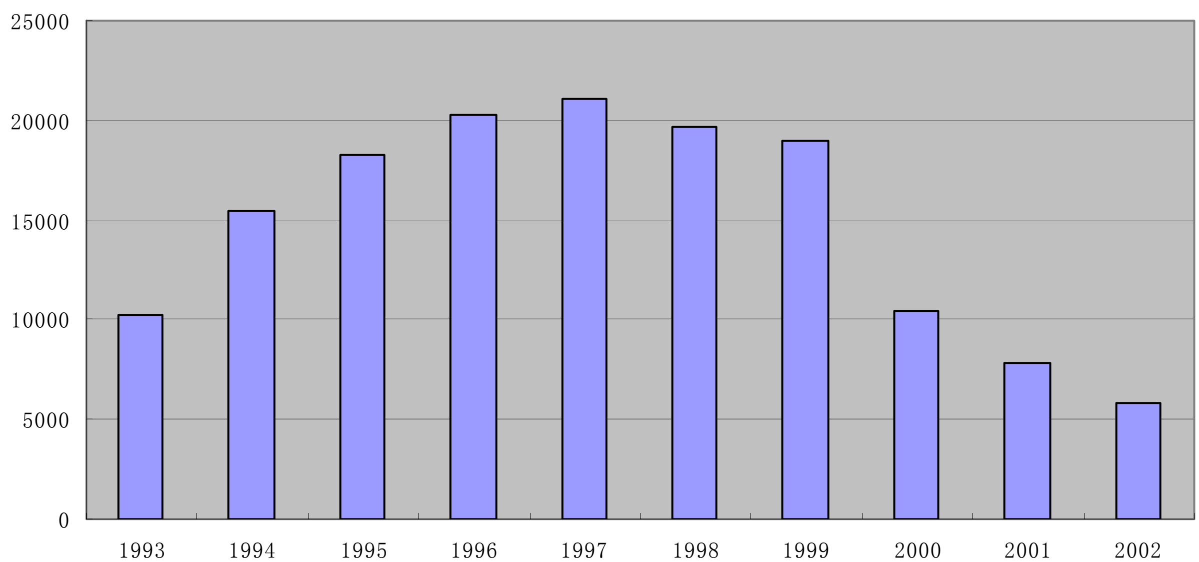
3.1.4 Methanol Vehicles

Methanol is an alcohol fuel. It is commonly made from natural gas, and can also be derived from coal or biomass. The domestic content of this fuel is about 90%, depending on the world market price (AFDC, undated-f). Similar to ethanol, M85, a blend of 85% methanol and 15% gasoline, is primarily used as an alternative fuel in light-duty vehicles, while M100 works best in heavy-duty vehicles. M85 vehicles produce slightly lower emissions than gasoline vehicles. Specifically, smog-forming emissions are generally reduced by 30-50%, and NO_x and hydrocarbon emissions are slightly lower. However, CO emissions are usually equal to or slightly higher than those of gasoline vehicles (PPRC, 1999).

Methanol vehicles have been widely used in California since the California Energy Commission (CEC) began to sponsor methanol programs in 1978. After the first flexible fuel vehicles were commercially produced in 1987, the number of M85 vehicles in use increased dramatically.

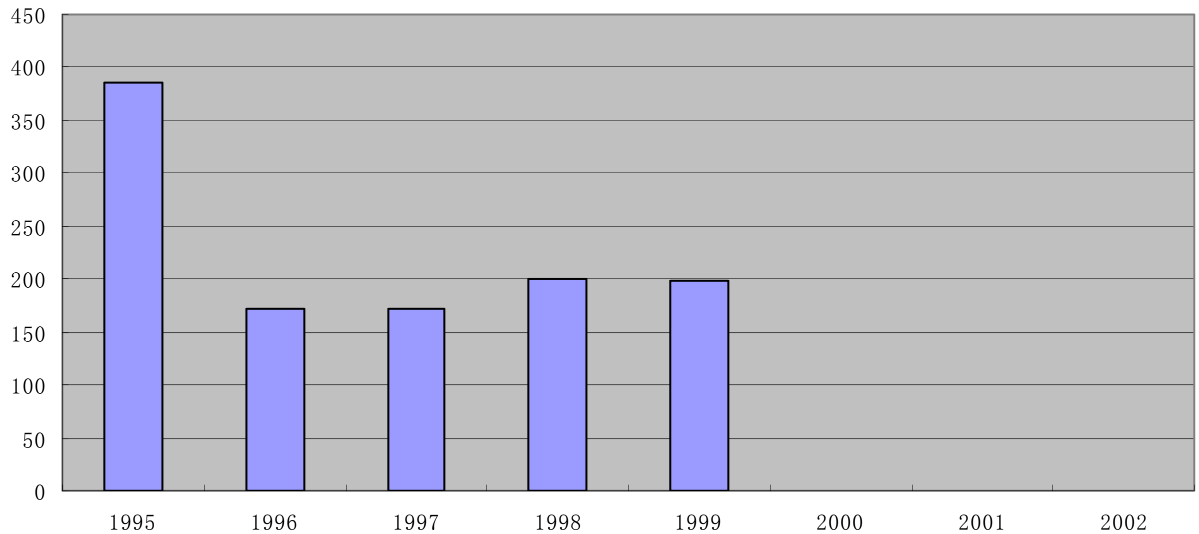
However, methanol prices are volatile. The price fluctuations in 1994 and 1997 greatly contributed to reduced use of methanol vehicles. After the partnership between CEC and major fuel retailers expired, the number of methanol vehicles continued to decline (Joyce, 2001). As shown in Figures 12 and 13, vehicles fueled by M100 were phased out by 2000, and the number of M85 vehicles has been declining since 1998. Further, automobile manufacturers have not provided new M85 vehicles for several successive model years (AFDC, 2001a, 2001b, 2002 and 2003). Consequently, the number of M85 vehicles in use will continue to decline as older vehicles are removed from service. These indicators suggest that M85 and M100 vehicles have lost or are losing their market viability.

Figure 12. Estimated Number of M85 Vehicles in Use in the U.S., 1993-2002



Source: same as Figure 2.

Figure 13. Estimated Number of M100 Vehicles in Use in the U.S., 1995-2002



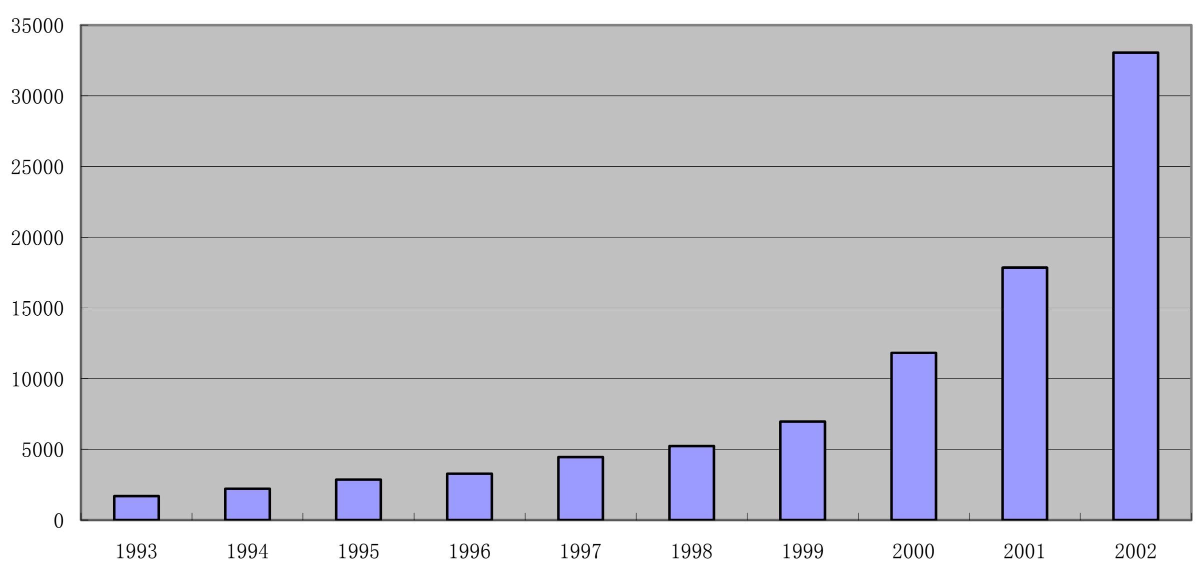
Source: same as Figure 2.

3.1.5 Electric Vehicles

Electricity is unique among the alternative fuels because mechanical power is derived directly from it, whereas the other alternative fuels release stored chemical energy through combustion to provide mechanical power. Motive power is produced from electricity by an electric motor. The electricity used to power vehicles is commonly provided by batteries. Electric vehicles produce zero tailpipe emissions, which is the most important motivation to launch them.

Although the number of battery electric vehicles (BEVs) has increased since 1993 (as shown in Figure 14), their production has been mainly motivated by ZEV regulations, not by the market. Currently, the technology does not meet most consumers' requirements due to its inherent limitations including long recharging time, poor performance, and, especially, limited range (typically, 50-130 miles). Even multi-vehicle households are reluctant to purchase BEVs (Andan and Faivre D'Arcier, 1997). Due to limited demand, BEVs have been abandoned by nearly all major automakers: General Motors suspended its production of BEVs in 1999; Honda abandoned its BEV project in 1999; and Toyota discontinued its production of the RAV4, the last BEV model for the retail market, in 2003. At present, almost all on-road BEVs in the U.S. were made years ago and are out of production. Further, amendments to the ZEV mandate approved by the California Air Resources Board (CARB) on April 24, 2003 offer another option to automakers — they can produce fuel cell vehicles instead of BEVs to meet their ZEV requirements. The amendments are likely to contribute to the continued stagnation or further decline of the market penetration of BEVs. On the other hand, it is believed that BEVs may have potential niche markets for community or neighborhood transportation uses, in places with cheap electricity and better accessibility, and in regions with zero-emission mandates (Chan, 2002). Daimler Chrysler was advertising its GEM neighborhood vehicle on television in California as late as fall 2002 or winter 2003. The EIA estimated that about 97% of 15,313 electric vehicles made available in 2002 are motorcycles and low speed vehicles such as neighborhood electric vehicles (NEVs). In contrast, Ford halted its production of Th!nk City (a NEV) in the U.S. in 2003 because of lackluster demand.

Figure 14. Estimated Number of BEVs in Use in the U.S., 1993-2002

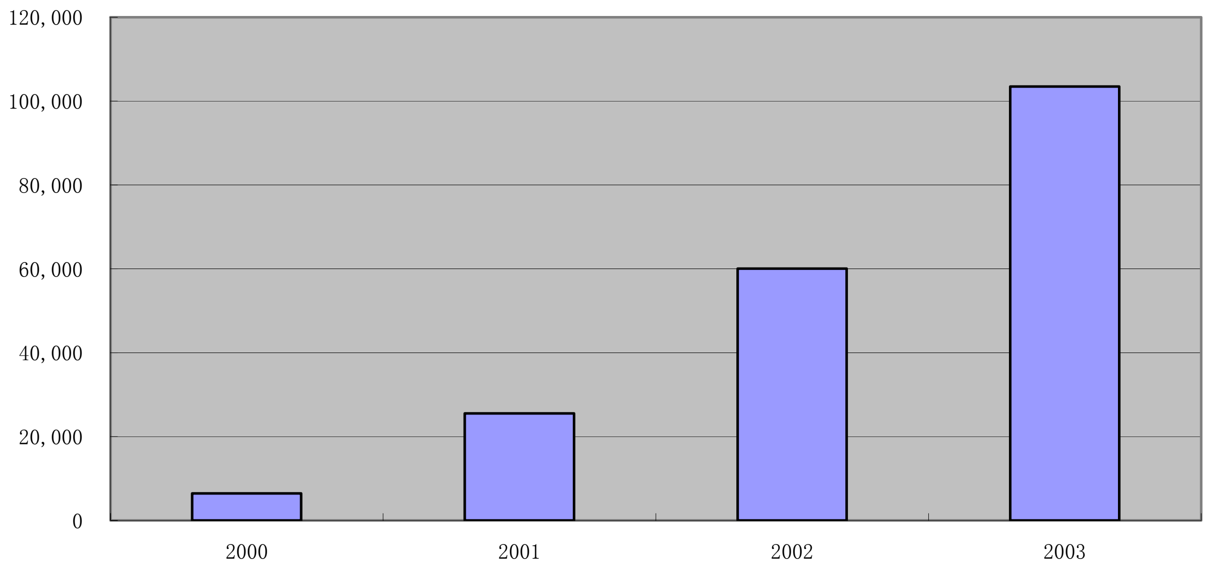


Source: same as Figure 2.

Although the introduction of BEVs in the U.S. has not been satisfactory, hybrid electric vehicles (HEVs) are advancing rapidly at the forefront of transportation technology. Different from BEVs, the batteries of HEVs do not need an external source since they are recharged during operation. Further, hybrid power systems address many underperformance issues of electric power systems, especially the limited range (actually, HEVs even double the range of conventional vehicles). Compared to conventional vehicles, HEVs greatly increase fuel economy, and produce low levels of GHG (CO_2) and tailpipe emissions. However, under EPACT92, HEVs are not considered to be AFVs since they still rely on gasoline. On the other hand, according to California's Zero Emission Vehicle mandate, HEVs are classified as AT-PZEVs, and could earn 0.2 ZEV credit. Currently, the Honda Civic Hybrid and Toyota Prius qualify for ZEV credits. However, the Honda Insight could not earn ZEV credits since it does not meet all requirements of AT-PZEVs, which are (1) to meet the standards of Super Ultra Low Emission Vehicle (SULEV) tailpipe emissions, (2) zero evaporative emissions, and (3) a 150,000-mile warranty on emission control equipment (CARB, 2001). The April 24 amendments to the CARB ZEV mandate acknowledged the increasing market popularity of HEVs and explicitly called for production targets. Specifically, it advocated 420,000 HEVs to be manufactured by 2011 (Rogers, 2003).

The HEVs available for sale are roughly cost- and performance-competitive to comparable gasoline vehicles, and demand for them is proliferating. In December 1997, Toyota introduced its Prius, the first commercial HEV, in Japan, and about 37,000 Toyota Prius vehicles were sold worldwide in 2001. In December 2003, Toyota said that it boosted the 2003 original production plan of its Prius hybrid by 31 percent (from 36,000 to 47,000) to help meet the vehicle's heavy demand in the U.S. Market (Fleets and Fuels, 2003b). As shown in Figure 15, there were altogether 103,468 HEVs registered in 2003 since the Honda Insight, Toyota Prius, and Honda Civic Hybrid were introduced to the U.S. in 1999, 2000, and 2002, respectively. Among them, 43,435 HEVs were new registrations in 2003, up 25.8% from the year before. California led the new registrations of HEVs (11,425 units) in the U.S. (Polk, 2004). Since the production of HEVs is mainly motivated by the market, not by mandates, HEVs have the capability of continued growth in the automobile market. According to J. D. Power and Associates' (2003) Hybrid Vehicle Outlook, the annual sales of HEVs are expected to increase to 500,000 units by 2008 and 872,000 by 2013. Alternatively, the Annual Energy Outlook (AEO) 2004 anticipated that the annual sales of HEVs will be 750,000 units in 2010 and 1.1 million units in 2025 (EIA, 2004a).

Figure 15. Estimated Number of HEVs Registered in the U.S., 2000-2003



Source: Polk (2004).

HEVs are dependent on petroleum products. However, a large population of HEVs on the road could significantly reduce gasoline consumption in the transportation sector, and hence reduce the importation of oil. Also, they are beneficial to air quality. Therefore, although HEVs are not considered AFVs by EPA, their environmental performance has led to legislation to promote their market penetration. Until 2004, HEVs are eligible for federal and state tax deductions. So far, according to federal statute, HEVs do not qualify to use the HOV lanes. However, Virginia has recently allowed single occupant HEVs with special clean fuel license plates to use the state's HOV lanes until July 1, 2006 (VDOT, 2004). Although its status after July 2006 is uncertain, this exemption is likely to motivate more consumers to purchase HEVs. Currently, California and Arizona are pursuing federal support of similar HEV exemptions, and the Congress is considering legislation to automatically permit states to allow HEVs to use HOV lanes. These policies will encourage the market penetration of HEVs. For all these reasons, the HEV is considered a viable alternative in this study.

Another type of electric vehicle is the fuel cell vehicle (FCV). The fuel cell is accepted worldwide as a very promising technology for use in vehicles. Unlike BEVs, FCVs convert chemical energy to electricity on board, and hence they do not need a long recharge time. Depending on their configurations, FCVs could operate on a variety of fuels such as hydrogen, methanol, natural gas, and so on. The FCVs are powered by an electric motor. They offer quiet operation, rapid acceleration, and potentially lower maintenance requirements (Sperling and Ogden, 2004). Further, they potentially have the same driving range and convenience as a conventional vehicle (CARB, 2002). FCVs produce zero or near-zero tailpipe emissions, depending on the fuel used in the fuel cell; an FCV with hydrogen fuel would be credited as a pure ZEV. Superior to other AFVs, FCVs are expected not only to be environment-friendly but also to provide private benefits to customers (Sperling and Ogden, 2004).

However, FCV technology is currently in the development stage. Many automobile manufacturers have invested billions of dollars into FCV development. In October 2002, the first hydrogen station in the San Francisco Bay Area opened to fill up 16 fuel-cell prototypes being tested by the California Fuel Cell Partnership (CaFCP). The 2003 Honda FCX, fueled by hydrogen, is the first FCV to be certified by the EPA and CARB, and Honda plans to lease 30 FCVs in California and Tokyo during the next two or three years. Until April 2004, 14 of Honda's FCVs are in use in the U.S. and Japan (EIN, 2004a). General Motors Corporation (GM) recently announced it has signed a two-year agreement to lease a fuel cell-powered minivan to the United States Postal Service (USPS) for use in mail delivery around Washington, D.C. (EIN, 2004b).

Other automakers – Ford, Daimler Chrysler, Nissan, and Toyota – have announced plans to sell a limited number of FCVs in the U.S. by 2002-2004. However, none of them have publicized plans for the mass production of FCVs (DOE, undated-a).

Conventional wisdom holds that the mass sale of FCVs will not be possible until 2010 (Sperling, 2002). The April 24, 2003 amendments to the California Zero Emission Vehicle mandate require the large automakers to produce approximately 250 FCVs by 2008, 2,500 by 2011, and 25,000 by 2014 as an option to meet their ZEV requirements (CARB, 2003; Rogers, 2003)[1]. The Hydrogen Fuel and FreedomCAR Initiatives have as their goal to commercialize hydrogen-powered FCVs by 2015 (EDTA, 2004). More conservatively, Romm (2004a, p. 10) concluded that "hydrogen and fuel-cell vehicles should be viewed as post-2030 technologies".

In view of the discussion above, we select CNG vehicles, E85 vehicles, HEVs, and FCVs as the alternatives for this research. Since CNG vehicles, E85 vehicles, and HEVs are currently commercially available, they are considered to be near-term alternatives. On the other hand, FCV technology is the least mature technology among these, and not likely to be a near-term panacea. Therefore, the FCV is treated as a medium-to-long term alternative.

3.2 Limitations of Alternative Fuel Vehicles[2]

Table 4 presents a comparison of AFVs to conventional vehicles on key dimensions. Currently, the major barrier for widespread use of CNG, E85, and LPG vehicles is the availability of refueling stations. Among these, LPG vehicles have the largest number of refueling stations, as shown in Table 4. However, the number of available LPG stations represents less than 2% of the number devoted to gasoline and diesel services. Also, only 2.2% of vehicles that are capable of being

[1] The amendments also require the production of 3.4 million partially zero emission vehicles (PZEVs) by 2010. These are gasoline vehicles with especially low emissions (5% of the usual amount), including current models such as the Toyota Camry, BMW 325, and Nissan Sentra. Although analysis of PZEVs is beyond the scope of this study, they should be kept in mind as a serious competitor to both conventional gasoline vehicles and the AFVs studied here.

