TOPIC 15
TRAVEL CHOICE AND
DEMAND MODELLING

A DYNAMIC FORECASTING SYSTEM FOR VEHICLE MARKETS WITH CLEAN-FUEL VEHICLES

DAVID S. BUNCH
Graduate School of Management
University of California
Davis, CA 95616, USA

DAVID BROWNSTONE
Department of Economics
University of California
Irvine, CA 92717, USA

THOMAS F. GOLOB
Institute of Transportation Studies
University of California
Irvine, CA 92717, USA

Abstract

A microsimulator modelling system for forecasting future vehicle transactions, fuel usage, and (electric vehicle) time of day recharging in both the residential and commercial fleet markets of Southern California has been developed. The system, a base-case forecasting scenario, and preliminary market penetration results for the residential vehicle market are presented and discussed.

RESEARCH OBJECTIVES

This research deals with demand for automobiles and light-duty and medium-duty trucks. Planners concerned with energy consumption, air quality and the provision of transportation facilities must have dependable forecasts of vehicle ownership and use from both the residential (personal-use vehicle) sectors and the fleet (commercial and governmental) sectors. As long as vehicles evolved slowly, it was possible to base such forecasts on extrapolations of observed demand. However, in an era of increasing environmental awareness, mandated in part by the U.S. Clean Air Act Amendments (US EPA, 1990), government agencies are now concerned with promoting clean-fuel vehicles; vehicle manufacturers are faced with designing and marketing clean-fuel vehicles; and suppliers of fuels other than gasoline must plan infrastructure and pricing policies.

In California, and potentially also in a number of Northeast States, stringent vehicle emission standards have been adopted or proposed and specific zero-emissions and ultra-low-emissions vehicle mandates are in place. The California Air Resources Board (CARB) requires that new cars sold in the state emit 80 percent less hydrocarbons by the year 2000, and 50 to 75 percent less carbon monoxide and nitrogen oxide. CARB has also mandated the production and sale of zero-emission (presumably electric) vehicles, beginning with 2 percent of annual car sales in 1998 and increasing to 10 percent in 2003. Elsewhere in the United States, clean-air and fuel-management legislation (U.S. DOE, 1994) specifically targets fleets as markets for clean-fuel vehicles. Research is needed to establish the extent to which there is demand for clean-fuel vehicles. In reaction to this need, the Southern California Edison Company and the California Energy Commission is sponsoring a project to develop a dynamic demand forecasting model for clean-fuel vehicles in California. In this paper we briefly describe the forecasting system being developed and summarize some preliminary results.

Clean-fuel vehicles are potentially different from conventional gasoline or diesel vehicles in terms of many attributes that can be of prime importance to consumers. Such attributes include, but are not limited to: range between refuelling, overnight recharging requirements (electric vehicles), the potential availability of at-home refuelling (compressed natural gas vehicles), the limited availability of refuelling or recharging stations, vehicle performance levels, and cargo carrying capacity, as well as substantial differences in capital and operating costs.

This research builds upon previous efforts to provide quantitative estimates of demand for electric and alternative fuel vehicles. These estimates are useful for evaluating incentive polices, vehicle design and marketing strategies, and fuel demand management. It is not possible to discuss all of these precursor studies here, but, on the residential vehicles side, important studies are those of Beggs and Cardell (1980), Bèggs, Cardell and Hausman (1981), Hensher (1982), Calfee (1985), Greene (1989; 1990), and Train (1980). On the fleet side, Berg, *et al.* (1984), Easton (1991), Hill (1987), and Macro (1992) provide pioneering studies.

The model system is designed to forecast demand for vehicles and also fuel usage for each type of vehicle in each of a number of geographical regions. To determine the impact of electric vehicle recharging on the electric transmission and distribution system, the system forecasts recharge demand for electric vehicles by time of day in each of approximately forty districts that correspond to distribution planning areas. Currently, peak electricity demand in California occurs during summer afternoons, and minimum demands occur between midnight and 6:00 A.M. Therefore, electric vehicle recharging will be much cheaper and less polluting if it takes place during late night hours when electricity is generated by hydroelectric and other clean baseline plants. The current version of the system produces charging profiles under the assumption that consumers plug in their vehicles in an unconstrained fashion; the data source was a distribution of plug-in times from a vehicle trials program. Future versions of the system will use behavioral models to examine the extent to which consumers are willing to recharge electric vehicles off-peak at lower rates.

Forecasts are produced for various vehicle 'classes': All conventional-fuel and clean-fuel vehicle types that are anticipated to be available have been included. Makes and models of vehicles are grouped into relatively homogeneous classes with similar attributes, such as emission levels. The model system uses 14 residential vehicle body-type-and-size classes (7 car classes and 7 light truck classes) and 5 fuel technology types. Vehicles are further classified according to 10 model-year vintage groupings. The fleet demand sub-model also contains a medium-duty truck class and a small bus (shuttle bus) class in addition to all of these light-duty truck and car classes.