[2] The limitations of LPG vehicles are also discussed in this section due to their large market share.

fueled by E85 are operating on E85 in 2000, mainly due to deficient fuel infrastructures (most E85 stations are located in the Midwest). In California, there were more than 172,000 E85 FFVs registered in April 2003. However, since E85 fuel was not available here until recently, all those E85 FFVs were exclusively powered by gasoline (CEC, 2003). In August 2003, the first E85 refueling station in California was opened in San Diego, which remains the only one in California up to now.

Table 4. Comparison of AFVs to Conventional Vehicles on Key Dimensions

Fuel Type	Gasoline	CNG	E85	LPG
Number of Stations	170,700[a]	1,038 [b]	151 [b]	3,339 [b]
Fueling Time	-	Slow fill (up to 8 hours) Quick fill (3-5 minutes) [f]	Same as gasoline [g]	Comparable with gasoline [e]
Relative Range [1]	1	0.5[c]	> 0.7[d]	Somewhat < 1[e]
Incremental Cost	-	Automaker's price premium: \$1,500-\$6,000 Conversion: \$2,000-\$3,000 [f]	Same as gasoline vehicle [g]	Conversion: \$2,500[e]
Fuel Price [h]	\$1.52 per gallon	\$0.89 per GGE	\$1.80 per GGE	\$1.62 per GGE
Maintenance and Reliability	-	Gas tanks require periodic inspection and certification. [f]	Require special lubricants and E85 replacement parts. [g]	-
Safety	-	Require special training to operate and maintain vehicles. Training and certification technicians are required.[f]	Require special training to operate and maintain vehicles. [g]	Require special training to operate and maintain vehicles. [e]

1. Relative range = (range of the vehicle) / (range of a comparable gasoline vehicle)
Sources:
a. (EI, 2003); b. (AFDC, 2004); c. (CEC, 1999); d. (NEVC, 2001); e. (AFDC, undated-c); f. (AFDC, undated-d); g. (AFDC, undated-e); h. (AFDC, 2000);

Another common shortcoming of these AFVs is that their ranges are less than those of conventional vehicles. Among these, CNG vehicles have the shortest ranges, 150 – 250 miles, which are about half of conventional vehicle ranges (CEC, 1999). Similar to CNG, the low energy density of E85 leads to shorter ranges of E85 vehicles. Therefore, CNG and E85 vehicles may require more frequent refueling. A larger fuel tank may help compensate for the loss of vehicle range, but at the expense of occupying more of the limited vehicle space. The reduced range makes these AFVs uncompetitive with conventional vehicles, at least for long-distance commuters. Further, these three AFVs require special training on vehicle operation and maintenance, which is inconvenient for consumers.

As for fuel prices, E85 and LPG have higher prices per gasoline-gallon-equivalent (GGE) than gasoline. As GAO (2000) concluded, the low price of gasoline remains an important impediment to AFV penetration. The National Defense Council Foundation (NDCF) reported that the true cost of gasoline is $5.20 per gallon, counting the cost of Mideast military outlays (Fleets and Fuels, 2003c). However, increasing the gasoline tax has historically been, and remains, politically unpopular. Currently, most E85 and LPG vehicles are FFVs or bi-fuel vehicles, and can be powered by gasoline. The higher alternative fuel prices will inhibit private consumers' voluntary use of E85 and LPG. Although ethanol used as a transportation fuel is subsidized by the Federal excise and energy tax, the price of E85 per GGE still ranks highest. Further, the incentive will shrink from 54 cents per gallon in 2001 to 51 cents per gallon by 2005, and is scheduled to remain in effect through 2007 (Joyce, 2001). However, ethanol prices are expected to be higher after 2007. Most ethanol in the U.S. is made in the Midwest from excess corn crops in that region, and thus their feedstock directly affects ethanol prices. For example, the severe flooding of the Mississippi River in 1993 led to a temporary increase in regional ethanol prices (CEC, 1999). Similarly, the volatile LPG prices remain a concern to the development of LPG vehicles (CEC, 2003).

The propane industry has been criticized by some for not promoting the fuel's use as an alternative transportation fuel (Joyce, 2001), particularly compared to the natural gas industry, which aggressively advertises its fuel for vehicular use. Propane industry officials have stated that the industry lacks the internal cohesion necessary to promote the use of propane as a transportation fuel. Officials have also noted that, traditionally, the propane industry has been made up of small-scale suppliers who primarily serve residential customers. Some of these suppliers fear that growth in the use of propane as a transportation fuel would cause the deterioration of the suppliers' smaller businesses. And some propane consumers have expressed concern that increasing demand for propane as a vehicle fuel would increase prices. However, the GAO concluded that there will only be a small increase in propane's use as an alternative transportation fuel over the next 10 years and that propane consumption by non-transportation sectors will not be affected by this increased demand. In particular, it projected that the overall price of LPG will increase only 3.28 cents per gallon by 2010, and thus has little impact on the propane industry (GAO, 1998).

As presented in Table 4, the incremental costs of CNG vehicles and LPG vehicles will limit their demand. The initial costs of CNG vehicles, whether directly manufactured or converted, are higher than those of their counterparts. The incremental costs of a Ford Crown Victoria CNG vehicle were $3,802 in model year 2002 (GSA, 2002). Although the price of CNG itself is much lower than that of gasoline, the additional costs of CNG vehicles cannot be compensated for by the low fuel price (CEC, 1999). With respect to LPG vehicles, most vehicles are conversions, with the conversion costing about 10 percent of the conventional vehicle base price (AFDC, undated-c). LPG vehicles made by manufacturers are more expensive than equivalent conventional vehicles. In 2002, a bi-fuel Ford F-150 cost about $3,500 more than a gasoline Ford F-150 (GSA, 2002). Tax incentives provided by federal, state, and local governments may offset some of these price premiums. Through the year 2004, a clean fuel passenger vehicle is eligible for a federal tax deduction, but the deduction amount declines $500 each year, from $2,000 in 2001 to $500 in 2004. California incentives go up to $3,000 for dedicated natural gas vehicles through March 1, 2004 (DOE, undated-b). However, these incentives are not enough to compensate the incremental costs. Further, it is uncertain whether the tax deductions will continue after 2004. Therefore, the higher initial costs of CNG and LPG vehicles continue to be an obstacle for their market penetration.

Specifically for CNG vehicles, natural gas needs to be compressed to about 3000 psi for vehicular use, thus pressurized tanks require periodic inspection and certification. Although the tanks have been designed to be as safe as gasoline tanks, safety may still be a concern for consumers. Refueling is another drawback of CNG as an alternative fuel. First, a slow fill will last up to eight hours, which is not likely to be appealing to private consumers. A small refueling station costs about $3,500 per vehicle (Sudradjat and Iswandi, 2000). Thus, even if private consumers have space to install home refueling appliances, the additional installment cost will make them reluctant to do so. Second, a quick fill station costs about $300,000, significantly more than the cost of refueling stations for gasoline (Nichols, 1994; GAO, 2001). Except for their range, the operational performances of CNG vehicles are competitive to those of comparable conventional vehicles, but cylinder location and number may reduce their payload capacity (AFDC, undated-d). The demand for CNG vehicles in the future light-duty vehicle market will depend on the public acceptance of shorter range, technology advances, reduced costs because of mass production, and future policies (CEC, 1999).

Except for their range, the operational performances of E85 vehicles are also competitive to those of comparable conventional vehicles (AFDC, undated-e). The emissions of E85 vehicles are somewhat lower than those of conventional vehicles; the life-cycle emission reduction in greenhouse gases for ethanol is superior to most fuels. However, the higher volatility of E85 will result in higher evaporative emissions at fuel stations (CEC, 1999). The future demand for E85 vehicles is mainly dependent on fuel price and the availability of refueling infrastructures.

Generally, the operational performances of LPG vehicles are equivalent to those of comparable conventional vehicles (AFDC, undated-c). Their widespread use has the potential to reduce tailpipe emissions and our dependence on foreign oil. However, continued growth in the demand for LPG vehicles relies on the commercialization of conversion equipment, a “chicken-and-egg” dilemma. Without a steady and growing demand, the production of conversion equipment cannot form a viable market, and hence the variety and availability of LPG vehicles will be constrained to those provided by the auto manufacturers (CEC, 1999). Conversely, if the LPG vehicle selection is limited, the demand will be constrained.

Although HEVs are less expensive than BEVs, their initial prices are higher than conventional vehicles. Table 5 presents a previous comparison between the Honda Insight and Civic. The cost difference suggests that the Honda Insight is still relatively expensive even when fuel savings are considered in the long term (Yacobucci, 2000). However, as the price of gasoline increases, the purchase and operating costs of HEVs become competitive to (even lower than) those of conventional gasoline vehicles in the long term, as shown in Table 6. The purchase costs of HEVs are also expected to decrease with their mass production. On the other hand, earlier HEVs were two-seater vehicles (Honda Insight) or compacts (Toyota Prius and Honda Civic Hybrid), which limited their market shares. However, vehicle model selection will not be a major problem in the development of an HEV market, since according to automakers, more choices including SUVs, pickups and so on will be available in the next several model years (DOE, undated-c). For example, the model year 2004 Toyota Prius has been classified by EPA as a mid-size rather than a compact vehicle, and the Honda V6 hybrid Accord (sedan), GM hybrid Silverado (pickup), and Toyota hybrid Highlander (SUV) will be launched for general sale later this year or in the first quarter of 2005 (Fleets and Fuels, 2004c, 2004d, and 2004e). Another limitation of HEVs, however, is that their electronic components may require maintenance from certified dealers (Yacobucci, 2000).

Table 5. Cost Difference for Honda Insight (Hybrid) and Honda Civic (Gasoline)

Insight purchase price (MSRP) [a]	$18,800
Fuel cost savings [b]	$2,500
Insight net cost	$16,380
Civic purchase price (MSRP)	$12,100
Net cost difference	$4,280

a. This price has been subsidized by the manufacturer to motivate sales.
b. Fuel cost savings are over ten-year ownership (15,000 miles per year), at a gasoline price of $1.20 per gallon.

Source: (Yacobucci, 2000)

Among the four currently-available technologies being considered here, for several of them, a number of important factors have considerable uncertainty as far as prospective consumers are concerned: cost, maintenance, refueling, and so on. Compared to the others, HEVs may look especially attractive with respect to refueling and range, suggesting that the HEV could be a useful bridge or interim technology.

Table 6. Cost Difference for Honda Civic Hybrid and Gasoline

Civic Hybrid (5-speed, manual transmission) purchase price (MSRP)	$19,650
Annual fuel cost saving[a]	$607
Total fuel cost savings[b]	$4,687
Hybrid Civic net cost	$14,963
Civic Gasoline (LX, 5-speed, manual transmission) purchase price (MSRP)	$15,360
Net cost difference	-$397

a. Annual fuel cost saving calculation is based on 45% highway driving, 55% city driving, 15,000 annual miles, and gasoline price of $1.94 per gallon (national average, released by the EIA on May 10, 2004).
b. Total fuel cost savings are based on 10-year ownership and 5% discount rate.

The development of FCVs is facing many challenges. First, compared to an internal combustion engine (ICE), the cost of a comparable fuel cell stack is extraordinarily expensive, more than ten times as much as that of an ICE (Parrish, 2003). Therefore, significant effort will be required to reduce the stack cost, and hence lower incremental costs of FCVs. Second, hydrogen is currently the most promising primary fuel for FCVs. If the principal sources of hydrogen are fossil fuels, hydrogen FCVs are not a cost-effective pollution reducer, considering the upstream emissions required to produce the hydrogen (Romm, 2004b). Third, the scarcity of hydrogen refueling infrastructures is a major barrier to the widespread adoption of FCVs, and consumers may be required to pay a premium to support its growth (Yacobucci, 2000). There are only seven hydrogen stations nationwide at present, so the growth of hydrogen refueling infrastructures will take significant money and time. On April 20, 2004, California governor Arnold Schwarzenegger came to the University of California, Davis, and signed an executive order creating a public and private partnership to build hundreds of hydrogen refueling stations statewide. A true network that makes hydrogen accessible to every Californian is expected to be established by 2010 and cost 100 million dollars (Fleets and Fuels, 2004f; UCD, 2004).

Similar to other alternative fuels, the expense of hydrogen ($4.00 per GGE) will impede the public acceptance of FCVs (Romm, 2004b). Furthermore, limited range is another barrier for the development of FCVs. The range of the Honda FCX is 170 miles, significantly less than that of a conventional vehicle, due to limited storage capacity (DOE, undated-a). Therefore, additional effort will be involved to develop the pressurized tanks or hybrid systems that are required in order to store hydrogen more effectively. Cold-weather operation is also a major problem for the development of FCVs since a certain temperature is required for fuel cells to achieve full performance, and water, a byproduct of fuel cells, can freeze at low temperatures (DOE, undated-d). In addition, the competition with other technologies such as HEVs is a challenge for the development of FCVs (Romm, 2004b). Other limitations of FCVs include safety issues, weight and specialized maintenance requirements (DOE, undated-d; Romm, 2004b; Yacobucci, 2000). Compared to other AFVs, there are more barriers for the development of FCVs. An analysis conducted by MIT concluded that there is no current basis for preferring FCVs over the next 20 years or so, based on the assessment of energy consumption and GHG emission (Weiss, et al., 2003). Therefore, the future of FCVs is full of uncertainty.

A number of debates have taken place around the popular proposition of hydrogen FCVs recently. Romm (2004b) synthesized the key issues reducing the "hope of hydrogen" by presenting seven main barriers to the development of hydrogen fuel. He concluded that promoting FCVs is not a viable strategy for fighting climate change in the near or medium term. On the other hand, in a response to Romm's points, Thomas (2004) defended the optimistic future of FCVs by providing additional evidence on the barriers. Sperling and Ogden (2004) also stand by the transition to hydrogen as a transportation fuel. They pointed out that hydrogen is the most compelling long-term alternative fuel; FCVs can offer both environmental benefits to society and private benefits to customers; there are no economic enemies for hydrogen (oil companies oppose BEVs, whereas they support FCVs because they can potentially obtain economic benefits from the hydrogen market); and the auto industry strongly promotes the introduction of FCVs. However, they also admitted that hydrogen is neither an easy nor a straightforward way to gain large air pollution, GHG, or oil reduction benefits in the near and medium term.

4 DATA AND THE VARIABLES

The estimation of AFV diffusion models relies on time-series data. The data used in this study came from various sources, as summarized in Table 7. The dependent variables are annual sales of different kinds of AFVs. Separate models are developed for each AFV both because each type is of individual interest and because the model calibration process confirms that the best models for each type are not similar enough to justify pooling the data (see Chapter 5). As illustrated in the last chapter, the EIA, DOE, provides relatively complete data on the AFVs in use in the U.S. from 1993-2002 (not including HEVs). However, most data did not distinguish the numbers of light-duty vehicles, medium-duty vehicles, and heavy-duty vehicles for each calendar year. Since the demand of *light-duty* AFVs is the focus of this study, it is necessary to obtain their time-series data for us to be able to estimate the models. The Transportation Energy Data Book by the Oak Ridge National Laboratory (ORNL) becomes a useful complement to the EIA data. We assume that the differences between the numbers of AFVs in use in two consecutive years represent the annual sales in the later calendar year. Furthermore, since the AFVs in use include both OEM productions and conversions, the annual sales comprise these two segments.

Based on the literature review, we identified several potential explanatory variables in determining the aggregate demand of AFVs: the number of AFV models available in the market (model availability), the number of alternative fuel refueling stations (station availability), fuel prices, the purchase/incremental costs of AFVs, and the range of AFVs. In Table 7, vehicle incremental costs refer to the "price premium" for an AFV, or the amount by which the purchase price of an AFV model exceeds that of the comparable conventional gasoline model.

A number of other variables could be expected to influence AFV sales, but since data are not available for them they could not be incorporated into the models. For example, Greene (2001) incorporated acceleration performance, luggage space, and maintenance costs of AFVs as well as other variables into his nested multinomial logit model. The variables shown in Table 7 comprise the most fundamental objective influences on sales. We discuss each variable in turn.

Table 7. Data Source for Variables

Variables	Fuel Type	Data Source
AFV annual sales	Hybrid	Polk Automotive Intelligence http://www.polk.com/news/releases/2004_0422.asp
	E85 CNG	The EIA, DOE http://www.eia.doe.gov/fuelalternate.html Transportation Energy Data Book, ORNL
Model availability	Hybrid	Hybrid Electric Vehicle Program, DOE http://www.ott.doe.gov/hev/
	E85	National Ethanol Vehicle Coalition http://www.e85fuel.com/ Fuel Economy Guide, DOE and EPA http://www.fueleconomy.gov
	CNG	Uncle Mark's Alternative Fueling Station http://www.altfuels.org/general/myvan.html Fuel Economy Guide, DOE and EPA http://www.fueleconomy.gov
Conversions	E85 CNG	The EIA, DOE http://www.eia.doe.gov/fuelalternate.html
Station availability	E85 CNG	Alternative Fuel Data Center, DOE http://www.afdc.doe.gov Transportation Energy Data Book, ORNL
AFV incremental costs	E85 CNG	Federal Supply Service, GSA http://www.gsa.gov
Fuel Price	Gasoline	History: 1993 – 2001, the EIA, DOE http://www.eia.doe.gov/emeu/aer/txt/ptb0522.html Projection: 2002 – 2025, Annual Energy Outlook 2003, the EIA, DOE http://www.bo.cnr.it/www-sciresp/GdL/Energia-Crisi_Globali/Materiali/DOE/DOE-Eia/aeotab_3.htm
	E85	History: 1993 – 2000, Coltrain (2001) Projection: 2001 – 2025, same as gasoline price
	CNG	History: 1993 – 2001, the EIA, DOE http://www.eia.doe.gov/emeu/aer/txt/ptb0608.html Projection: 2002 – 2025, same as gasoline price
AFV range	Hybrid	Hybrid Electric Vehicle Program, DOE http://www.ott.doe.gov/hev
	E85	National Ethanol Vehicle Coalition http://www.e85fuel.com/pdf/E85ColumbiaSC.pdf
	CNG	California Energy Commission http://www.energy.ca.gov/afvs/reports/1999-11_500-99-013.PDF

Prior to their OEM production, conversions of AFVs played an important role in their market penetration. Therefore, it is necessary to consider conversions' potential effects on the adoption of AFVs. However, as shown in Figure 4, the numbers of CNG, E85, and LPG as well as other alternative fuel conversions are confounded in the total number of alternative fuel conversions. That is, we cannot separate the numbers of CNG and E85 conversions from the total number of conversions, due to the availability and nature of the conversion data. Alternatively, we created a variable, the conversion indicator, to represent the role of conversions. The conversion indicator is expressed as the ratio between the number of all alternative fuel conversions at each year and the maximum number of all conversions (occurring in 1996). The higher the conversion indicator is, the larger the number of conversions that occurred that year. As illustrated in Figure 4, the number of conversions has been decreasing since 1996. Therefore, the importance of conversions in the AFV market has been decreasing accordingly. Consistent with the fuel price projections of the AEO 2003 report, the nominal historical fuel prices were converted to real dollars in 2001, based on the U.S. consumer price index (CPI).

Model availability of AFVs is assumed to be positively associated with their sales. Having a larger number of AFV models available in the market indicates that consumers face a more diverse choice set. Each AFV model may offer some unique attributes, which are preferred by some consumers. Thus, as the number of AFV models increases, the probabilities that AFVs meet consumers' requirements increases (Greene, 2001). Further, the AFV models offered by different automakers may attract potential consumers with strong brand loyalty. Therefore, expending the diversity of the choice set available to consumers is likely to enlarge the size of the potential market for a given AFV. Similarly, the availability of conversion facilities offers consumers an option to adopt AFVs without sacrificing their other requirements. So we assumed that the conversion indicator has a positive impact on AFV sales. The scarcity of refueling infrastructures, higher purchase costs, and higher fuel prices are the main obstacles to impede the penetration of AFVs. It is thus reasonable to expect that station availability is positively related to AFV sales, and vehicle incremental costs and fuel prices have negative influences on the demand for AFVs. By contrast, when the gasoline price increases, individuals are more likely to shift from the conventional vehicle market to an advanced-technology vehicle market. The limited range is another important drawback of CNG and E85 vehicles. Therefore, an increase in range is likely to motivate some consumers to purchase these AFVs. Similarly, the greater-than-conventional range offered by HEVs is presumably a selling point for some consumers.

Although vehicle incremental costs potentially have negative impacts on the penetration of AFVs, the scarcity and poor quality of these data make it difficult to incorporate them in the model. First, to capture the impacts of incremental costs, it is necessary to obtain their time-series data back to 1993. However, we found complete data on vehicle incremental costs for only three model years: 2001, 2002, and 2003. Further, inspection of these data suggests that incremental costs of different models do not change in a systematic way but randomly fluctuate, as shown in Table 8. Similarly, complete time-series data on AFV ranges are not available. The detailed data are presented in Appendix 1.

Table 8. Incremental Costs of CNG and E85 Vehicle Models

Model Year	**CNG Vehicles**			**E85 Vehicles**		
	Crown Victoria	F-150	B3500	Taurus	Tahoe	Caravan
2001	$7,781	$1,703	$3,314	$369	-	$10
2002	$3,802	$2,654	$3,933	$0	$5,605	$1,502
2003	$4,805	$4,154	$3,481	$0	$0	$1,803

Data source: General Service Administration.

5 MODEL CALIBRATION AND RESULTS

5.1 Model Assumptions

In this study, we developed diffusion models of light-duty AFVs in the U.S., built on the Bass model. We relaxed one major assumption underlying the basic first-purchase Bass model — we assumed that the market potentials of AFVs do not keep constant but vary as explanatory variables change. Further, we assumed that there are no replacement sales in AFVs' initial launching stage (specifically, 1993-1002). In fact, the AFV annual sales may consist of replacement sales as well as first-purchase sales, especially for LPG vehicles. Current AFV data do not allow us to separate these two types of sales. However, for the AFVs empirically analyzed in this study (CNG vehicles, E85 vehicles, and HEVs), their commercial production by OEMs is generally no more than 10 years old. Therefore, it is reasonable to assume that their replacement sales account for only a tiny fraction of their annual sales for these years. However, as these vehicles age, replacement sales may represent a substantial proportion of sequential annual sales later on, given typical vehicle lifecycles and replacement rates.

In addition, we assumed that: (1) the coefficients of explanatory variables, and the innovation and imitation coefficients, keep constant within the specified timeline; (2) there are no interactions among the AFVs studied here; (3) the capacity for production and conversion of AFVs equals or exceeds their demand; and (4) government policies and marketing strategies such as advertising, demonstrations, and campaigns do not affect the penetration of AFVs (simply for lack of complete quantifiable data on these policies and strategies). Although the effects of current policies promoting AFV development were not considered in model calibration, the influences of future policies can be tested by changing future input variables such as costs.

It is worth noting that, in reality, the diffusions of AFVs in the market may be inconsistent with these assumptions. First, the market environment and performance of AFVs may affect the magnitudes of the innovation and imitation coefficients. For example, if gasoline prices keep increasing, the high fuel efficiency of HEVs will make them more attractive, and hence HEVs' innovation and learning effects may increase. Second, the marginal contribution of some explanatory variables may decline over time. For instance, based on surveys of diesel vehicle purchasers, Sperling and Kurani (1987) found that station availability is not a major concern for them if the fraction of refueling stations that carry diesel is about 10-20%. Therefore, the coefficients of station availability will decrease sharply as the shares of alternative fuel stations increase to some level. Third, it is likely that demands for AFVs powered by different fuels are not independent of each other. Different AFVs provide similar environmental benefits. If one type of AFV becomes popular in the market, the attractiveness of other types of AFVs will most likely decrease. That is, the diffusion of one dominant type of AFV may affect the diffusions of others. Fourth, it is not always the case that AFV supply meets the market demand. For example, Toyota had received 12,000-unit pre-orders before the 2004 model year Prius launched in mid-October 2003 (Fleets and Fuels, 2003b). The lag in supply may delay the diffusion of HEVs to some extent. Fifth, marketing strategies affect individuals' awareness of AFVs, and hence influence their adoption. Four consecutive surveys conducted in 2000, 2001, 2002, and 2003 found that awareness of HEVs grew from 36% of the respondents to 53% over that time period (EERE, 2004). This growth is partly due to advertising and news related to HEVs. Finally, if the development of AFVs lacks policy support, such as fleet acquisition requirements in particular, it is difficult for AFVs to gain a toehold in the market (Leiby and Rubin, 2001). Therefore, public policies have influenced the development of AFVs since and even before their introduction. Previous policies have initiated the early penetration of AFVs. It is important to evaluate the potential impacts of future policies on the development of AFVs when we predict the demand for AFVs. However, as mentioned in the last chapter, the data used here consist of at most 10 points in time. The limited number of observations makes it impossible to estimate a complex model.

5.2 Modeling Procedure and Results

As discussed in Chapter 2, three techniques (OLS, MLE, and NLS) have been used by previous researchers to estimate the parameters in the Bass model. Among them, NLS is theoretically and practically the best technique. When we directly applied the NLS approach to estimate the three parameters p, q, and m in the basic Bass model, parameter estimates were sensitive to their initial values, especially the market potential m. Therefore, we began the model calibration procedure with OLS estimation, which yields approximate ranges of initial values for these parameters. The next section will describe the model calibration procedure in detail, with the diffusion of CNG vehicles as an example.

5.2.1 Natural Gas Vehicle Diffusion Model

Based on the data for CNG vehicles, we applied the OLS technique to estimate the parameters in Equation 2, and indirectly obtained estimates of the three parameters in the basic Bass model. Table 9 presents these parameter estimates and their p-values respectively. We then set the indirect estimates of p, q, and m as their initial values in the NLS estimation. Equation 3 was used to estimate the basic Bass model. The model outcomes are also presented in Table 9. Both models yield similar parameter estimates, but the model using the OLS technique provides a higher R^2. According to both model results, the ceiling on the market potential of CNG light-duty vehicles is about 100,000 if it remains constant. Compared to a total fleet vehicle size of 87,340 in 2002, this constant market potential shows that the total number of CNG vehicle adopters is close to the ceiling, and that the annual sales of CNG vehicles is leveling off. Furthermore, the parameter estimates developed from the basic Bass model provide approximate magnitudes of the innovation and imitation coefficients.

Table 9. The OLS and NLS Parameter Estimates of the Basic Bass Model for CNG Vehicles

Parameters		**a**	**b**	**c**	**p**	**q**	**m**	**R^2**
OLS	Coefficients	2105.8	0.2442	-0.000002640	0.0210	0.265	100371	0.652
	p-value	0.434	0.051	0.028	-	-	-	
NLS	Coefficients	-	-	-	0.0210	0.265	100142	0.592
	p-value	-	-	-	0.055	0.010	0.0002	

In the next step, we relaxed the assumption of constant market potential, allowing it to vary with explanatory variables. Previous studies defined market potential as an exponential or power function of marketing-mix variables such as prices (e.g., Kamakura and Balasubramanian, 1988; Jain and Rao, 1990). However, it is also plausible that market potential has linear relationships with these variables. Therefore, the market potential can be expressed in either of the following forms:

$$m(t) = \exp(\sum_{i=0}^{n} \beta_i X_{it}) \text{, or} \tag{7}$$

$$m(t) = \sum_{i=0}^{n} \beta_i X_{it} \text{,} \tag{8}$$

where X_{it} is the observed value of explanatory variable X_i at the year t (including the constant term), and β_i is the coefficient of the variable X_i. Combining with Equation 3, the extended Bass model has the following form:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \text{, and}$$

$$S(t) = m(t)F(t) - m(t-1)F(t-1) + \varepsilon(t) \text{.} \tag{9}$$

Therefore, Equations (9) and (7/8) together establish the extended version of the basic Bass model.

There are 10 observations in the data available to estimate the parameters in the extended Bass model. The more explanatory variables we include in the model, the fewer the degrees of freedom are. That is, incorporating more variables in the model leads to idiosyncratic fits to the particular observations available, while reducing the generalizability or transferability of the model. In the extreme, including as many variables as there are observations would result in a model having perfect fit to the existing data, but limited applicability to new data, or ability to forecast future sales. To better understand innovation effects and imitation effects, we adopted a two-step method to estimate the parameters. In the first step, we allow the coefficients of the explanatory variables for market potential, the innovation coefficient, and the imitation coefficient to change at the same time in the model, given various combinations of their initial values. After the model reaches an optimal solution, we fix the coefficients of the explanatory variables and rerun the model to estimate the innovation and imitation coefficients. Therefore, in the second step, the final estimates of the innovation and imitation coefficients are conditioned on the fixed impacts of explanatory variables on the market potential. Although this approach obscures rather than solves the degrees of freedom problem, it appeared to give better results than a straightforward one-step process.

The initial model specification for CNG vehicles contained five explanatory variables for market potential: model availability, station availability, fuel price, gasoline price, and conversion indicator. When estimating the extended Bass model, we found that two of these variables had statistically insignificant impacts on sales: the conversion indicator and station availability. We therefore dropped these two variables from our model specification.

Table 10 presents the outcomes of our next models when the market potential function is expressed in an exponential form. In Model 1, vehicle model availability, CNG price, and gasoline price enter the model with expected signs, and the R^2 of the second-stage model is 0.862. After a few experiments, we found that Model 2 offers a better model fit than Model 1 (a 2.2-percentage-point increase in R^2), with fuel price ratio (gasoline price/CNG price) replacing CNG price in Model 2. This non-linear form suggests that individuals do not evaluate a simple weighted difference in CNG and gasoline prices when they purchase CNG vehicles, but rather that the comparison between CNG and gasoline prices has a different impact at different levels of gasoline prices.

The limited number of refueling stations is a critical factor in the marketability of AFVs. Although station availability entered the model with a counterintuitive sign, we tried to incorporate it in the model in another way. Specifically, we used the effective-cost function of station availability proposed by Greene (1998). Station availability can impose large effective costs on consumers if it is lower than 10% (Sperling and Kurani, 1987). Greene (1998) proposed several functions (specifically, exponential, power, logarithm, and linear functions) to estimate the monetary value to consumers of station availability using a U.S. household survey. Similar to Leiby and Rubin (2001), we chose the exponential function to measure the effective costs of station availability. In Greene (1998), the effective costs of station availability are expressed in the following form:

$$\text{Effective Cost} = \$\, 3.2651\, (\exp(-5.35\, S) - \exp(-5.35)) / 9.1451, \qquad (10)$$

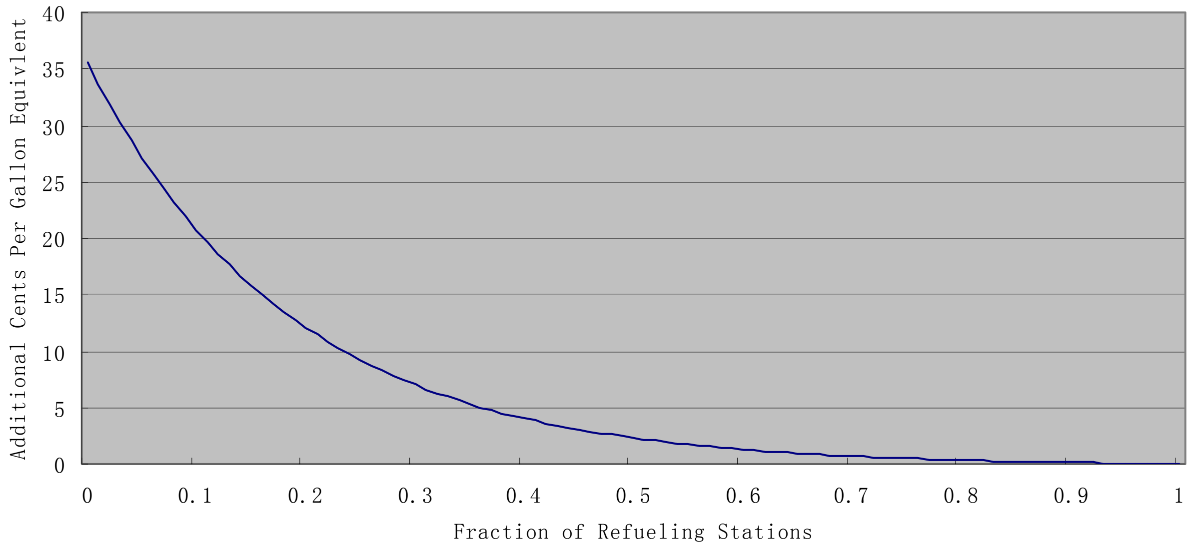
where S is the share of stations offering the alternative fuel. According to this formulation, if 50% of stations provide the fuel, the cost penalty of station availability is equivalent to about 2.3 cents per gallon higher fuel costs to the consumers (see Figure 16), which seems reasonable. Before estimating the model, we added the cost penalty to CNG prices. However, including the effective costs in the model did not yield plausible coefficients in terms of their signs, neither for the additive nor for the fuel price ratio formulation of CNG prices. On the contrary, the model fit became even worse. Ultimately, we had to discard station availability in model calibration.

Table 10. Intermediate Models of CNG Vehicle Diffusion

	Model 1 (Additive CNG Price)		**Model 2 (Fuel Price Ratio)**	
	Coefficients	p-value	Coefficients	p-value
Innovation effect p	0.02625	2E-5	0.02581	1E-5
Imitation effect q	0.2043	4E-7	0.2060	2E-7
Constant	11.59	3E-7	11.48	2E-7
Model availability	0.004758	0.315	0.004557	0.276
CNG price	-0.1441	0.138	-	-
Gasoline price	0.09152	0.057	0.01943	0.564
Fuel price ratio (gasoline / CNG)	-	-	0.05349	0.087
R^2	0.862		0.888	

Note: the values and p-values of the innovation and imitation coefficients, as well as R^2, are calculated based on the model outcomes in the second step, whereas the other coefficients and p-values are obtained from the first-stage model.

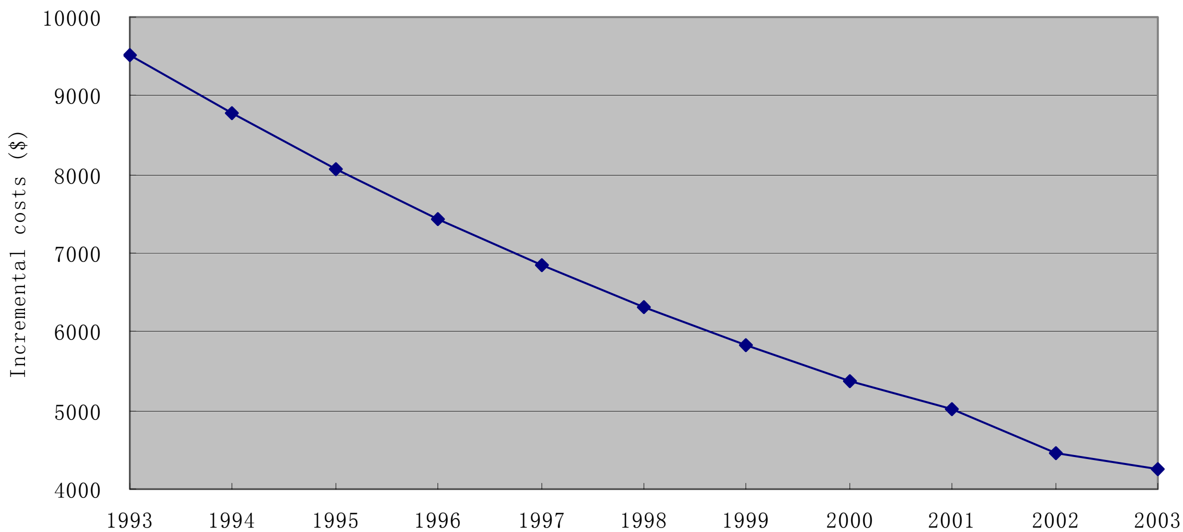
Figure 16. Effective Costs of Station Availability



In addition, we did some experiments to indirectly include vehicle incremental costs in the model. We assumed that vehicle incremental costs follow a decreasing exponential curve. Based on the average incremental costs of all CNG models available in model year 2001, 2002, and 2003, we extrapolated historical incremental costs of CNG vehicles, as shown in Figure 17. We then allocated these incremental costs to CNG prices based on the assumption of 15,000 annual miles traveled, 25 miles per GGE, and 10-year life cycle. However, similar to the effective costs of station availability, none of these experiments led to promising results. Therefore, we gave up our attempts to incorporate vehicle incremental costs in the model.

We also estimated the extended Bass model of CNG vehicles when the market potential function is expressed in a linear form. The model outcomes (Model 3) are summarized in Table 11. "Marginal impact" in Table 11 denotes the change in market potential when an explanatory variable increases from 0 to 1. The marginal impacts in Model 2 are theoretically comparable with the coefficients in Model 3. Both models yield similar results in terms of the magnitude of the marginal impacts. Model 3 offers a negligibly higher model fit than Model 2, but has higher p-values for two of the three important variables in the model. Consistent with previous studies, the market potential function with an exponential form was selected as the default when we estimated the extended Bass model. So we chose Model 2 as our final best model.

Figure 17. Incremental Costs of CNG Vehicles



Note: 1993-2000 costs estimated based on 2001-2003 data.

Table 11. Final Models of CNG Vehicle Diffusion with Exponential-form and Linear-form Market Potentials

	Model 2 (Exponential)			**Model 3 (Linear)**	
	Coefficient	Marginal Impact	p-value	Coefficient	p-value
Innovation effect p	0.02581	-	1E-5	0.02582	1E-5
Imitation effect q	0.2060	-	2E-7	0.2059	2E-7
Constant	11.48	96985	2E-7	95543	0.003
Model availability	0.004557	443	0.276	518	0.311
Gasoline price	0.01943	1903	0.564	2245	0.558
Fuel price ratio (gasoline / CNG)	0.05349	5329	0.087	6136	0.112
R^2	0.888			0.889	

Note: the values and p-values of the innovation and imitation coefficients, as well as R^2, are calculated based on the model outcomes in the second step, whereas the other coefficients and p-values are obtained from the first-stage model.