Since we are primarily interested in forecasting the demand for new types of vehicles, the model must be able to forecast the technology adoption process. This requirement rules out the classic static vehicle demand models, such as Train (1986). Our system produces a separate forecast for each period, with each period's forecast depending on all the previous forecasts. The current system does not account for vehicle demand from state and federal government rental car fleets: this will be added in future versions.

BASIC STRUCTURE OF THE FORECASTING SYSTEM

The forecasting system is comprised of two main subsystems, the residential (personal-vehicle) demand subsystem and the fleet demand subsystem. Due to space limitations, it is only possible in this paper to describe and report preliminary results for the residential subsystem, but we also outline the basic structure of the fleet subsystem. Preliminary results from the fleet demand subsystem are presented in Golob, *et al.* (1995).

The forecasting system starts from a baseline database of households and commercial fleets, and then simulates a sequence of vehicle transactions at six-month intervals so that vehicle stocks are dynamically determined. Results are reported annually. The data for the baseline year, 1993, are derived from large-scale surveys of household vehicle holdings, and from a large-scale survey of fleets, augmented by vehicle registrations data. The forecasting method is similar to Hensher (1992), in which the household population is represented by a relatively small number of "synthetic" households. The present use of a large sample of actual households and fleets instead of a synthetic sample requires more computation, but the results should be more accurate.

Both the residential and fleet demand subsystems are based on transactions models. These models predict whether a vehicle transaction will occur during the current period and what type of transaction it will be. The inputs to the models are the current characteristics of the household (or fleet) and the current vehicle inventory and utilization. Since vehicle type decisions are discrete, the models can only provide probabilities that a particular household or firm will choose a particular type of vehicle. Forecasting a particular choice from these models requires simulating an actual choice, which introduces some random noise into the forecasting process. Fortunately, the effect of this randomness disappears when forecasts for individual households or fleets are aggregated to predict market demand. The predicted changes in vehicle holdings and utilization are then combined with initial holdings to forecast vehicle stocks for the next period (Brownstone, *et al.*, 1994).

DATA

Household survey

Since we are concerned with the demand for a new product that does not yet exist, we asked respondents to make choices among hypothetical vehicles. These "stated preference" questions (Louviere, 1988) have been successfully used in a pilot study of consumer preferences for alternative fuel vehicles (Bunch, et al., 1993; Golob, et al. 1993). This pilot study, sponsored by the California Energy Commission, confirmed that information about attribute trade-offs gained through our "stated preference" method are consistent with results of previous studies of actual vehicle purchase behavior (eg, Train, 1980, 1986; Hensher, 1992).

Stated preference questionnaires require that respondents receive different hypothetical vehicles according to a pre-specified experimental design. The questionnaires also contain enough background information so that respondents can fairly evaluate the hypothetical vehicles. In addition to stated preference questions, we also ask extensive questions about respondents' existing vehicle stock and utilization. The remainder of this section gives more detail about the three main data sets used to calibrate our models.

The first wave of our personal vehicle panel survey was carried out in June and July, 1993. The sample was identified using pure random digit dialling and was geographically stratified into 79 areas covering most of the urbanized area of California. A total of 7,387 households completed the initial computer-aided telephone interview (CATI). This initial CATI interview collected information on: household structure, vehicle inventory, housing characteristics, basic employment and commuting for all adults, and stated intentions for the next vehicle transaction.

The data from the initial CATI interview were used to produce a customized mail-out questionnaire for each sampled household. This questionnaire asked more detailed questions about each household member's commuting and vehicle usage, including information about sharing vehicles in multiple-vehicle and multiple-driver households. The mail-out questionnaire also contained two "stated preference" (SP) choice experiment tasks for each household. Each of these tasks described three hypothetical vehicles, from which the households were asked to choose their preferred vehicle. These hypothetical vehicles included both clean-fuel and gasoline vehicles, and the body types and prices were customized to be similar (but not identical) to the household's description of their next intended vehicle purchase. Households then indicated which of their current vehicles they would replace with the preferred vehicle, or if the preferred vehicle would be purchased as an additional vehicle.

After the households received the mail-out questionnaires, they were again contacted for a final CATI interview. This interview collected all the responses to the mail-out questions. Additional questions about the household's attitudes towards clean-fuel vehicles were also included in this interview. A total of 4747 households completed all phases of the survey.