The final model formulation of CNG vehicle annual sales is as follows:

$$m(t) = \exp[11.48 + 0.004557 X_1(t) + 0.01943 X_2(t) + 0.05349 X_3(t)],$$

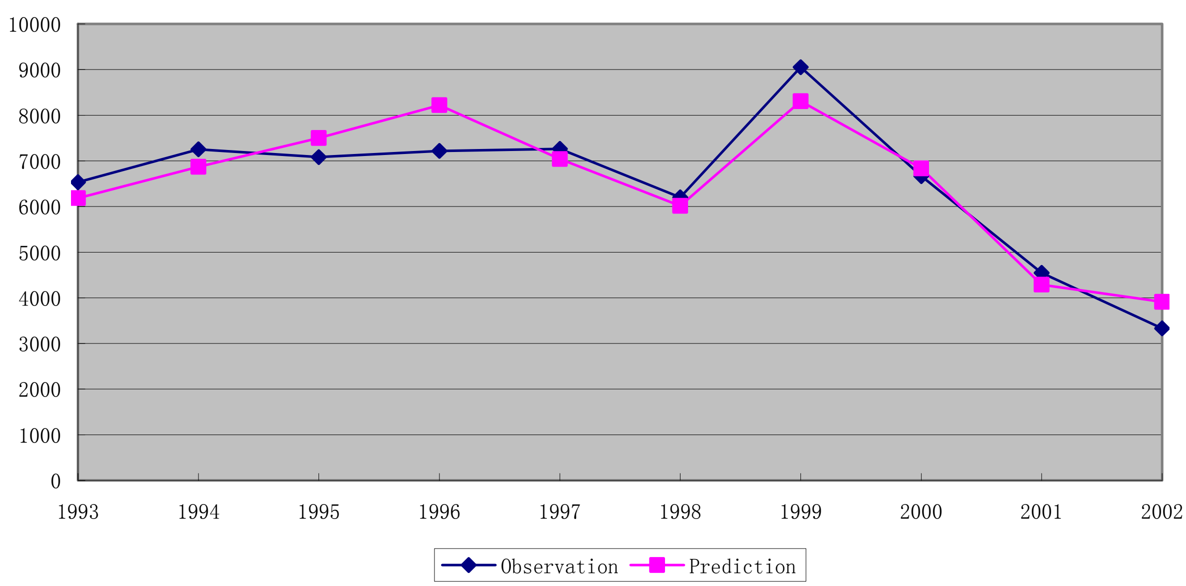
$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}, \text{ and}$$

$$S(t) = m(t)F(t) - m(t-1)F(t-1) + \varepsilon(t), \qquad (11)$$

where p = 0.02581, q = 0.206, and X_1, X_2, and X_3 stand for model availability, gasoline price, and fuel price ratio respectively.

Figure 18 compares the observations and predictions of CNG vehicle annual sales for 1993-2002. The predictions derived from Model 2 fit the observations very well. According to both the observations and predictions, the sales of CNG vehicles decline annually since 1999. This phenomenon suggests that the penetration of the CNG vehicle is approaching its saturation level, which is consistent with the results of the basic Bass model. If there are no substantial changes in the explanatory variables of the market potential, the annual sales of CNG vehicles will continue to decline.

Figure 18. Observations and Predictions of CNG Vehicle Annual Sales, 1993-2002



5.2.2 Ethanol Vehicle Diffusion Model

As presented in Section 3.1.3 (Figure 10), there is a huge jump in the number of E85 vehicles from 1999 to 2000 due to a different statistical tool being used since 2000. Obviously, this disturbance will greatly distort the apparent diffusion process of E85 vehicles. Therefore, it is necessary to minimize the influence of this unexpected spike. This disturbance can be modified in at least two possible ways. One is to assume that the total number of E85 vehicles in use in 2000 is correct while their numbers before 2000 are underestimated. In this case, we need to distribute that total number across previous years in some way. That is, we reduce the peak sales in 2000 and increase annual sales for the years prior to 2000 at the same time. In practice, however, we lack sufficient information to be able to make such modifications with confidence. Conversely, in the other case, we assume that the total number of E85 vehicles in use in 2000 is overestimated while their numbers prior to 2000 are correct. Under such an assumption, we need to fill in a number for E85 vehicle sales in 2000. This modification does not affect the annual sales for other years, and hence reduces the probability of artificial bias. Ultimately, we decided to modify the data in the second way. However, it should be kept in mind that we will tend to underestimate the diffusion rate of E85 vehicles if the first assumption is closer to reality. The principle used to establish the sales in 2000 is to find a value that maximizes the model fit by estimating the basic Bass model. After several calibrations, we found that the estimate of 10,850 E85 sales in 2000 achieved the best model fit. Therefore, we replaced the annual sales in 2000 (65,116 vehicles) with this value, and changed the numbers of E85 vehicles in use in 2001 and 2002 correspondingly.

A procedure similar to the one discussed in Section 5.2.1 for CNG vehicles was adopted here for E85 vehicles. Table 12 presents the parameter estimates of the basic Bass model using the OLS and NLS techniques. Both models yield similar outcomes, but the NLS estimates offer a higher model fit. These model outcomes provide fundamental information on the initial values of the parameters in the extended Bass model, for which the market potential is expressed as a function of several variables. The final best model for the diffusion of E85 vehicles is summarized in Table

13. Four explanatory variables — E85 price, gasoline price, station availability, and conversion indicator — enter the model with expected signs. The high R^2 (0.992) shows that the diffusion model replicates the observed data very well. The comparison between the coefficients of E85 price and gasoline price suggests that E85 price is a more important factor than gasoline price when consumers buy E85 vehicles. Further, the high p-value of the gasoline price coefficient implies that gasoline prices play a minor role in the penetration of E85 vehicles given the relatively low gasoline price levels for the calibration data. Therefore, reducing the E85 price is more likely to motivate the adoption of E85 vehicles than increasing the gasoline price.

Table 12. The OLS and NLS Parameter Estimates of the Basic Bass Model for E85 Vehicles

Parameters		**a**	**b**	**c**	**p**	**q**	**m**	**R^2**
OLS	Coefficients	1084.2	0.4865	-0.000001996	0.00441	0.491	245971	0.941
	p-value	0.268	0.009	0.533	-	-	-	
NLS	Coefficients	-	-	-	0.00133	0.435	250472	0.961
	p-value	-	-	-	0.051	0.008	0.298	

Table 13. Model Results for E85 Vehicles

	Coefficient	p-value
Innovation effect p	0.0007465	0.0002
Imitation effect q	0.5479	3E-10
Constant	13.23	0.0006
E85 price	-0.8573	0.152
Gasoline price	0.06421	0.883
Station availability	0.004076	0.311
Conversion indicator	0.8471	0.399
R^2	0.992	

Note: the values and p-values of the innovation and imitation coefficients, as well as R^2, are calculated based on the model outcomes in the second step, whereas the other coefficients and p-values are obtained from the first-stage model.

The final model formulation of E85 vehicle annual sales is as follows:

$$m(t) = \exp[13.23 - 0.8573X_1(t) + 0.06421X_2(t) + 0.004076X_3(t) + 0.8471X_4(t)],$$

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}, \text{ and}$$

$$S(t) = m(t)F(t) - m(t-1)F(t-1) + \varepsilon(t), \tag{12}$$

where p = 0.0007465, q = 0.5479, and X_1, X_2, X_3, and X_4 stand for E85 price, gasoline price, station availability, and conversion indicator respectively. Compared to the CNG vehicle diffusion model, the E85 vehicle diffusion model has a much higher coefficient of imitation, which suggests that word of mouth has a larger impact on the penetration of E85 vehicles in a niche market. This result is not surprising since E85 vehicles offer consumers an option to run on gasoline in the same fuel tank. This flexibility increases the possibility that consumers purchase E85 vehicles. When E85 is available, they may easily shift to the ethanol market. On the other hand, although bi-fuel CNG vehicles can also operate on gasoline, the loss of luggage space due to the two tanks makes them less attractive.

Figure 19. Observations and Predictions of E85 Vehicle Annual Sales, 1993-2002

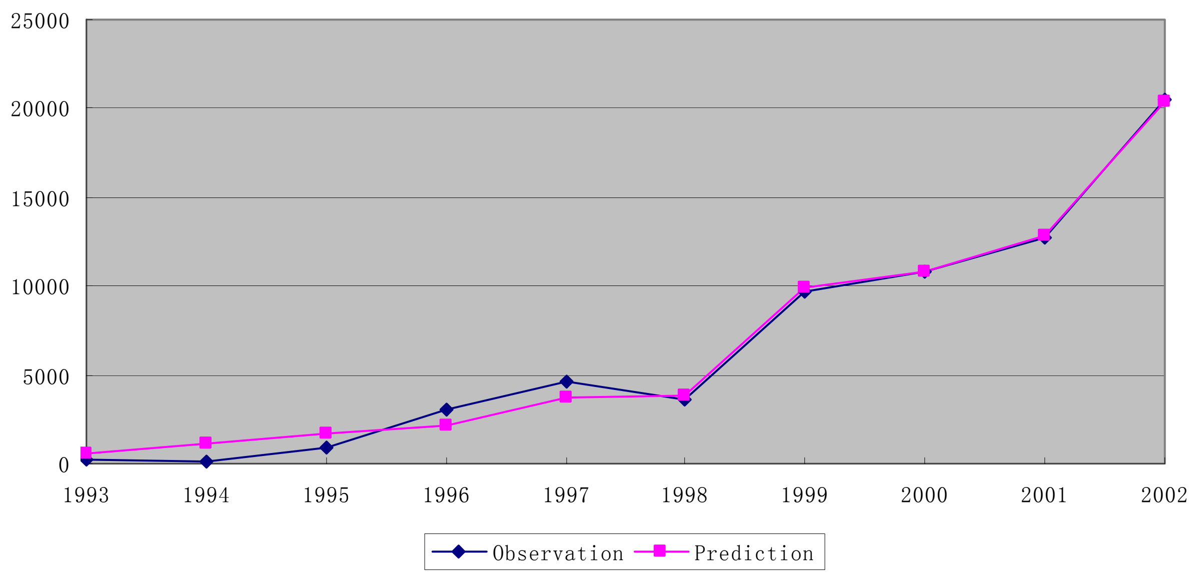


Figure 19 illustrates the observations and predictions of E85 vehicle annual sales for 1993-2002. It is not surprising that the differences between the observations and predictions of E85 vehicle annual sales are smaller than those for CNG vehicles, since the E85 vehicle diffusion model offers a higher model fit than the CNG vehicle diffusion model. The trend in E85 vehicle sales shows that the penetration of E85 vehicles is accelerating. Therefore, if the market and regulatory environments of E85 vehicles do not get worse, the number of E85 vehicles will keep proliferating.

5.2.3 Hybrid Electric Vehicle Diffusion Model

Honda Insight, the first HEV model in the U.S., was introduced in December 1999. Thus the number of observations on HEV sales is even smaller than that for CNG and E85 vehicle sales. Currently, our HEV data contain the annual sales for only four consecutive years: 2000-2003. Due to the limited data, we applied managerial judgment to the diffusion model of HEVs. First, since the estimates are sensitive to the initial values of the parameters due to the scarcity of the data, we specify the magnitude of the HEV market potential in the basic Bass model rather than estimate it. According to Ward's Communications (2002), there were an estimated 220,729,048 cars and trucks registered in the U.S. in 2000. Therefore, the ultimate market potential of HEVs is not likely to exceed this size. On the other hand, the AEO 2004 report estimated that HEV sales (including replacement sales) from 2001 to 2025 would total about 19.4 million (EIA, 2004b). Therefore, we assumed that the market potential of HEVs is around 10% of total car and truck registrations in 2000.

Four consecutive surveys show that 36%, 44%, 57%, and 58% of respondents (awareness rate) can name at least one HEV in 2000, 2001, 2002, and 2003, respectively (EERE, 2004). Since HEVs are fairly new to the automobile market, limited product awareness and lack of adequate professional advice is likely to delay the penetration of HEVs. Therefore, consumers' knowledge of HEVs will affect their choices. Similar to product price, product awareness may affect the adoption of a new product through changing the market potential, the adoption rate, or both. Similar to Kalish (1985), we assumed that product awareness only affects the size of the market potential. Specifically, we considered the market potential of HEVs to be proportional to the awareness rate. Accordingly, the basic Bass model used to estimate the diffusion of HEVs is expressed as follows:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}, \text{ and}$$

$$S(t) = 0.1 \times 220729048\, \mathrm{AR}(t)\, [F(t) - F(t-1)] + \varepsilon(t), \tag{13}$$

where AR(t) stands for the awareness rate in year t. The parameter estimates for Equation (13) (Model 1) are presented in Table 14.

Further, one advantage of HEVs is that they offer fuel savings to consumers. Therefore, it is reasonable to expect that gasoline prices are positively related to the adoption of HEVs. We did some experiments to incorporate gasoline prices in the diffusion model. Similar to Jain and Rao (1990), we assumed that gasoline prices affect the market potential of HEVs in a power form, as shown in Equation (14). After several attempts, we found that gasoline prices have a lagged effect on the adoption of HEVs:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}, \text{ and}$$

$$S(t) = [0.045 \times 220729048\, \mathrm{AR}(t)]\, \mathrm{P}^{a}(t\text{-}1)\, [F(t) - F(t-1)] + \varepsilon(t)\,^{1}, \tag{14}$$

where P(t-1) is the gasoline price at year t-1, and a is the exponent of gasoline price. The parameter estimates for this extended model (Model 2) are also presented in Table 14. In this model, the market potential varies around 10% of total car and truck registrations in 2000 as gasoline prices change, as shown in Figure 20. On one hand, we specified the market potential as a percentage of total car and truck registrations in 2000; on the other hand, the market potential is allowed to vary as gasoline prices and consumers' awareness change. Therefore, we refer to this market potential function as partially specified. The comparison of both models shows that the p-values of the parameter estimates in Model 2 become worse, which is not surprising since we incorporated one more variable in Model 2 (which therefore could potentially, and apparently did,

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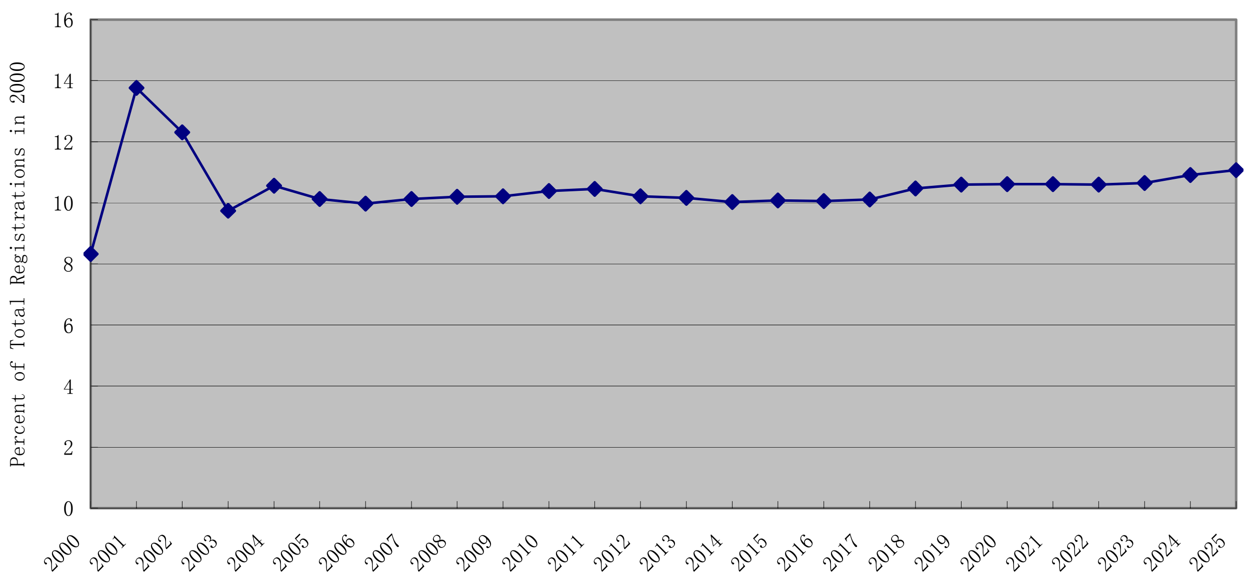
[1] In this equation, we consciously used 0.045 instead of 0.1 in order to keep the magnitude of the market potential (after incorporating gasoline price) similar to that in Equation (13).

absorb some of the explanatory power of the previously-included variables). However, Model 2 offers a better model fit than Model 1, which is also not surprising in view of the additional variable. Given the policy importance of this new variable (gasoline price), we chose Model 2 as our final best model for the diffusion of HEVs when their market potential is around 10% of total registrations in 2000. Figure 21 shows that the observed and predicted HEV annual sales are quite close for the four years of calibration data.

Table 14. Parameter Estimates of HEV Diffusion Models

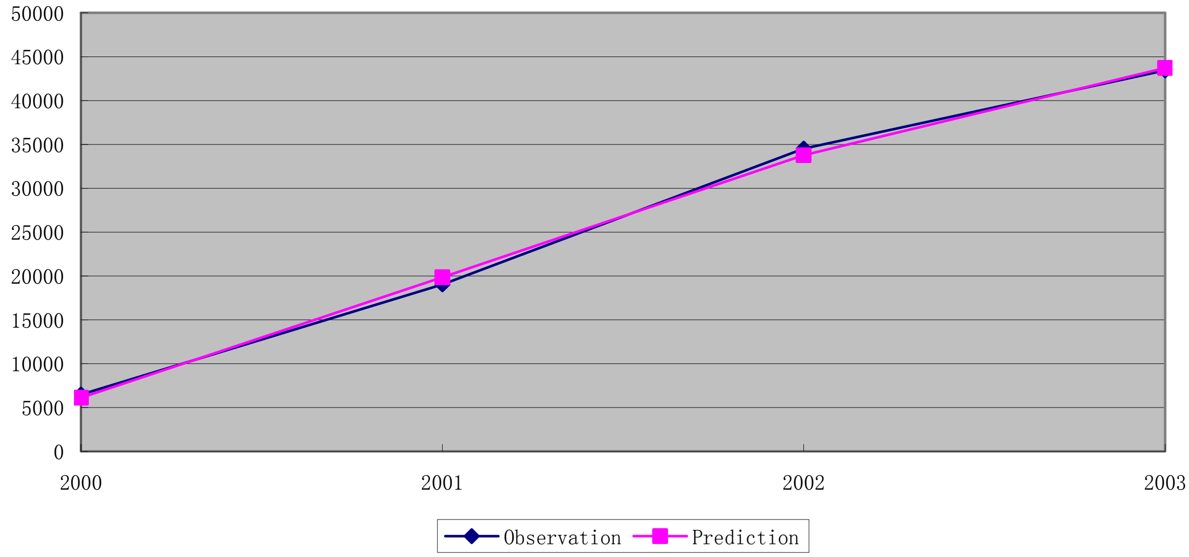
		Model 1	Model 2	Model 3	Model 4
Innovation coefficient: p	Estimate	7.720e-4	4.460e-4	2.359e-4	9.541e-5
	p-value	0.101	0.254	0.256	0.257
Imitation coefficient: q	Estimate	0.3593	0.4788	0.4771	0.4760
	p-value	0.052	0.071	0.067	0.068
Exponent of gasoline prices: a	Estimate	-	2.366	2.374	2.380
	p-value	-	0.169	0.170	0.170
R^2		0.961	0.998	0.998	0.998

Figure 20. Market Potentials of HEVs, 2000-2025



Note: the market potentials for HEVs are calculated on the basis of observed gasoline prices in 1999-2002 and the gasoline prices projected by the AEO 2003 report for 2003-2025. And individuals are assumed to have full knowledge of HEVs (AR(t) = 1.00 for all t).

Figure 21. Observations and Predictions of HEV Annual Sales, 2000-2003



However, it is worth noting that different partially specified market potentials yield different parameter estimates for the diffusion of HEVs. In Table 14, Models 3 and 4 represent the best diffusion models for HEVs when the market potentials are around 20% and 50% of total car and truck registrations in 2000, respectively. Although the magnitudes of the imitation coefficient and the coefficient of gasoline prices are quite similar for Models 2, 3, and 4, the differences in the innovation coefficient lead to different diffusion processes for HEVs, which will be illustrated in the next section.

6 SCENARIO ANALYSIS

In this section, we report on scenario analyses conducted using a user-friendly EXCEL worksheet, to evaluate the influences of different factors on the future development of CNG vehicles, E85 vehicles, and HEVs.

6.1 CNG Vehicle Scenarios

As presented in Section 5.2.1, besides the effects of mass media and word of mouth, the diffusion of CNG vehicles is affected by model availability, CNG price, and fuel price ratio between gasoline and CNG acting on the market potential. The input dialog box for CNG vehicles in the EXCEL file is shown in Figure 22 (please refer to the manual in Appendix 2 on how to use the dialog box). This dialog box allows users to flexibly compare different CNG vehicle scenarios under various specified conditions. The input dialog boxes for E85 vehicles and HEVs presented later have similar capabilities. In this report, scenario analyses are based on our own assumed conditions.

In the base scenario, the CNG and gasoline prices projected by the AEO 2003 report are adopted for the diffusion of CNG vehicles. Also, since we use real fuel prices rather than nominal prices in the model, we assumed that nominal dollars deflate at a rate of 1/1.03 annually, which is consistent with the assumptions of the AEO 2003 report. Further, we assumed that the number of CNG models available to the automobile market increases by one unit for each calendar year. As shown in Figure 23, new sales of CNG vehicles (first purchases only) decrease annually. This indicates that the market penetration of CNG vehicles is approaching the saturation level in the base scenario. In 2025, the total light-duty CNG vehicle population is forecast to reach about 123,000 units, compared to 87,340 light-duty CNG vehicles in 2002.

Figure 22. Input Dialog Box for CNG Vehicle Scenario Analysis

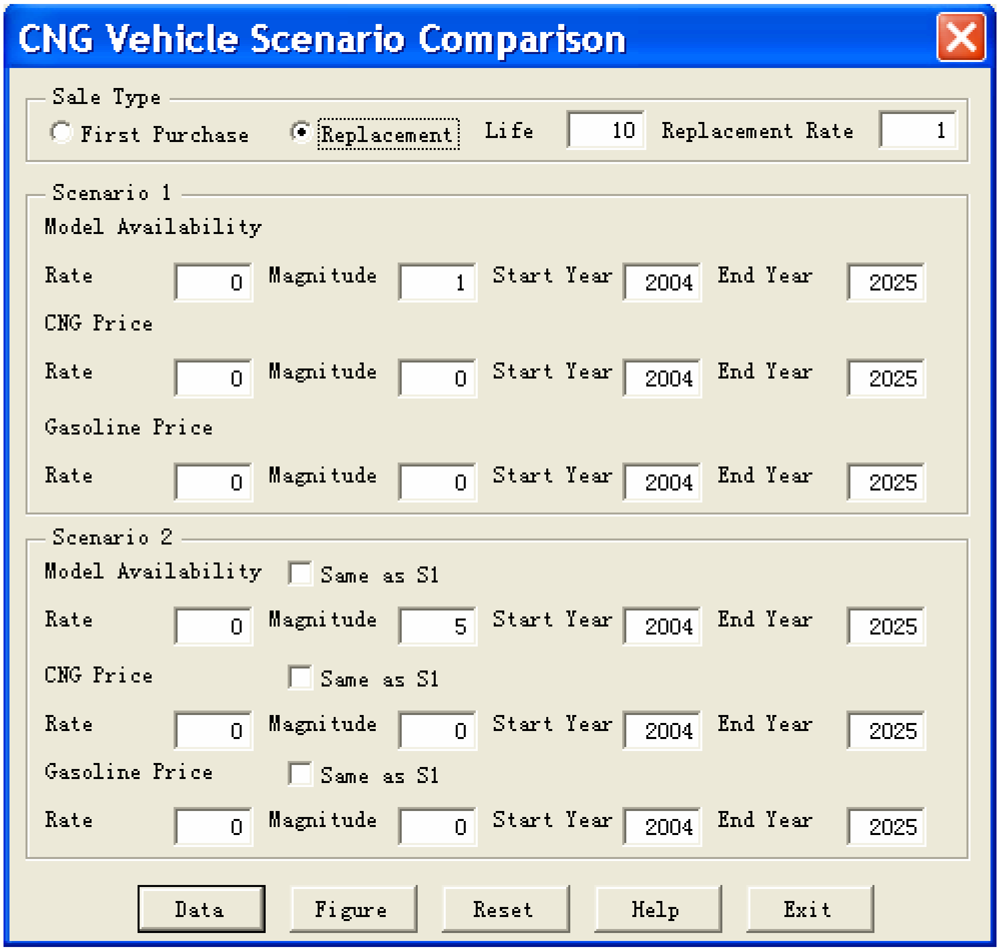


Figure 23. Annual Sales of CNG Vehicles in the Base Scenario (not including replacements)

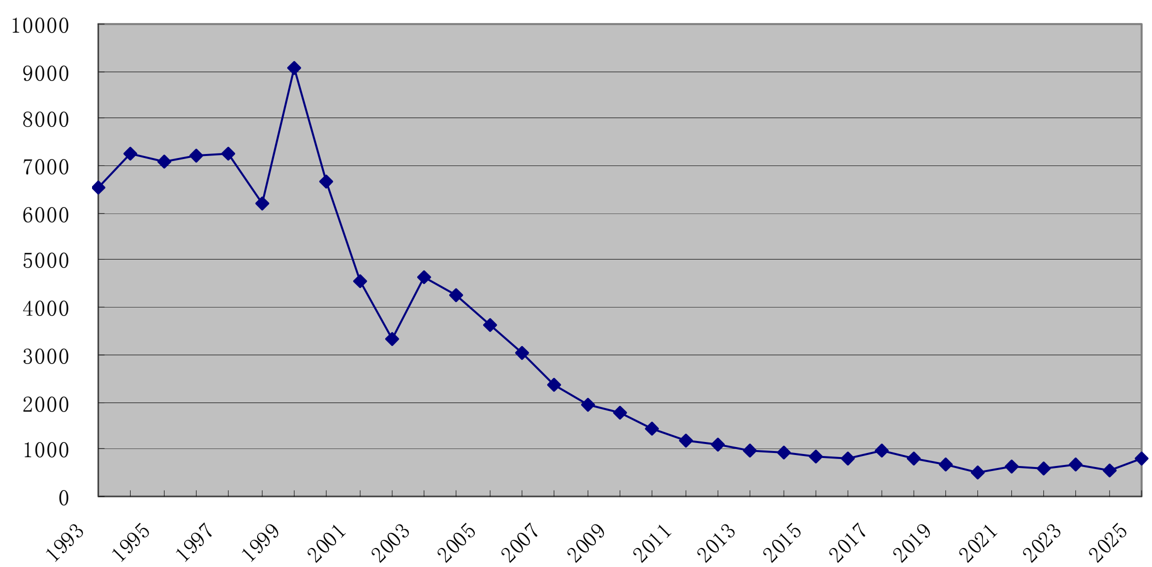
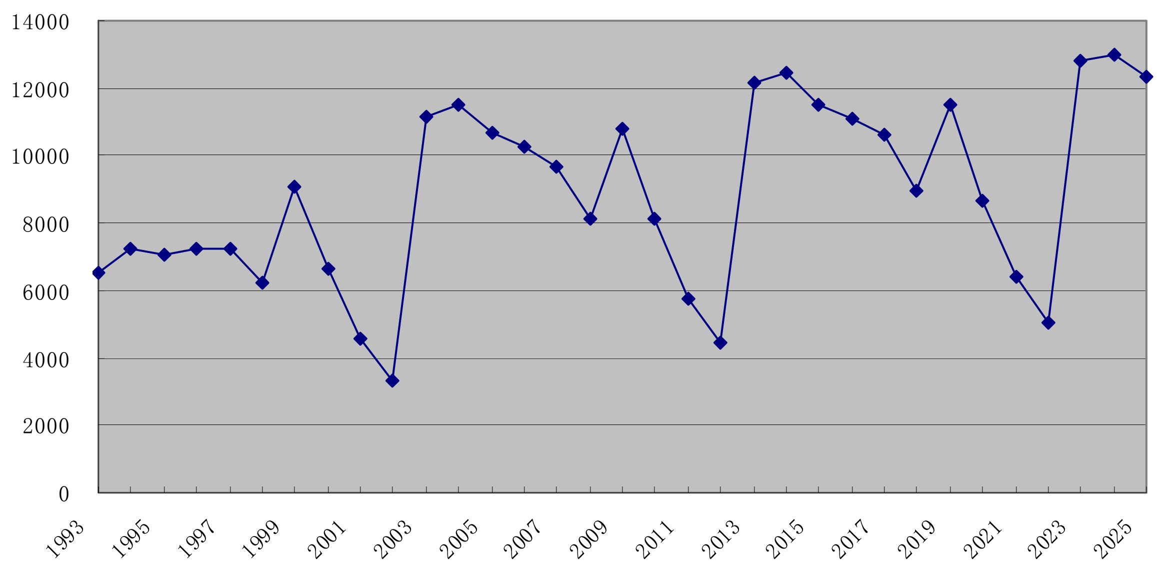


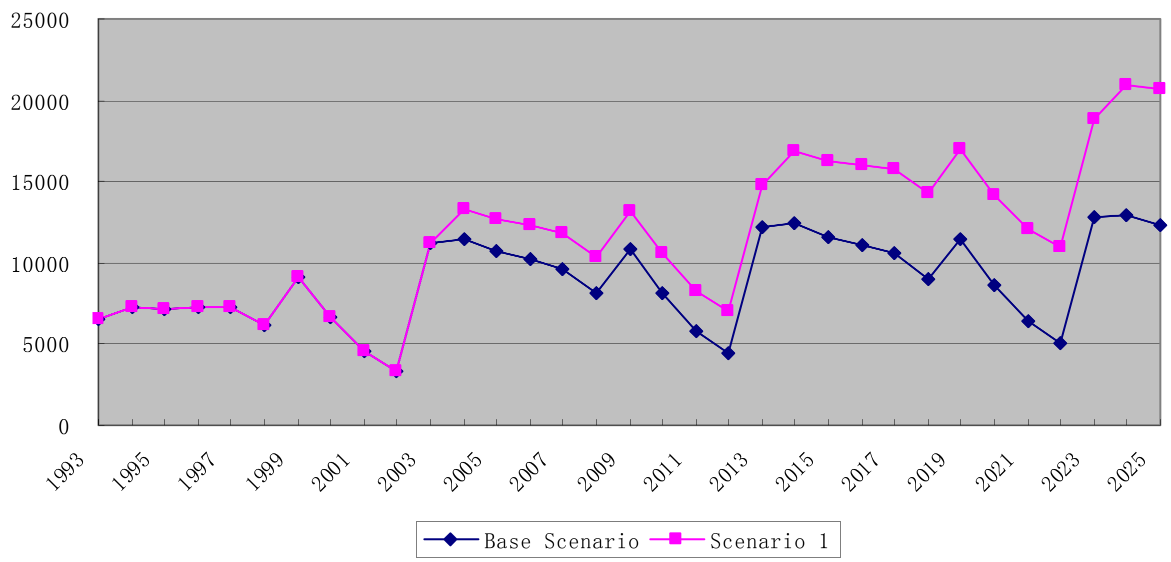
Figure 24 illustrates the annual sales of CNG vehicles in the base scenario, which include replacement sales. For the AFVs studied here, we made several assumptions for the replacement sales: (1) the average life cycle of an AFV is 10 years; (2) all aged AFVs are replaced by the same type of AFV, an optimistic assumption; (3) we consider that replacement sales commence in 2003, and that those before 2003 are minimal and hence were neglected. This final assumption explains the jump in CNG vehicle sales from 2002 to 2003 and the periodic nature of the series in Figure 24. In the base scenario, the sales of CNG vehicles from 2005 to 2025 average about 10,000 units per year, 87% of which are repeat purchases.

Figure 24. Annual Sales of CNG Vehicles in the Base Scenario (including replacements)



In Scenario 1, the CNG models available to the market are assumed to increase by five units annually, all else equal. Figure 25 illustrates the differences in CNG vehicle annual sales between the base scenario and Scenario 1. Model diversity does increase the annual sales, especially for the later window of the timeline. The annual sales of CNG vehicles from 2005 to 2025 average 14,000, 40% more than those in the base scenario. However, the maximum annual sales do not exceed 21,000 units, at best accounting for a tiny fraction of total light-duty vehicle annual sales in the U.S. (about 17 million in 2000). These results suggest that expanding model diversity is not likely to achieve substantial improvement in CNG vehicle growth.

Figure 25. The Influence of Model Availability on CNG Vehicle Annual Sales



Scenario 2 assumes that the government begins to levy a GHG tax or increase the gasoline tax from 2007 on, equivalent to a 50-cent (nominal) increase on the basis of the projected prices. There are two spikes in Figure 26. The first spike results from the increased gasoline price in 2007, and the second spike is a consequence of replacement sales after 10 years. The diffusion model of CNG vehicles implicitly assumes that consumers will fully and immediately respond to the changes in gasoline prices. As the gasoline price increases in 2007, the market potential of CNG vehicles in 2007 increases correspondingly. Thus, the new sales of CNG vehicles in 2007 grow sharply, compared to those in the base scenario. However, the changes in the market potential become minimal after 2007. So, the annual sales of CNG vehicles fall back to levels similar to the base scenario. On the other hand, if consumers have a lagged response to the increase in gasoline prices, the sharp growth in 2007 sales is likely to be distributed to the annual sales after 2007 in some way. However, whether consumers respond immediately or with a lag, the increase in gasoline prices does not lead to substantial growth in the total population of CNG vehicles, as shown in Figure 27. Therefore, increasing the gasoline price has a quite limited impact on the ultimate penetration of CNG vehicles.

Figure 26. The Influence of Gasoline Prices on CNG Vehicle Annual Sales

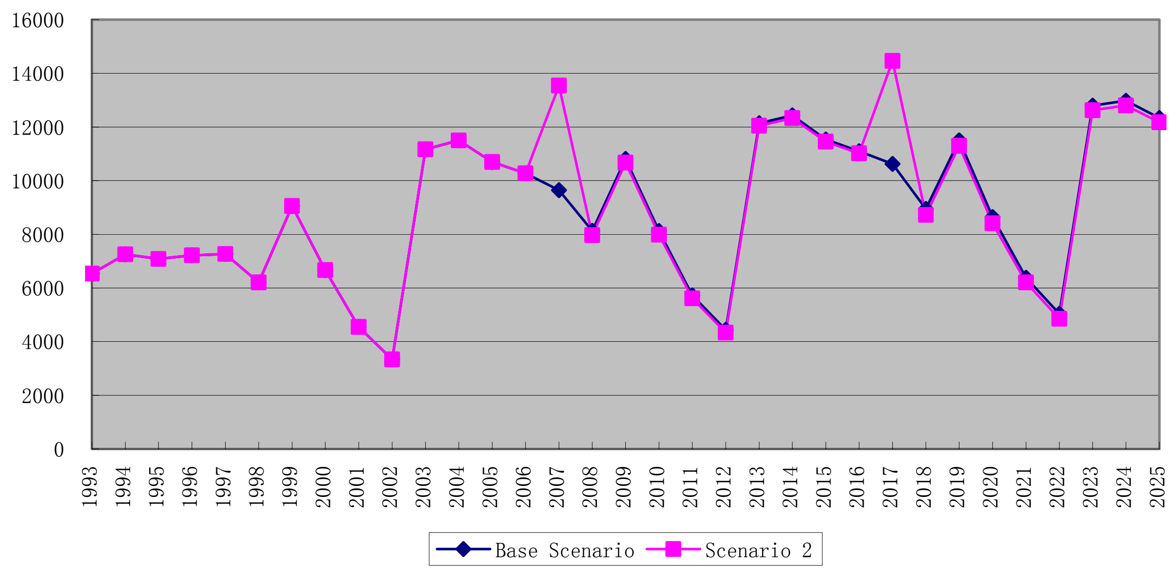
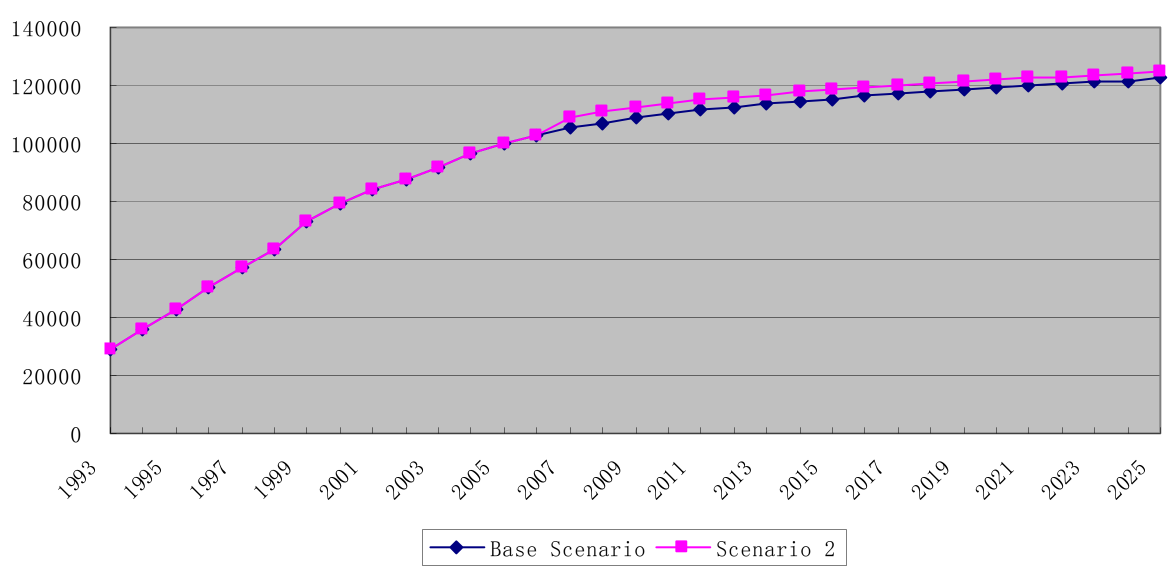
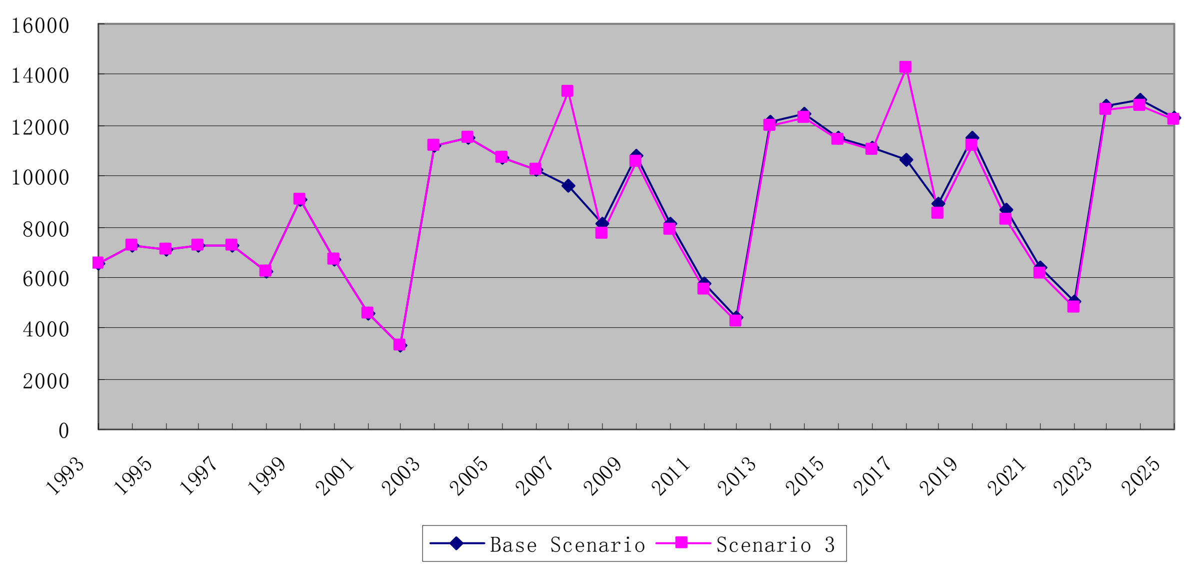


Figure 27. Total Population of CNG Vehicles Affected by Gasoline Prices



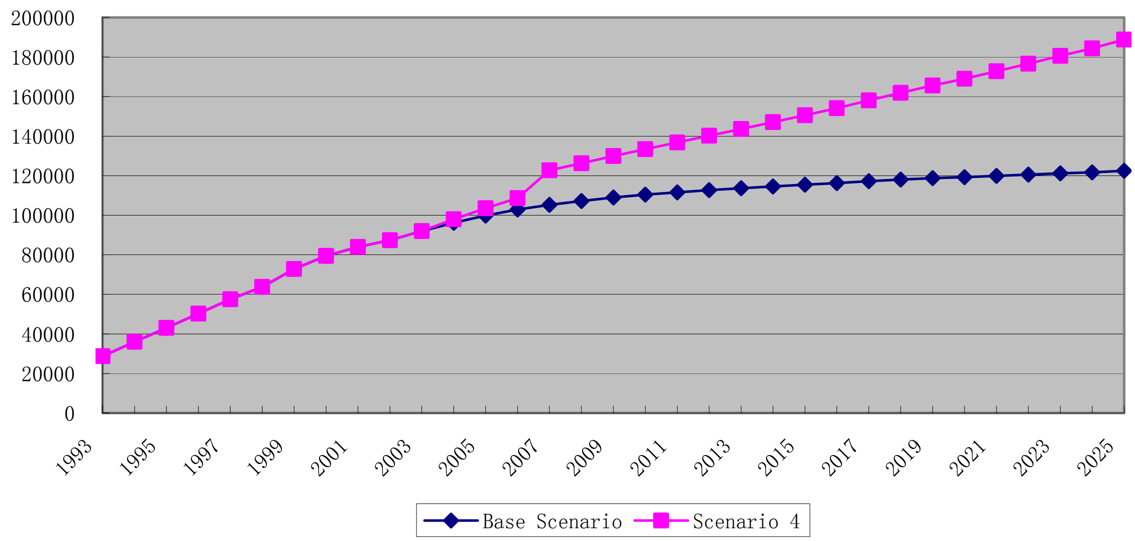
In Scenario 3, we assumed that CNG fuel is eligible for a tax credit of 25 cents (nominal) per GGE from 2007 on. That is, the projected CNG prices decrease by 25 cents from 2007 to 2025. This scenario yields similar results to Scenario 2. The annual sales of CNG vehicles increase sharply in 2007, and then return to their base level. It is worth noting that the market potential due to reduced CNG prices decreases annually, all else equal, since deflation makes the tax credit diminish. Therefore, for some calendar years, the annual sales of CNG vehicles in Scenario 3 are even smaller than those in the base scenario, as shown in Figure 28. Similar to the impacts of gasoline prices, the decrease in CNG prices does not lead to a significant growth in CNG vehicle sales.