Fleet site survey

The first task in surveying commercial and local government (city, county and regional) fleet operators was to establish a comprehensive list of fleets from which a survey sample could be drawn. This also established a 'fleet universe.' Many small to medium size fleet operators are not currently registered in fleet databases available from fleet managers' associations, governmental agencies, or commercial market research firms. Moreover, these databases are not generally up to date on the number and type of vehicles operated in a given fleet. Consequently, a comprehensive list of potential fleets was obtained from the 26.5 million records of the California Department of Motor Vehicles registration file.

A rule-based algorithm was developed to match and combine all vehicle registrations with a high probability of being from the same company or individual at the same site, taking into account differences in registrations due to abbreviations and spelling. Most clean-air mandates target fleet sites with ten or more vehicles, so all potential sites with five or more registrations were investigated because of the likelihood that registration sites would still be fragmented into two or more components based on unresolved differences in names or addresses. Since substantial numbers of households own or lease five or more vehicles, and many households even own ten or more vehicles, a knowledge-based system using rules and predicate logic for conflict resolution was developed to separate households from businesses. A sample was then drawn from the identified registration sites, and survey results were used to factor the total list of registration sites in order to estimate the universe of commercial and local government fleet sites.

The survey of 2,100 fleet sites was conducted as a combined CATI and mail-back questionnaire. The CATI portion of the survey established the fleet inventory and business functions, and gathered data on multi-site fleet operations. In the customized mail-back questionnaire, fleet operators provided detailed operation and acquisition data on up to two selected types of vehicles currently in their fleets. In the mail-out SP tasks, the operators chose future fleets of the selected types from among hypothetical conventional-fuel and alternative-fuel vehicles, and they allocated the chosen vehicles to the tasks typically performed by the fleet. There were also questions concerning organizational decision making and opinions about alternative-fuel vehicles. Preliminary analyses of the fleet survey are presented in Golob, Torous and Crane (1995) and Golob, *et al.* (1995).

MODEL SYSTEM COMPONENTS

Figure 1 is a schematic representation of the model system. The system has three types of components:

- *Exogenous datasets* that drive the forecasts are depicted as doubly-outlined boxes which are labeled 1 through 3.
- The principal *endogenous datasets* are depicted as heavy-outlined boxes which are labeled with the Roman numerals I through III.
- The component *models* are depicted in boxes with rounded corners and are labeled with the letters A through K (skipping I).

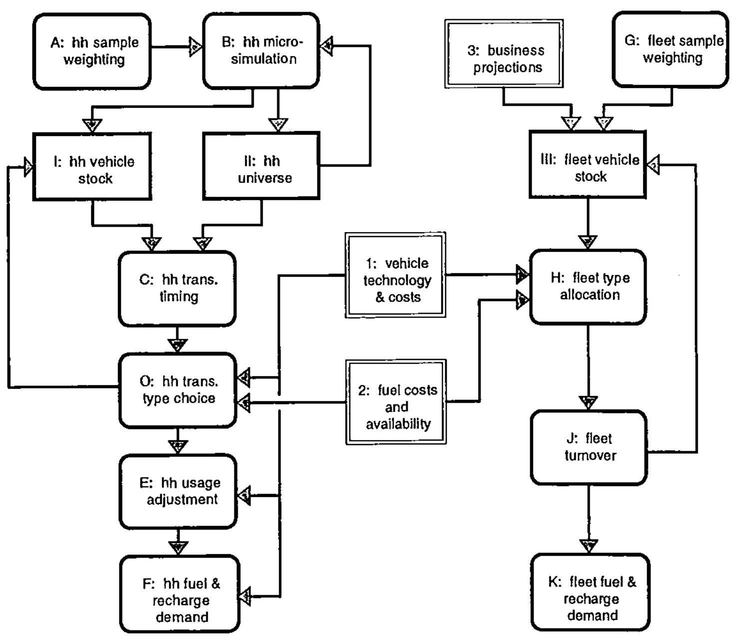

Figure 1 Schematic diagram of forecasting system

Exogenous inputs

The key inputs to the residential vehicle forecasting subsystem are vehicle technology, and fuel costs and availability. Vehicle technology (Box 1 in Figure 1) includes numerical values for both historical and future vehicle attributes, including fuel type, refuelling or recharging range, price, operating costs, vehicle tailpipe emissions, payload, and performance. Although it is relatively easy to forecast these attributes two to three years ahead, it is very difficult to predict the state of new technology ten or more years ahead. Forecasts from the model system crucially depend on future vehicle technology, and users of the model system will need to continually update this information as time progresses. Since the model produces forecasts for each year, it is also important to forecast when new technology vehicles will be introduced. Finally, the model system assumes that manufacturers are willing to provide as many vehicles as demanded at the forecast vehicle price.