Figure 28. The Influence of a CNG Fuel Tax Credit on CNG Vehicle Annual Sales



The fourth scenario combines all assumptions in the three scenarios discussed above. Figure 29 presents the combined effects of model availability, gasoline prices, and CNG prices on the total population of CNG vehicles. According to Figure 29, even though we adopt multiple strategies to promote the penetration of CNG vehicles, they are not likely to achieve significant growth. One primary reason for this phenomenon is that although CNG vehicles offer social benefits, their personal benefits are often perceived as inferior to conventional vehicles, and few consumers are likely to purchase CNG vehicles for public reasons. Therefore, the market development of CNG vehicles mainly relies on their own performance, and the impacts of exogenous factors are limited. In contrast, if some breakthrough in CNG technology makes CNG vehicles equivalent to or exceed the performances of conventional vehicles, model availability and fuel prices may have somewhat important impacts on the diffusion of the new-generation CNG vehicles. As developed by Norton and Bass (1987), a multiple generation diffusion model is required to reevaluate the effects of these factors. This multi-generation application is beyond our current application of diffusion models: we cannot deal with such a hypothetical situation since no data are available.

Figure 29. The Combined Effects of Model Availability, Gasoline Prices, and CNG Prices on Total Population of CNG Vehicles



6.2 E85 Vehicle Scenarios

The diffusion of E85 vehicles is influenced by station availability, fuel prices, and conversion indicator acting on the market potential. The input dialog box for the E85 vehicle scenario analysis is presented in Figure 30. Since most large OEMs provide E85 vehicles and the number of E85 converters has leveled off in recent years, E85 converters are not likely to increase substantially in the future. Therefore, we assumed that the conversion indicator remains constant in the studied period. The gasoline and E85 prices projected by the AEO 2003 report were used in the base scenario for the diffusion of E85 vehicles. We also assumed that the growth in the number of refueling stations is 10 units per year. Figure 31 presents the annual sales of E85 vehicles (including replacements) in the base scenario. Because E85 prices keep increasing but at different rates after 2005, the effects of increased station availability are partly offset by the high E85 prices for some calendar years. Therefore, the annual sales of E85 vehicles greatly fluctuate within the studied timeline. On average, the yearly sales of E85 vehicles from 2005 to 2025 are about 24,000 in the base scenario. In 2025, the total population of E85 vehicles is forecast to reach 280,000 units.

Figure 30. Input Dialog Box for E85 Vehicle Scenario Analysis

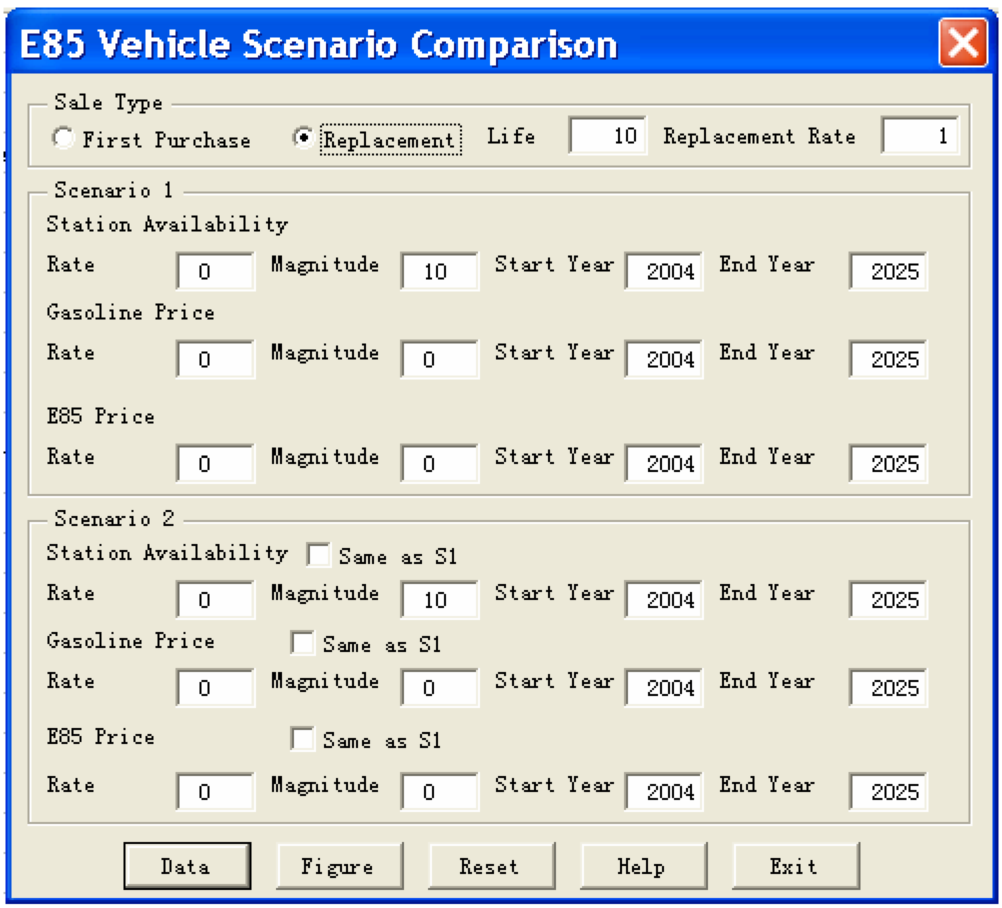
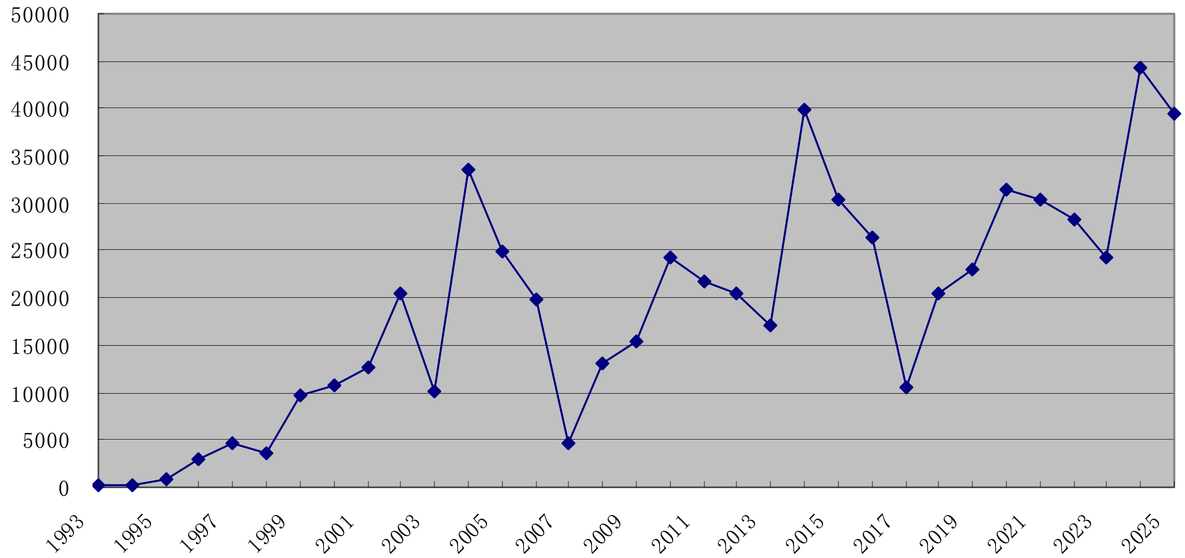


Figure 31. Annual Sales of E85 Vehicles in the Base Scenario



In Scenario 1, the number of fuel stations is assumed to increase by 50 annually, all else equal. As shown in Figure 32, it is forecast that 2 million E85 vehicles will be sold in 2025. The average yearly sales of E85 vehicles from 2005 to 2025 are around 533,000, 21 times more than those in the base scenario. These results imply that the availability of fuel stations plays a very important role in the diffusion of E85 vehicles. However, the likelihood that fuel providers will build more E85 stations depends on consumers' patronage. If E85 prices are higher than gasoline prices, consumers are less likely to choose E85, and hence fuel providers will be reluctant to offer more E85 stations. Therefore, the number of E85 stations is presumably a function of E85 prices and gasoline prices. However, we cannot capture these effects in our models due to data limitations. On the other hand, since the importance of station availability is likely to decrease as the number of stations increases (Greene, 2001; Sperling and Kurani, 1987), the constant coefficient may exaggerate the influence of station availability on the diffusion of E85 vehicles.

The current ethanol tax credit, 54 cents per gallon, will expire in 2007. In Scenario 2, it is assumed that the tax credit will continue until 2025. This credit is equivalent to a reduction of 68 cents per GGE in the projected E85 prices. Figure 33 presents the impacts of decreased E85 prices on the total population of E85 vehicles. In 2025, total E85 vehicles increase to 370,000, 32% higher than in the base scenario. Therefore, continuing the tax credit for ethanol appears to be useful for promoting the penetration of E85 vehicles.

Figure 32. The Influence of Station Availability on E85 Vehicle Annual Sales

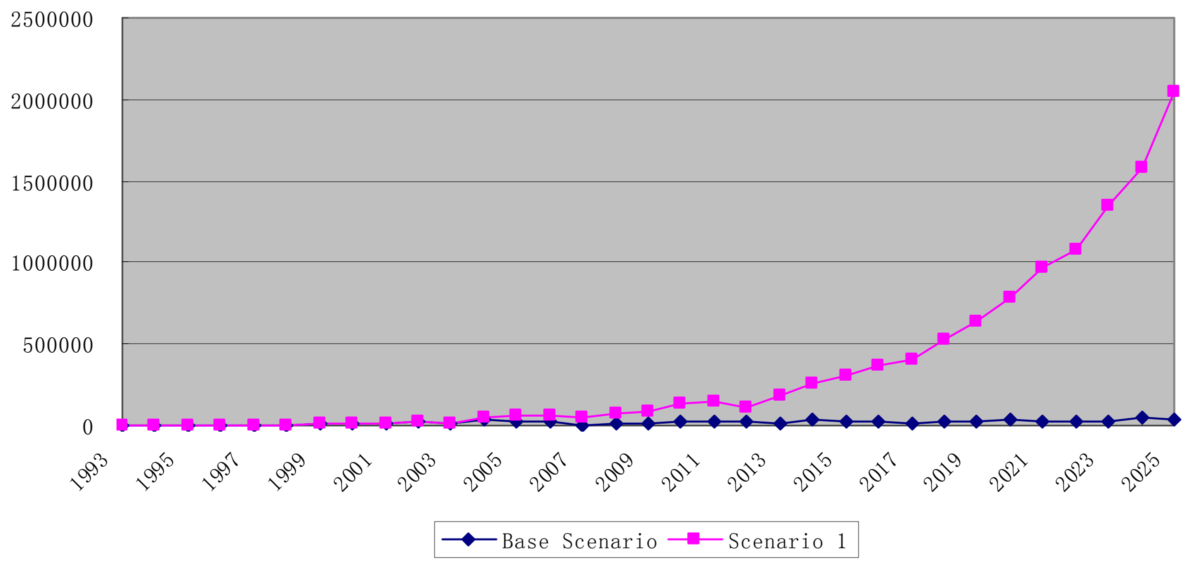
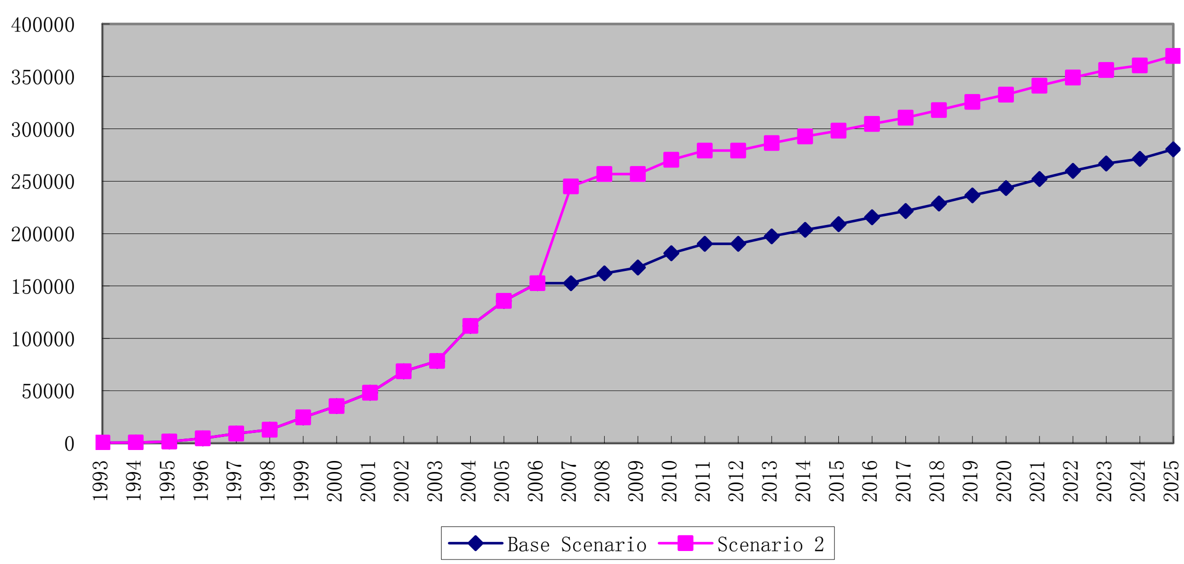
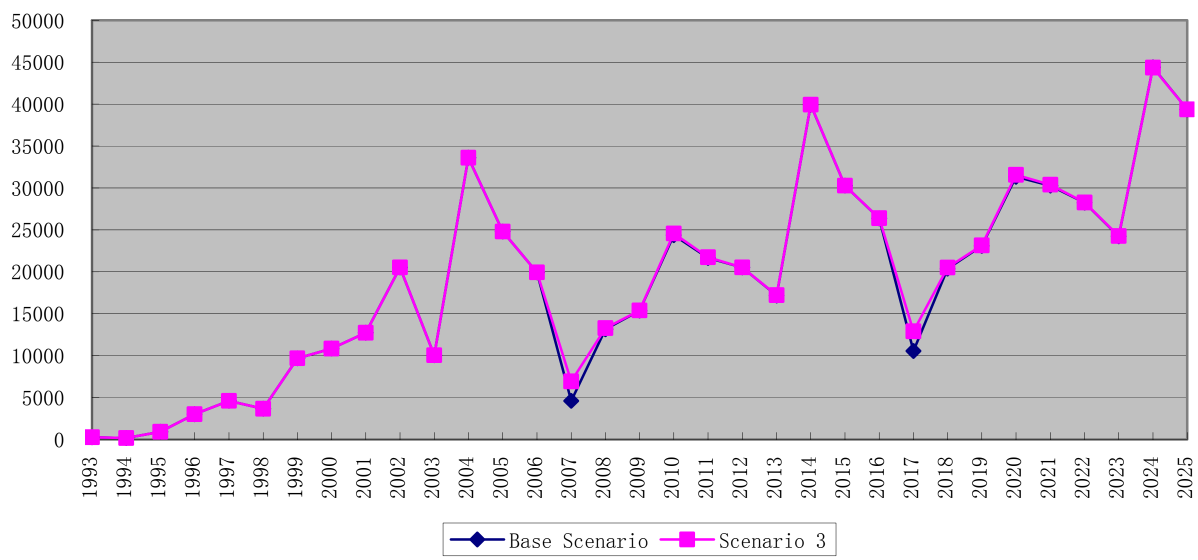


Figure 33. The Influence of E85 Prices on E85 Vehicle Population



In Scenario 3, we assumed that gasoline prices increase 50 cents (nominal) per gallon from 2007 onward over the basis of the projected prices. As illustrated in Figure 34, the effects of increased gasoline prices are minimal. This is not surprising, since the coefficient of gasoline prices in the model is much smaller than that of E85 prices. Therefore, given high E85 prices, an increase in gasoline prices is not likely to achieve substantial improvement in E85 vehicle sales.

Figure 34. The Influence of Gasoline Prices on E85 Vehicle Annual Sales



In conclusion, building more E85 stations is expected to greatly contribute to the diffusion of E85 vehicles, and reducing E85 prices has a moderate impact. In contrast, the impacts of increasing gasoline prices are quite limited.

6.3 HEV Scenarios

The market penetration of HEVs is affected by gasoline prices and consumers' awareness of HEV technology acting on the market potential, in addition to innovation and imitation influences. The input dialog box for HEVs is illustrated in Figure 35. Similar to CNG and E85 vehicles, gasoline prices projected by the AEO 2003 report are used to forecast HEV demand in the base scenario.

We also assumed that the market potential of HEVs is around 10% of total car and truck registrations in 2000, and that consumers' awareness increases by 2 percentage points annually. As shown in Figure 36, the series of HEV annual sales (including repeat purchases) in the base scenario contains two peaks. The first peak is mainly due to first purchases (first purchases account for 97.8% of HEV sales in 2013), while the second peak is largely a result of replacement sales (replacement sales account for 95.7% of HEV sales in 2023). In the base scenario, HEV new sales are forecast to increase to about 510,000 in 2008 and reach 2 million, the first peak, in 2013. Thereafter, they fluctuate between 1.2 million and 2.1 million due to the assumptions made for replacement sales. On average, the annual sales of HEVs are around 1.7 million from 2011 to 2025 in the base scenario, about 10% of new light-duty vehicle sales in 2000.