Fuel costs and availability (Box 2 in Figure 1) is another exogenous input to the model system. Although fuel costs are typically very difficult to forecast, we only need accurate forecasts of relative fuel prices. The prices of three of the fuels considered in our model—gasoline, compressed natural gas, and electricity—have tended to move together with the price of crude oil during the past decade. However, if crude oil prices start to rise substantially, then the off-peak electricity price may diverge from recent patterns since in California off-peak electricity is primarily generated by hydroelectric power. Fuel infrastructure describes the availability of alternative clean fuels. For compressed natural gas and methanol this is expressed as the ratio of the number of service stations relative to gasoline.

Many proposed incentives (such as, sales tax and vehicle registration fee subsidies) simply lower the capital and/or operating costs of these vehicles, so the effects of these incentives can be modelled by changing the appropriate cost variables in the vehicle technology and fuel cost files. Other proposed incentives, such as free parking, solo driver access to high-occupancy vehicle (carpool) lanes, or extended vehicle warranties, cannot currently be captured in the vehicle technology or fuel technology inputs. The forecasting system is being expanded in 1995 so that both the residential and fleet demand subsystems will be sensitive to such incentives.

Sample weighting

The 7387 survey households must be weighted to accurately represent the target population. We first created sampling weights that just accounted for the geographic stratification and the differential number of household telephone lines. These weights were then adjusted using statistical matching to the 1993 U.S. Census Current Population Survey (CPS) so that the weighted sample matched the CPS joint distributions of household composition, age, and income. Finally, these weights were further adjusted using a binomial logit model to account for non-random selection from the original 7387 survey households down to the forecasting sample.

Household microsimulation

Model B in Figure 1 is a suite of dynamic competing-risks hazard models which age each household, and simulate births, deaths, divorces, children leaving home, etc. Once the new household structure is determined, other models in Box B determine the household's income and employment status. The models produce an updated Household Universe File (Dataset II) which is used as the starting point for aging the household in the next period; this cycling is depicted by the feedback from Dataset II to Box B in Figure 1. The household microsimulation models are mostly calibrated from the Panel Study of Income Dynamics (Hill, 1992) because the personal vehicle survey does not track households over a sufficiently long time period to be used as a calibration source. The household microsimulation model is documented in Kazimi (1994) and Kazimi and Brownstone (1995).

Transactions timing

Model C in Figure 2 takes the updated household and current (aged) vehicle holdings as inputs. It then decides whether or not a vehicle transaction takes place during this period. The period length is set at six months, in order to limit the number of transactions per period to one, but model system outputs are given annually. A vehicle transaction is defined to include: disposing of an existing vehicle, replacing an existing vehicle with another one, or adding a new vehicle to the household's fleet.

Transactions type choice

If the simulation from Transactions Timing Model B predicts that a vehicle transaction has taken place, the Transaction Type Choice Model in Box D determines exactly what type of transaction takes place. The household's vehicle holdings are updated accordingly, and these are used as inputs to the vehicle utilization model in Box E as well as starting values for the next period's forecast (the feedback loop from Box D to Dataset I). The model outputs for each year accumulate the probabilities of all actions to the total numbers of vehicles owned or leased by type and vintage. For new vehicles, this represents market penetration. The transactions type choice model is documented in Ren, *et al.* (1995).

Vehicle usage adjustment

A utilization model, Box E, then takes the updated vehicle holdings and household structure and predicts changes in the annual vehicle miles travelled (VMT) for each household vehicle. The model, described in Golob, Bunch and Brownstone (1995), is estimated on combined revealed preference (RP) and stated preference (SP) data from the household survey. The RP data involves reported usage levels for existing household vehicles, and the SP data involves responses to questions concerning how chosen hypothetical future vehicles would be used by various household members. Structural equation models are used to capture VMT and driver allocation for each household vehicle as a function of vehicle age, type, operating cost, range, and household characteristics. These models predict changes in VMT due to vehicle aging and driving aging effects, even if households make no vehicle transactions and all household characteristics are unchanged. Forecasts of VMT are generated by calculating expected usage at the beginning and end of each period and applying the percent changes in expected levels to the observed VMT base level, thus preserving sample heterogeneity (Golob, Bunch and Brownstone, 1995).

Fuel and recharge demand

Finally, the usage forecasts are converted to fuel demand by using average miles per gallon for liquid fuels and miles per equivalent gallons for non-liquid fuels. For electric vehicles, the utilization model also predicts recharging load by time of day.

INITIAL FORECASTS

Base case scenario

Users of the forecasting system must specify all underlying assumptions regarding future market conditions and competitors. This information resides in the two exogenous files: 1. Vehicle Technology, and 2. Fuels Costs and Availability (Figure 1). The vehicle technology file establishes the market availability of various gasoline and alternative-fuel vehicle types and forecasted vehicle characteristics (eg, purchase price, body type, range, acceleration). The fuels file contains forecasts of fuel prices and service station availability for four fuels (gasoline, methanol, natural gas, and electricity).

The vehicle technology file contains historical data on gasoline vehicles during the period 1976 to 1994. However, forecasts of future market penetration depend on two critical determining factors: (1) the types of vehicles that will be available, in terms of vehicle class (body type and size), and fuel type, and (2) the timing of vehicle introduction. The initial forecasts presented here are generated using a base case scenario (BCS) vehicle and fuel technology files briefly described below.

The forecasting system begins its microsimulation calculations in the year 1994, which is the first year that alternative-fuel vehicles (AFV's) might potentially be available. The BCS assumes that nineteen types of AFV's will eventually be available in the market, giving a total of 33 vehicle types, as shown in Table 1. It assumes that no alternative fuel vehicles will be widely available in the market until 1997. Nine of the nineteen AFV's appear in 1997, with the remainder appearing in 1998.

In addition to details on vehicles, the model requires information about future fuel prices and infrastructure. Decisions to purchase vehicles depend on fuel operating costs, which in turn depend on both vehicle fuel efficiency and the cost of fuel at the pump (or at the electrical outlet). In addition, purchase decisions depend on the availability of refuelling stations. After vehicles have been purchased, the amount they are driven (annual vehicle miles travelled) depends on fuel operating cost.

Table 1 Base case scenario—market availability of alternative fuel vehicles

Fuel type	Class	Size	1997	1998+
Methanol	Car	Intermediate		
	Car	Large		
	Car	Luxury		
	Pickup	Standard		
	Van	Standard		
Ded. CNG	Car	Subcompact		
	Car	Compact		
	Car	Intermediate		
	Car	Large		
	Pickup	Standard		
	Van	Compact		
	Van	Standard		
Dual CNG	Pickup	Standard		
Electric	Car	Mini		
	Car	Subcompact		
	Car	Compact		
	Car	Sports		
	Pickup	Compact		
	Van	Compact		

The fuels prices used in the Base Case Scenario are the most recent ones available from the California Energy Commission (CEC). The electricity prices in California vary widely within the state: the values used here are those for the Los Angeles area. With regard to refuelling station availability, the BCS assumes that the ratio of alternative fuel stations to gasoline stations is 0.1 for all years. The future fuel price trends used in the BCS are summarized in Figure 2. The BCS vehicle operating costs that are a result of these fuel prices and assumed vehicle fuel efficiencies are listed in the Appendix.

Presented in the Appendix are excerpts of the BCS vehicle and fuel technology files for two years: 1998 and 2005. These two years are of special interest because they correspond to years in which there are CARB mandate targets, and the year 2005 represents a ten-year time horizon relative to today's date. In addition to the details provided in the tables, there are three additional assumptions: (1) refuelling times for gasoline, methanol, and natural gas vehicles at service stations are 7, 7, and 5 minutes, respectively, (2) home recharging for electric vehicles takes 3 hours starting in 1998 (but 8 hours prior to 1998), (3) the service station availability index is 1 for gasoline and 0.1 for other alternative fuels.

There are some noteworthy features in these tables. Various technological improvements are expected to occur for different vehicle types. Due to relatively low fuel prices, natural gas vehicles are less expensive to operate than gasoline and methanol vehicles. High methanol fuel prices cause methanol vehicles to be more expensive to operate than other vehicles. Gasoline vehicles have substantially more range than other vehicle types. Ranges for electric and methanol vehicles improve over time. Electric vehicles are assumed to have substantially higher capital costs than other vehicles, but with the gap narrowing as time progresses. Other AFV's have capital costs comparable to gasoline. Natural gas vehicles are quite clean. Gasoline and methanol vehicles are much less clean, but they get cleaner over time. (Electric vehicles, of course, have zero tailpipe emissions.) In the BCS, battery replacement costs are included as part of vehicle operating cost for electric vehicles.