Figure 35. Input Dialog Box for HEV Scenario Analysis

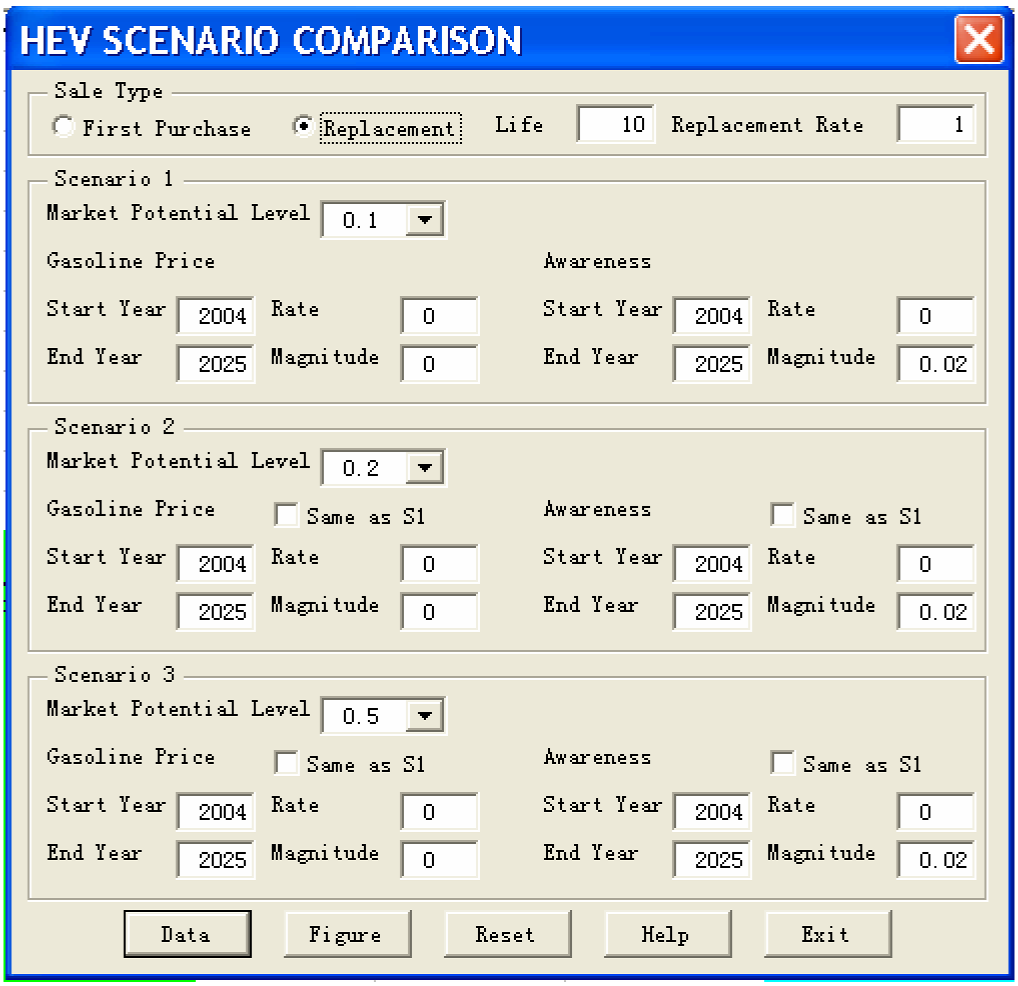
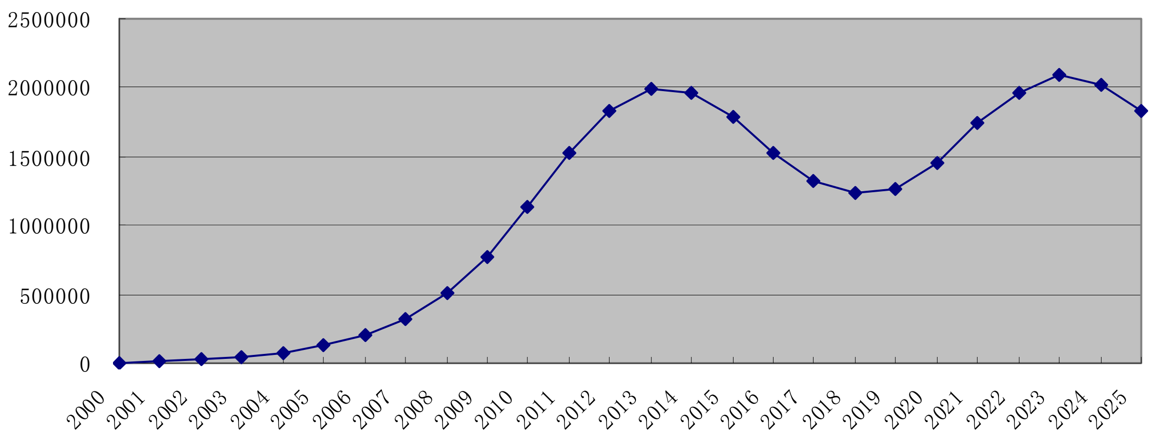


Figure 36. Annual Sales of HEVs in the Base Scenario



In Scenarios 1 and 2, we assumed that gasoline prices increase 25 cents and 50 cents (nominal) per gallon from 2007 on, respectively. According to Figure 37, the annual sales of HEVs grow rapidly as gasoline prices increase. The forecasted average annual sales of HEVs from 2011 to 2025 are 2.2 million and 2.8 million in Scenario 1 and Scenario 2, respectively, representing 30% and 65% increases from the base scenario. Furthermore, the total populations of HEVs in the U.S. in 2025 are forecast to approach 16.5 million, 21.3 million, and 27.0 million in the base scenario, Scenario 1, and Scenario 2 (see Figure 38). Therefore, an increase in gasoline prices appears to greatly contribute to the penetration of HEVs.

Figure 37. The Influence of Gasoline Prices on HEV Annual Sales

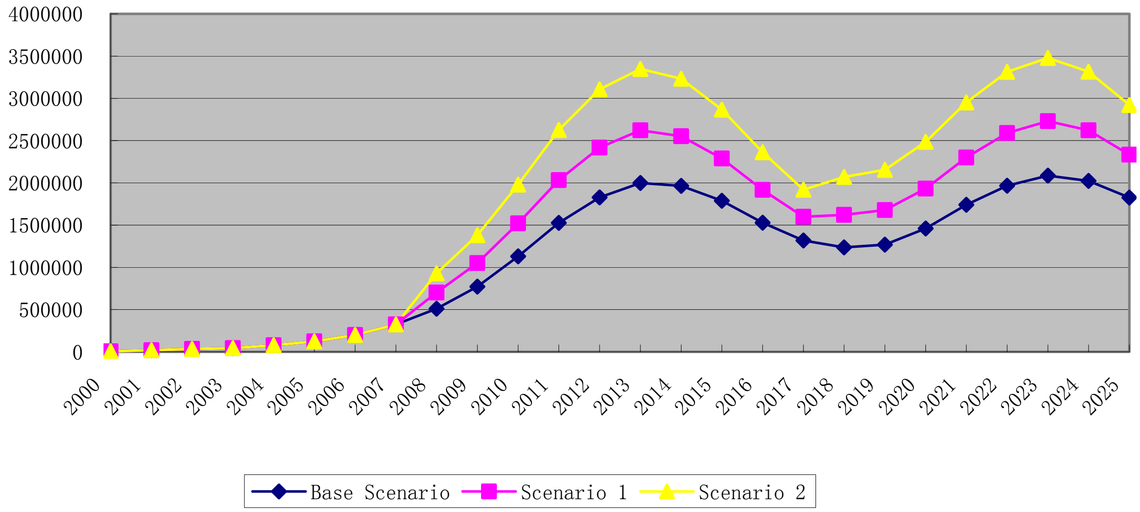
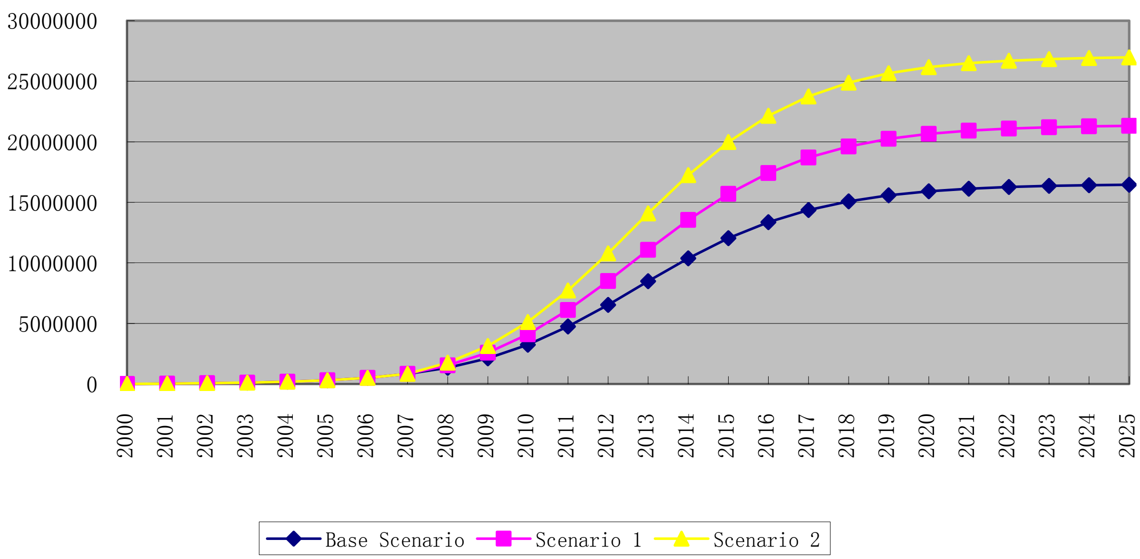
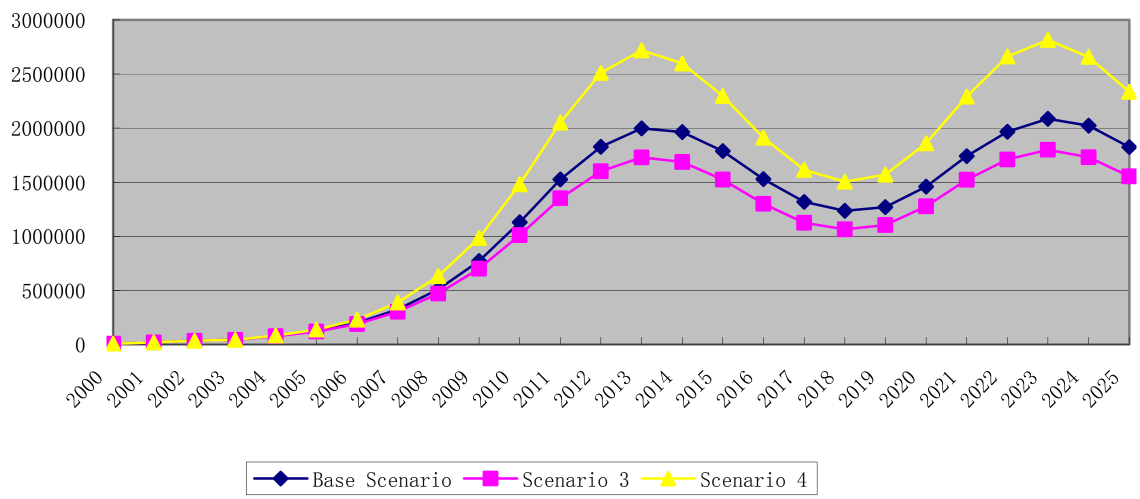


Figure 38. Total Population of HEVs Affected by Gasoline Prices



In Scenarios 3 and 4, the consumers' awareness of HEV technology is assumed to increase 1 and 5 percentage points annually instead of 2 percentage points. As shown in Figure 39, the higher the annual growth in consumers' awareness, the higher the annual sales of HEVs. Specifically, when the annual increase in consumers' awareness is 1 percentage point, the average annual sales from 2011 to 2025 are about 1.5 million HEVs, 0.2 million less than those in the base scenario. On the contrary, Scenario 4 increases the annual sales of HEVs from 2011 to 2025 by more than 0.5 million units on average. Therefore, consumers' knowledge of HEV technology plays an important role in the development of HEVs. Further, the total HEV population in 2025 in Scenario 4 is approximately 21.2 million (see Figure 40), equivalent to that in Scenario 1. That is, an increase in consumers' awareness of 5 percentage points annually has a similar effect on the total population of HEVs in 2025 to that of imposing a tax of 25 cents per gallon on gasoline from 2007 onward. Since increasing the gasoline tax has little public support, it would be all the more valuable to increase consumers' familiarity with HEVs.

Figure 39. The Influence of Awareness on HEV Annual Sales



Finally, if we consider both the effect of gasoline prices in Scenario 2 and the effect of consumers' awareness in Scenario 4 at the same time, the total population of HEVs in 2025 even doubles that in the base scenario, as shown in Figure 41. Also, the combined effects of gasoline prices and consumers' awareness (35 million units) are larger than the summation of their separate effects (27 + 21.2 – 16.5 = 31.7 million units). The implication is that the adoption of these two strategies simultaneously would have a synergistic effect on the sales of HEVs, and both should be promoted if possible.

Figure 40. Total Population of HEVs Affected by Awareness

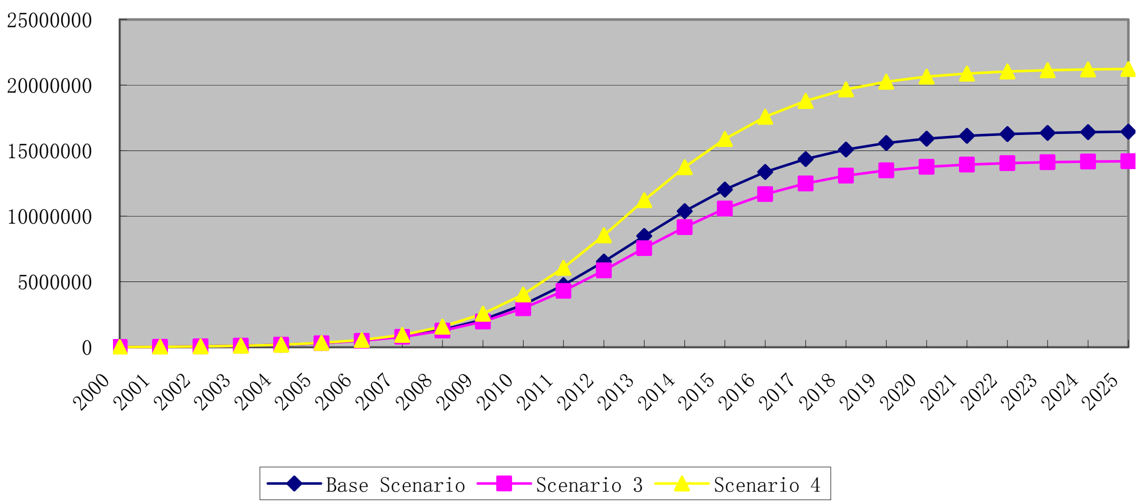
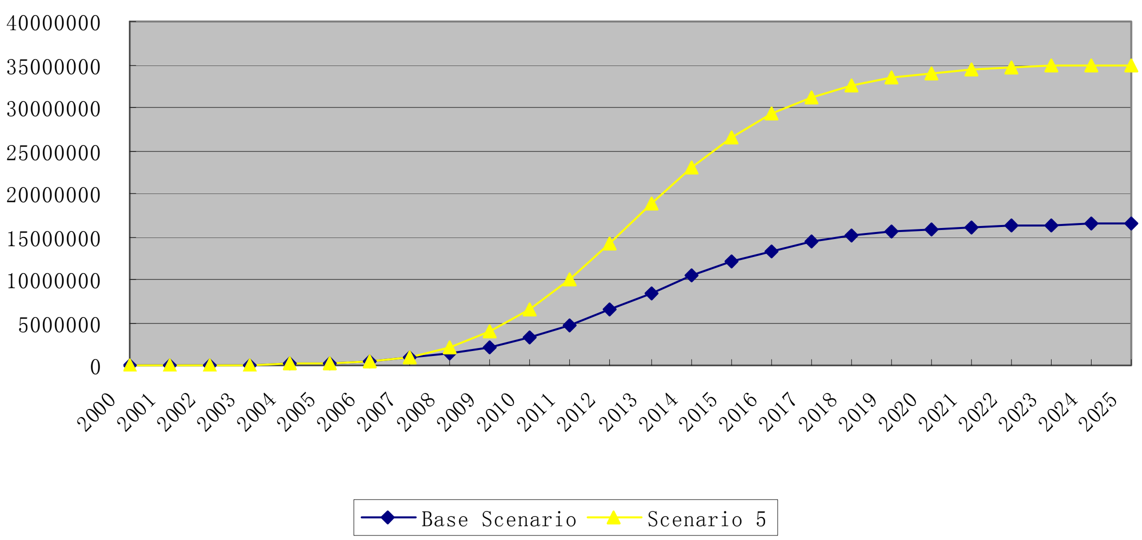


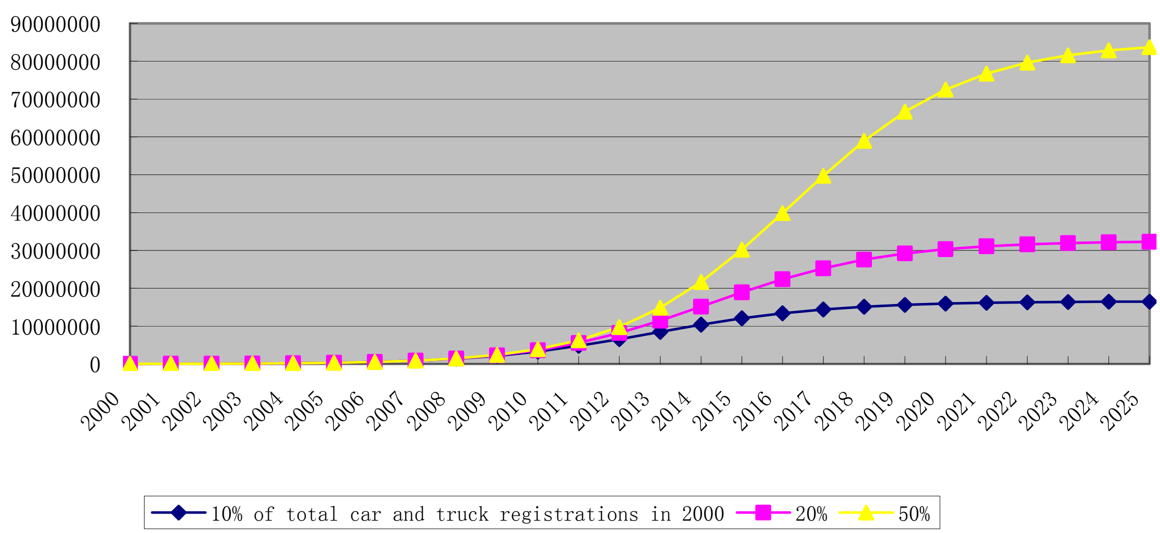
Figure 41. Total Population of HEVs Affected by Gasoline Prices and Awareness



However, it should be kept in mind that the discussions above are based on the assumptions that the market potential of HEVs is about 10% of total car and truck registrations in 2000. Figure 42 illustrates the total HEV populations of the base scenarios when the market potential is 10%, 20%, and 50% of the total registrations, respectively. Gasoline prices and consumers' awareness have similar effects on the penetration of HEVs when we choose different specified market potentials. Interested readers could conduct similar scenario analyses using the attached EXCEL file.