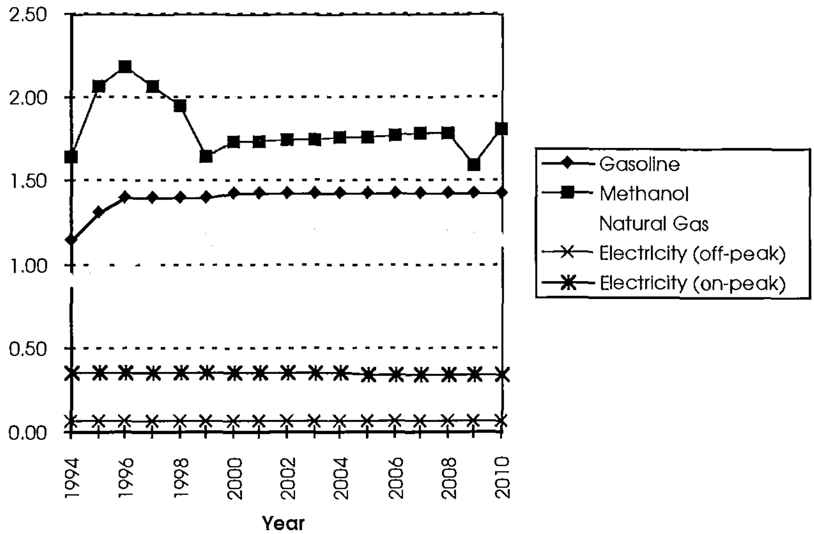

Figure 2 **Fuel price forecasts**

The forecasts are predicated on the assumptions contained in the vehicle technology and fuels forecast input files. Changing the values in these files will produce different results. Gaining a full understanding of the forecasting model and its behavior will require additional testing and re-running of simulations to see how the results are affected by changes in the attribute values such as purchase price, vehicle range, fuel availability, and so forth.

Finally, it should be noted that the forecasting system is a scenario analysis tool that makes the following assumptions:

1. When vehicles are identified as "available in the market," it is assumed that all consumers are fully aware of the existence of these vehicles, and are also familiar with the vehicle attributes through advertising, education programs, personal experience or word-of-mouth, etc.
2. Vehicles are widely available throughout the market, ie., full channels of distribution through dealerships are in place.
3. Supplies of vehicles are fully available at the assumed purchase price. Thus, this model produces results under the assumption of what automobile companies call "free expression."

Microsimulation forecasts for the base case scenario

This section reviews some *aggregated* results obtained from an initial run of the microsimulation forecasting model. These results cover the California South Coast Air Basin for the years 1994 to 2010.

Starting in 1997, alternative fuel vehicles are introduced in California and begin penetrating the market. The forecasting system simulates the vehicle purchase and behavior of households in the Southern California Edison (SCE) service area. Figure 3 shows how the system behaves in regard to overall vehicle purchases over time. The top line represents total vehicles in California as predicted by our model. The current version of the model is likely to contain some over-prediction of vehicle totals until a more sophisticated scrappage model can be added in the next version. It should also be noted that these figures include vehicles from all sources (new and used) so that some of the personal vehicles could have been purchased from, eg, rental car or commercial fleets. One feature of the forecasting system (which cannot be seen from aggregate figures), is that, in addition to the number of households increasing, the number of vehicles per household is forecasted to increase. The total number of gasoline vehicles in California is seen to level off as more alternative vehicles penetrate the market.

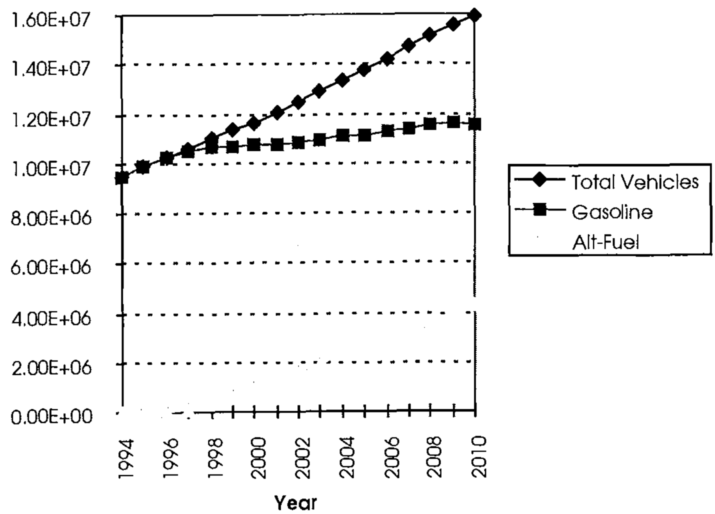

Figure 3 Personal vehicles in SCE service area

Some figures of special interest, due to the CARB clean fuel vehicle mandates, are the new vehicle sales shares by fuel type in the years 1998, 2003 and 2010. See Figure 4. The strongest AFV competitor under the BCS is natural gas. This is apparently due to a highly competitive combination of low operating cost, cleanliness, medium-level range, and capital cost to gasoline vehicles. Under the BCS, electric vehicles meet the 2% mandate in 1998. Sales shares increase in 2003 and 2010 as the prices of electric vehicles fall, causing natural gas to loose some sales shares. We note that these figures only are based on sales of personal vehicles in the Southern California Edison service territory, and do not include commercial fleets. Other results from our model that cannot be included here due to space limitations indicate that there could be a sizeable used vehicle market for personal AFV's, where these vehicles would first be purchased as new vehicles by rental car and commercial vehicle fleets.

One important observation that may be of interest to those concerned with air quality is the cumulative effect of these vehicle purchases. After twelve years of vehicle purchase behavior, what is the overall share of clean fuel vehicles on the road? This information is summarized in Figure 5 for personal vehicles. Simulating personal vehicle purchases using our dynamic model and the BCS yields a prediction of a 25% overall share of AFV's in the year 2010. The shares of methanol, natural gas, and electric are 9, 13, and 6 percent, respectively.

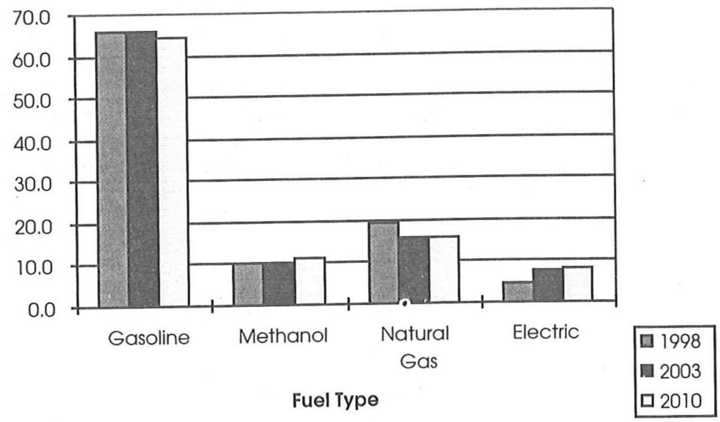

Figure 4 New vehicle sales shares (personal)

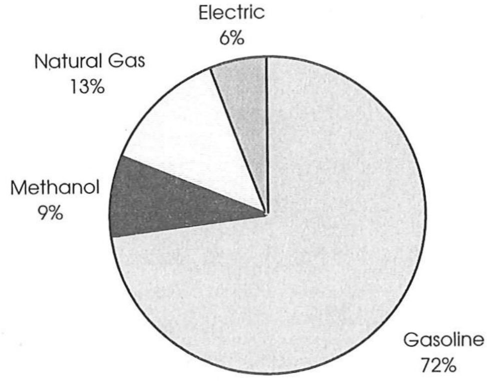

Figure 5 Fuel type shares for all personal vehicles in 2010

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

Results from the current version of our microsimulation forecasting system indicate that market penetration of alternative fuel vehicles could occur in a manner consistent with the CARB mandate targets, under the assumptions stated previously and assuming the values contained in the Base Case Scenario adopted for this research study. One conclusion is that the combination of characteristics associated with natural gas vehicles could be particularly competitive in future vehicle markets. However, the results described here are preliminary, representing the first attempt to integrate into one comprehensive system the models and data from our ongoing research program.

The next stage of our program involves numerous improvements and enhancements to the current system. Wave 2 data from the panel study will allow us to perform important and useful validation checks on our results, as well as supporting the development of an updated set of models. This will include (but is not limited to): vehicle choice models with an expanded set of vehicle attributes, more detailed behavioral models on vehicle utilization, more accurate transaction models, and increased integration of all model components. The importance of hybrid electric vehicles will be assessed. More complete integration of the commercial fleet and residential demand models, including used vehicle price equilibration, will also be incorporated. This feature of our model will be particularly important, since our preliminary results indicate that an important component of AFV penetration into the personal vehicle market could occur as used vehicle sales from rental car and commercial vehicle fleets.

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APPENDIX BASE CASE SCENARIO

Table A1 Natural gas vehicle assumptions in base case scenario

Class	Size	Year	Price	MPG	Acceleration	Top Speed	Relative Emissions	Range	Operating Cost
Car	Subcompact	1998	14902	30	4.0	106	0.09	180	3.60
Car	Subcompact	2005	15858	32	3.7	106	0.09	180	3.70
Car	Compact	1998	19580	25	4.0	110	0.09	180	4.34
Car	Compact	2005	20518	26	3.7	110	0.09	180	4.46
Car	Intermediate	1998	21710	24	3.7	105	0.09	180	4.61
Car	Intermediate	2005	22601	24	3.5	105	0.09	180	4.90
Car	Large	1998	23140	21	3.7	99	0.31	180	5.12
Car	Large	2005	24335	22	3.5	99	0.31	180	5.34
Pickup	Standard	1998	20516	15	4.9	91	0.31	180	7.10
Pickup	Standard	2005	21918	16	4.6	91	0.31	180	7.49
Van	Compact	1998	23266	21	4.2	96	0.31	180	5.29
Van	Compact	2005	24200	21	3.9	96	0.31	180	5.58
Van	Standard	1998	20898	15	5.2	91	0.31	180	7.17
Van	Standard	2005	22396	16	4.9	91	0.31	180	7.31
Pickup	Standard (Dual Fuel)	1998	21456	14	5.2	91	0.31	160	8.19
Pickup	Standard (Dual Fuel)	2005	22953	15	4.9	91	0.31	160	7.27