Based on the analyses above, HEV annual sales have the potential to capture more than 10% of new light-duty vehicle sales after 2011. Increases in gasoline prices and acceleration of consumers' awareness of HEV technology are likely to greatly contribute to the market penetration of HEVs.

Figure 42. Total HEV Populations under Different Specified Market Potentials



7 CONCLUSIONS

The objective of this study is to predict the aggregate demand of light-duty AFVs in the U.S., with a timeline from 2005 to 2025. A qualitative description (see Section 3) offers a general picture of the current development of all AFVs ever used in the U.S. Further, using the limited historical data available on their use in the U.S. and other characteristics, we have calibrated separate aggregate diffusion models for the major types of AFVs (specifically, CNG, E85, and hybrid electric vehicles). The models have been embedded into an EXCEL worksheet with a user-friendly interface for modifying various inputs to explore "what if" scenarios. This quantitative analysis (see Section 6) evaluates the influences of various factors and policies on the future penetration of CNG vehicles, E85 vehicles, and HEVs based on some specified conditions.

Methanol vehicles and ethanol 95 vehicles have dropped out of the AFV market. The future penetration of LNG vehicles is dependent on their performance in the heavy-duty vehicle market. Although BEVs are the most environment-friendly and overwhelmingly advocated in the past decade, their inferior performance frustrates most consumers, automakers, and policy makers. As pointed out by Sperling and Ogden (2004), the history of BEVs is largely a history of failure. Therefore, the development of BEVs greatly relies on niche markets such as electric motorcycles and NEVs, where consumers' requirements can be met. In summary, these types of AFVs are unlikely to be successful in substituting for gasoline-powered automobiles in the future.

Although LPG vehicles have the largest population of current light-duty AFVs, their flat growth in recent years indicates that their market penetration is approaching the ceiling. Since the interest of most automakers, fuel providers, and government agencies in AFVs has shifted to HEVs and FCVs in recent years, it will be hard for light-duty LPG vehicle technology and hence its market to gain any significant improvement. Further, after the production of the only model currently being offered by OEMs, the Ford F150 bi-fuel LPG vehicle, is terminated in 2005, light-duty LPG vehicles will be gradually phased out as the current stock ages.

E85 and CNG vehicles shoulder the second and third largest proportion of current light-duty AFVs, respectively. However, their future development is facing many challenges. Similar to BEVs, the inferior performance of CNG vehicles greatly dampens consumers' interest. Based on the scenario analysis of CNG vehicles, their penetration is not likely to obtain any substantial growth even when multiple strategies are adopted to promote their market development. In addition, the exit of Ford from the CNG vehicle market is likely to make the penetration of CNG vehicles even worse. On the other hand, light-duty CNG vehicles may be viable in a niche market such as taxicabs and shuttle vans (CEC, 2003). However, they are not expected to be a feasible substitute for conventional vehicles in 2025.

For E85 vehicles, the high fuel prices and limited refueling infrastructures remain the main impediments for their development. Their current penetration is largely pushed by the fleet requirement. In the base scenario, the total E85 vehicle population is about 280,000 in 2025, accounting for less than 0.2% of total car and truck registrations in 2000. However, further scenario analyses suggest that offering more E85 stations is expected to increase the penetration of E85 vehicles. Specifically, the new sales of E85 vehicles are forecast to increase to 2 million if the number of E85 stations increases by 50 units per year. However, the magnitude of the actual increase in the number of E85 stations inevitably depends on E85 prices. The continuation of the E85 tax credit is helpful to promote the development of E85 vehicles, while changes in gasoline prices are not expected to have a strong influence given the current low gasoline prices. Compared to CNG vehicles, the fuel flexibility offered by E85 vehicles makes them more attractive to consumers. Although most E85 vehicles are powered by gasoline, they are likely to switch to E85 when E85 prices are competitive to gasoline prices and E85 stations constitute at least 10-20% of total refueling stations. In this case, consumers' behavior is not driven by the fleet requirement but by personal benefits. Therefore, E85 vehicles could substitute for a large proportion of conventional vehicles when these conditions are met. However, with vast amounts of ethanol demanded by a large number of E85 vehicles, the development of E85 vehicles may be retarded by e capacity constraints on the supply of ethanol in the future.

HEVs have the potential to replace a large proportion of conventional vehicles in the near to medium term. In the base scenario, HEV new sales are forecast to increase to about 510,000 in 2008 and reach 2 million in 2013, with 16.5 million HEVs on the road in the U.S. in 2025. We found that the market penetration of HEVs is highly sensitive to gasoline prices and consumers' awareness of HEV technology. Specifically, a 50-cent increase in projected gasoline prices boosts the total population of HEVs in 2025 by 10.5 million, and 5 percentage points' annual growth in consumers' awareness leads to 21.2 million HEVs in use in 2025. In addition, allowing HEVs to use HOV lanes, offering a tax credit to purchase HEVs, and expanding model diversity will theoretically accelerate their development. Mass production is also likely to reduce the incremental costs of HEVs, and hence their market penetration will increase at an even faster pace.

The hydrogen FCVs are the most promising but the least mature long-term alternative. Their future development is full of uncertainty. Many breakthroughs in FCV technology and wide-spread refueling infrastructures are required to initiate the penetration of FCVs. If the major limitations of FCVs listed in Section 3.2 are not fully overcome, FCVs may end up like BEVs. Conversely, if favorable conditions prevail, FCVs may become the desired panacea for the problems of oil independence, air pollution, and GHG emissions.

Overall, the higher cost of purchasing and operating alternative fuel vehicles, their poor performance, and the lack of refueling infrastructures are the most important obstacles in the development of AFVs. These factors are not isolated but correlated with each other. Without competitive fuel prices and performance, most private consumers are less likely to accept AFVs, automakers lack sufficient incentive to invest in AFVs, and fuel providers are reluctant to build more alternative fuel stations. Therefore, cooperation among the different sectors is necessary to promote the development of AFVs. To accelerate the reduction of these barriers, government policies are critical for supporting the AFV market.

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APPENDIX 1: Data Used in the Study

Compressed natural gas vehicles

Year	Total Population	Annual Sales	Model Availability	Station Availability	Gasoline Price	CNG Price	Conversion Indicator
1992	-	-	0	349	1.502	0.648	1.000
1993	28714	6536	1	497	1.444	0.663	1.000
1994	35970	7256	1	1042	1.398	0.622	1.000
1995	43052	7082	1	1065	1.406	0.586	0.995
1996	50270	7218	5	1418	1.456	0.621	1.000
1997	57534	7264	4	1426	1.423	0.621	0.598
1998	63739	6205	5	1268	1.217	0.632	0.316
1999	72792	9053	6	1267	1.297	0.584	0.176
2000	79459	6667	6	1217	1.604	0.722	0.175
2001	84007	4548	7	1232	1.530	0.836	0.097
2002	87340	3333	5	1229	1.386	0.744	0.099

Ethanol 85 vehicles

Year	Total Population	Annual Sales	Revised Sales	Model Availability	Station Availability	Gasoline Price	E85 Price	Conversion Indicator
1992	-	-	-	0	2	1.502	2.262	1.000
1993	439	272	272	0	7	1.444	1.887	1.000
1994	605	166	166	0	32	1.398	1.840	1.000
1995	1527	922	922	1	37	1.406	1.855	0.995
1996	4536	3009	3009	1	68	1.456	2.165	1.000
1997	9130	4594	4594	1	71	1.423	1.854	0.598
1998	12788	3648	3648	4	40	1.217	1.643	0.316
1999	24454	9676	9676	6	49	1.297	1.503	0.176
2000	87570	65116	10850	10	113	1.604	1.944	0.175
2001	100287	12717	12717	11	154	1.530	2.195	0.097
2002	120809	20522	20522	15	151	1.386	2.195	0.099

Hybrid electric vehicles

Year	Total Population	Annual Sales	Consumers' Awareness	Gasoline Price	Year of Price
2000	6479	6479	0.36	1.297	1999
2001	25512	19033	0.44	1.604	2000
2002	60033	34521	0.52	1.530	2001
2003	103468	43435	0.53	1.386	2002

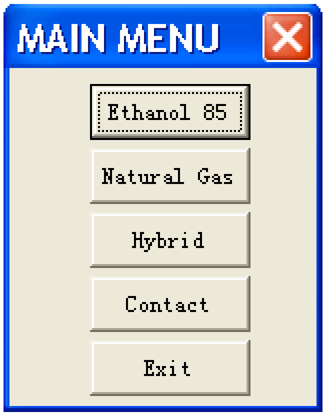
APPENDIX 2: Manual for the EXCEL Worksheet

The menus in the EXCEL worksheet comprise four components: a welcome frame, a main menu, submenus, and worksheet menus. The remaining of this section shows readers how to use this worksheet to create user-specified scenarios.

Before opening this worksheet, you should make sure that macros are allowed in your computer. If the macros are forbidden, please adjust the settings of EXCEL as follows: Tools ⇒ Macro ⇒ Security, and then set security level as low. After you open the worksheet, a welcome frame, as shown in Figure 43, automatically pops up. Please click the menu button to activate the main menu (see Figure 44). On the main menu, there are five command buttons: Ethanol 85, Natural Gas, Hybrid, Contact, and Exit. The first three buttons are directly linked to the submenus for ethanol 85 (E85), compressed natural gas (CNG), and hybrid electric vehicle (HEV) scenario analysis, which are illustrated in detail later. Clicking the "Contact" button shows the authors' contact information, while the "Exit" button allows reading the introduction for this project.

Figure 43. Welcome Frame

Figure 44. Main Menu



The submenus for E85 vehicle, CNG vehicle, and HEV vehicle scenario analysis are presented in Figures 45, 46, and 47. Before we explain these submenus in detail, it should be kept in mind that all specified conditions should be input through these menus and any revisions directly to the cells in the worksheet may yield erroneous outcomes since macros are pervasively used in the worksheet. There are five command buttons at the bottom of all these submenus. The "Data" and "Figure" buttons allow users to choose a specific format (either a worksheet or figure) to read the results; the "Reset" sets all specified conditions back to their default values; the "Help" shows users the definition of terminologies; and the "Exit" closes this menu without any operation.

The "Sale Type" block offers users two options to compare different scenarios: first purchase and replacement. If first purchase is chosen, the worksheet will present the data or figure for the alternative fuel vehicle (AFV) in terms of first purchases only. Conversely, if replacement is selected, additional information regarding the assumed average life of the AFV and the average replacement rate is required. The replacement rate specifies what percent of AFV adopters will repurchase the same type of AFV after their AFVs retire. For example, the new sales of HEVs are 43,435 units in 2003; if their average life is 10 years and their replacement rate is 0.8, there will be 43,435 * 0.8 = 34,748 HEVs sold in 2013 due to replacement, in addition to first purchases.

These submenus allow the creation of user-specified conditions for up to three different scenarios at once. To examine the influence of station availability on the diffusion of E85 vehicles, users can modify the inputs for station availability in the E85 menu. Specifically, the number of refueling stations within the assumed period is expressed in the following form:

$$N_{FS}(t) = N_{FS}(t-1)[1 + Rate] + Magnitude,$$

where $N_{FS}(t)$ stands for the number of fuel stations at year t. By setting Rate = 0 and Magnitude to some number, say 10, the users can test the impact on sales of increasing the number of E85 stations by that number (10) each year between the specified start and end years. By setting Magnitude = 0 and Rate to some number, say 0.1, the users can test the impact on sales of increasing the number of E85 stations by the corresponding percentage (10%) each year. Positive values for both Rate and Magnitude simultaneously are also permissible. A similar formulation is applied to model availability (the number of CNG models available to the market) in the CNG menu and awareness (consumers' knowledge of HEV technology) in the HEV menu.

On the other hand, changes in fuel prices within the specified period are expressed in a different form as follows:

$$FP_{Assumed}(t) = FP_{\Pr ojected}(t)[1 + Rate] + Magnitude,$$

where $FP_{Assumed}(t)$ is the assumed fuel price at year t, and $FP_{\Pr ojected}(t)$ denotes the fuel price at year t projected by the Annual Energy Outlook 2003. Thus, altering Rate and Magnitude for fuel prices permits testing various policies or market disruptions that would change fuel prices (upward or downward) compared to their natural forecasted levels without (further) policy intervention or market disruption. Fuel prices for CNG and E85 are to be input in terms of dollars per gasoline gallon equivalent (GGE). The conversion formulas are, respectively,

1 ft^3 CNG = 0.00789 GGE, and

1 gallon E85 = 0.714 GGE.

Figure 45. The Submenu for E85 Vehicle Scenario Analysis

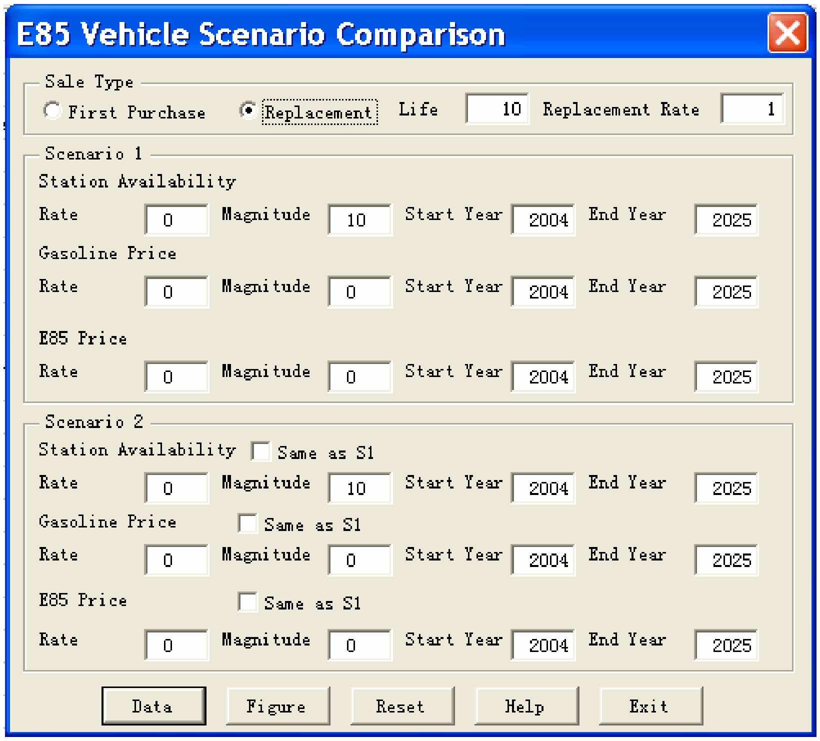


Figure 46. The Submenu for CNG Vehicle Scenario Analysis

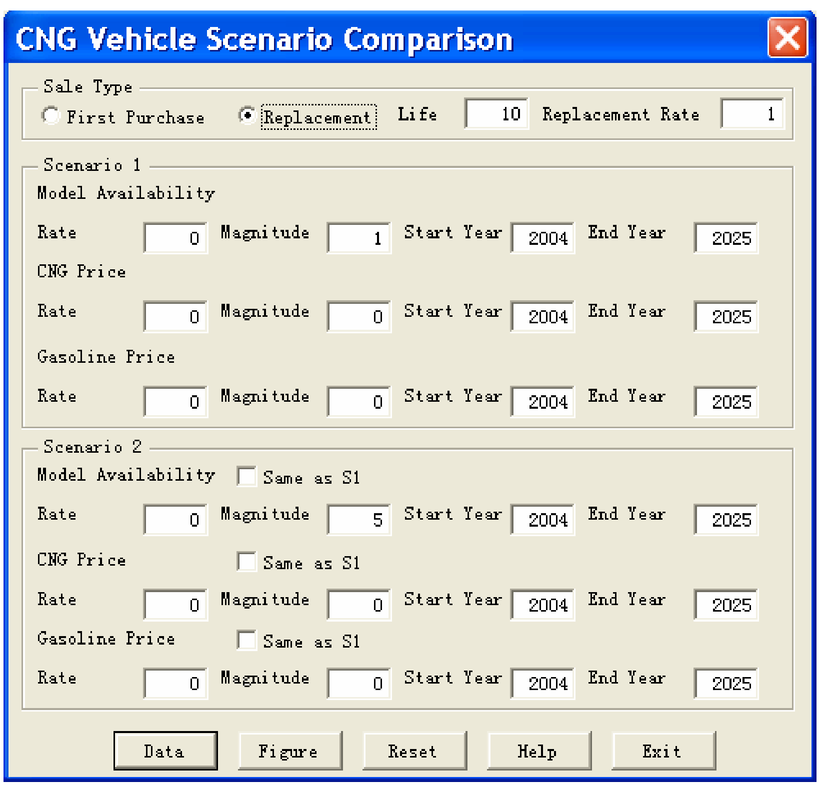
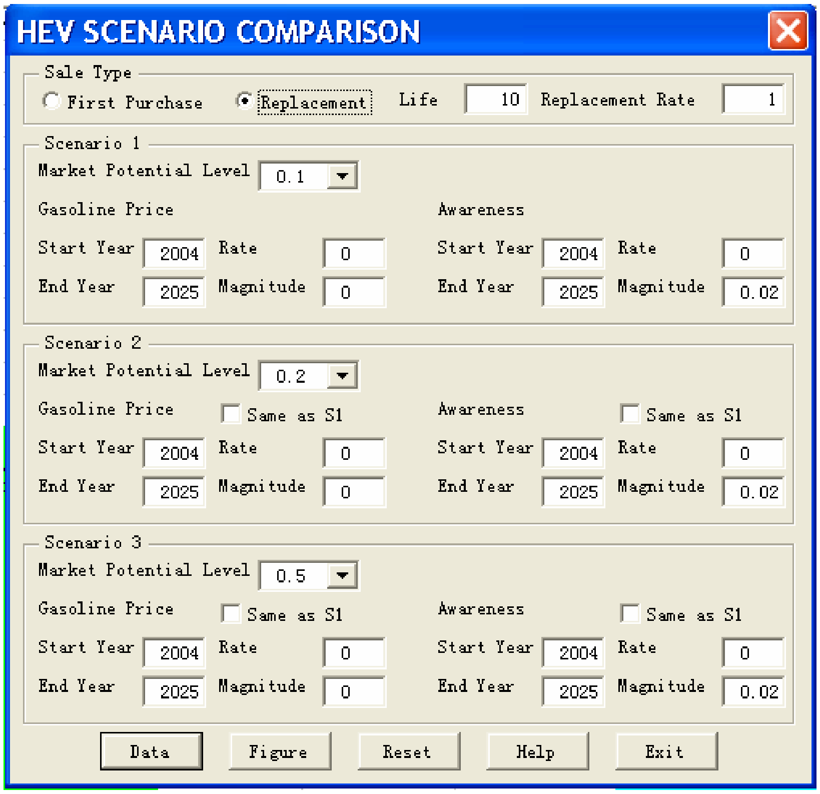


Figure 47. The Submenu for HEV Scenario Analysis



For efficiency, choosing the box "Same as S1" next to the label of an explanatory variable will set the assumed conditions of this variable to be the same as those in Scenario 1.

In the HEV menu, users are also required to specify the market potential level. The market potential level indicates the proportion of total car and truck registrations in the U.S. in 2000 that HEVs are expected to ultimately account for. Since the market potential is affected by both gasoline prices and consumers' awareness, the proportion is an approximate value.

Finally, there is a menu in the upper right corner of each worksheet, as shown in Figure 48. This menu offers transitions among different worksheets and different menus. For example, the "Main Menu" button returns the user to the main menu showing in Figure 44, and the "Data" button allows the user to review the data when the current worksheet illustrates figures. If the current worksheet illustrates data, a "Figure" button appears instead of "Data".

Figure 48. The Worksheet Menu for CNG Vehicle Scenario Analysis