Table A2 Electric vehicle assumptions in base case scenario

Class	Size	Year	Price	Miles per KWH	Acceleration	Top Speed	Relative Emissions	Range	Operating Cost*
Car	Mini	1998	27038	5	5.7	65	0.00	80	7.89
Car	Mini	2005	18924	5	5.3	71	0.00	113	7.79
Car	Subcompact	1998	32448	4	5.7	65	0.00	100	8.39
Car	Subcompact	2005	22706	4	5.3	71	0.00	141	8.27
Car	Compact	1998	37853	2	5.7	65	0.00	100	9.87
Car	Compact	2005	26492	3	5.3	71	0.00	132	8.76
Car	Sports	1998	40559	3	4.0	75	0.00	100	8.88
Car	Sports	2005	28384	3	3.7	87	0.00	132	8.76
Pickup	Compact	1998	32948	2	7.5	60	0.00	120	9.87
Pickup	Compact	2005	23063	2	6.3	69	0.00	138	9.73
Van	Compact	1998	48461	2	7.6	64	0.00	120	9.87
Van	Compact	2005	33916	2	6.4	71	0.00	138	9.73

Table A3 Gasoline vehicle assumptions in base case scenario

Class	Size	Year	Price	MPG	Acceleration	Top Speed	Relative Emissions	Range	Operating Cost
Car	Mini	1998	13354	32.64	3.5	112	0.80	400	4.30
Car	Mini	2005	14207	34.09	3.3	112	0.52	400	4.18
Car	Subcompact	1998	12582	29.69	3.7	116	0.80	400	4.73
Car.	Subcompact	2005	13424	30.99	3.5	116	0.52	400	4.59
Car	Compact	1998	17260	24.68	3.5	120	0.80	400	5.69
Car	Compact	2005	18084	25.70	3.3	120	0.52	400	5.54
Car	Intermediate	1998	19390	23.22	3.3	115	0.80	400	6.05
Car	Intermediate	2005	20167	23.39	3.1	115	0.52	400	6.09
Car	Large	1998	21025	20.91	3.2	109	0.80	400	6.72
Car	Large	2005	21884	21.48	3.0	109	0.52	400	6.63
Car	Luxury	1998	37799	19.62	3.0	141	0.80	400	7.16
Car	Luxury	2005	38592	19.67	2.8	141	0.52	400	7.24
Car	Sports	1998	17696	22.67	2.8	131	0.80	400	6.2
Car	Sports	2005	18610	23.23	2.6	131	0.52	400	6.13
Pickup	Compact	1998	13894	21.29	3.7	103	0.80	400	6.6
Pickup	Compact	2005	14679	21.66	3.5	103	0.52	400	6.57
Pickup	Standard	1998	17658	15.08	4.3	101	1.00	400	9.32
Pickup	Standard	2005	18389	15.32	4.0	101	0.86	400	9.29
Van	Compact	1998	20380	19.81	3.9	106	1.00	400	7.09
Van	Compact	2005	21199	20.14	3.6	106	0.86	400	7.07
Van	Standard	1998	18036	14.92	4.6	101	1.00	400	9.42
Van	Standard	2005	18861	15.68	4.3	101	0.86	400	9.08
SUV*	Compact	1998	22157	18.56	3.9	100	1.00	400	7.57
SUV	Compact	2005	23007	19.15	3.6	100	0.86	400	7.44
SUV	Standard	1998	24070	13.82	3.7	104	1.00	400	10.2
SUV	Standard	2005	24909	14.68	3.5	104	0.86	400	9.7
SUV	Mini	1998	14874	26.17	3.9	100	1.00	400	5.37
SUV	Mini	2005	15939	27.88	3.6	100	0.86	400	5.11

"SUV" = "Sport Utility Vehicle.

Table A4 Methanol vehicle assumptions in base case scenario

Class	Size	Year	Price	MPG	Acceleration	Top Speed	Relative Emissions	Range	Operating Cost
Car	Intermediate	1998	19621	25	3.1	115	0.80	267	7.87
Car	Intermediate	2005	20498	25	2.9	115	0.52	269	7.05
Car	Large	1998	21296	22	3.0	109	0.80	261	8.74
Car	Large	2005	22270	23	2.8	109	0.52	268	7.68
Car	Luxury	1998	37853	21	2.9	141	0.80	264	9.31
Car	Luxury	2005	38669	21	2.7	141	0.52	265	8.39
Pickup	Standard	1998	17927	16	4.0	101	1.00	300	12.12
Pickup	Standard	2005	18775	16	3.7	101	0.86	300	10.76
Van	Standard	1998	18305	16	4.3	101	1.00	300	12.25
Van	Standard	2005	19247	17	4.0	101	0.86	300	10.52