1. OBJECTIVES, MOTIVATION, AND INNOVATION

Transportation is a major activity that contributes to crude oil consumption and greenhouse gas (GHG) emissions. Within the transportation sector, on-road vehicular travel accounts for a substantial portion of GHG emissions. In the category of on-road vehicular travel-based GHG emissions, passenger cars and light duty trucks (SUVs, pickup trucks, vans and minivans) are the largest sources, accounting for nearly two-thirds of the emissions attributable to vehicular travel in the United States [1]. Also, there is a substantial vehicle mix by body type and make/model on roadways that contribute differentially to GHG emissions. A related dimension is the fuel type of the vehicles on the road. Nearly all vehicles in use today are powered by fossil fuel from crude oil. However, over the next 15 to 20 years, and driven by fossil fuel independence and global climate change considerations, energy fuel composition and power sources are likely to change and the number of vehicle fuel options for consumers is expected to increase significantly. Conventional gasoline will likely be blended with plant-derived ethanol or possibly substituted with high-ethanol-content blends such as E85 (85% ethanol); petroleum diesel may also be blended with or completely replaced by biodiesel; and with improvements in technology rapidly being introduced, electric powered vehicles are expected to play a larger role. Another important dimension relevant to GHG emissions within any given vehicle body type and fuel type is the age (vintage) of the vehicle, with older vehicles contributing more to GHG emissions relative to newer, more fuel-efficient, vehicles.

In the above emerging contexts of climate change and energy considerations, as well as in the traditional context of traffic congestion considerations, planning agencies at national, state, and regional level are exploring policy actions aimed at (1) changing the household and
commercial vehicle fleet mix toward “greener” cars and trucks, (2) lowering polluting fuels, and (3) decreasing the vehicle miles travelled. As expected, analytic methods to examine policies in this area are rapidly advancing. However, there is no single tool to assess the effectiveness of the range of policies that planning agencies would want to evaluate. This is primarily because of limited data available to analyze vehicle acquisition choices and the potential penetration of new vehicle and fuel types. Latest vehicle and fuel technology innovations are unfolding rapidly and any model developed using revealed choice data (cross-sectional or panel) in such a changing vehicle market would not be sensitive to innovations because the new vehicle and fuel types were not part of the household’s choice set when they purchased the vehicle. Also, most of the earlier vehicle type choice studies have focused on the choice process for a single vehicle in a household (such as the vehicle type of the most recently purchased vehicle, or on the most used vehicle), with the characterization of vehicle type based on a narrow definition of aggregate body type (such as a car or an SUV). Such modeling approaches are inadequate for analyzing the vehicle fleet choice process in multiple vehicle households. Lastly, earlier vehicle transaction studies impose restrictive assumptions on the number of transactions allowed each year (for example, allowing only one transaction each year i.e., the household can either replace one vehicle or add a vehicle but not both in the same year). However, fleet evolution decisions usually include multiple transactions, including decisions regarding replacing existing vehicles, when and how to dispose vehicles, and if and when to add vehicles.

In the current study, we refine and update the vehicle fleet simulator recently developed in [2] to address the many considerations identified above. More importantly, we formulate and develop a microsimulation platform to apply the modeling system to simulate the effects of a multitude of policy actions, and analyze the predicted vehicle fleet composition and usage results through sensitivity tests. That is, we forecast the vehicle composition and usage for future years as well the associated fuel consumption and GHG emissions under several alternative technology and policy scenarios.

2. METHODOLOGY

2.1. Overview of the Vehicle Fleet Simulator

All the models in the vehicle fleet simulator developed in [2] are estimated using a unique dataset that includes comprehensive information on vehicle ownership and usage decisions of households, including current fleet composition, potential future fleet composition, and vehicle evolution plans. The vehicle fleet simulator incorporates innovative methodological approaches to address the problem of multiple vehicle holdings and use, as well as to deal with the gamut of vehicle evolution decisions, all in a comprehensive and implementable forecasting framework. Specifically, the simulator encompasses state-of-the-art household vehicle type choice, usage, and evolution models estimated using a unique 2008-2009 vehicle survey data set collected from 6577 households in the State of California by Resource Systems Group, Inc. (RSG) for the California Energy Commission (CEC). The survey has three components - (1) a revealed choice (RC) component, which collected information about current vehicle holdings and usage, (2) a stated intentions (SI) component, which collected information on replacement plans of existing vehicles and vehicle addition plans, and (3) a stated preference (SP) component, which collected information about vehicle purchase decisions under hypothetical scenarios.
The vehicle fleet simulator consists of two principal components- (1) The vehicle selection module, and (2) The vehicle evolution module. Each vehicle type alternative in the vehicle selection module is defined as a combination of six vehicle body types (compact car, car, small cross utility vehicle, sport utility vehicle or SUV, van, and pick-up truck), seven fuel types (gasoline, flex fuel, plug-in hybrid, compressed natural gas (or CNG), diesel, hybrid electric, and fully electric), and five age categories (new, 1-2 years, 3-7 years, 8-12 years, and more than 12 years old). Thus, there are a total of 211 vehicle type alternatives including the alternative of no-vehicle. The model system accommodates multiple vehicle ownership and usage dimensions by assuming that vehicle fleet and usage decisions are determined through a series of unobserved (to the analyst) repeated discrete-continuous choice occasions. This framework mimics the dynamics in the vehicle acquiring process by accommodating the impacts of the types of vehicles already owned on the type of vehicle that may be purchased in a subsequent purchase decision. The number of choice occasions in such a “vertical” choice behavior is linked to the number of adults in the household. In particular, since the number of vehicles is almost never greater than the number of adults in the household plus two in the data, the number of choice occasions is set to be equal to the number of adults plus two. At each choice occasion, the household may choose not to purchase a vehicle or to acquire a vehicle of a certain type. However, the choice of vehicle ownership, vehicle type and vehicle utilization are likely to be multiple dimensions of a single choice bundle at each choice occasion. This joint nature of decisions is recognized at each choice occasion by using a copula-based joint discrete-continuous framework. Also, SP and SI choice behavior is pinned to revealed choice behavior by adopting a combined revealed preference-stated intention-stated preference estimation technique of including a scale parameter differential between the RC and the SP and SI processes. In the framework, the decision of the number of vehicles owned by the household is endogenously, even if implicitly, determined as the sum of those choice occasions when the household selects a certain vehicle type. Overall, the vehicle selection module jointly models all base year vehicle fleet characteristics in a unifying framework.

In the vehicle evolution module, the number of choice occasions for evolving the vehicle fleet each year is set to the current vehicle fleet plus one (this assumes that households do not add more than one vehicle to their current fleet, after considering replacements; however, the model structure easily handles any number of additional vehicles by increasing the number of choice occasions to number of vehicles plus “x”, where “x” is appropriately chosen depending upon the empirical context). For the choice occasions corresponding to an existing vehicle, the household has three options: (1) Keep the vehicle, (2) Dispose the vehicle, and (3) Replace the vehicle (and vehicle type and usage of replacement vehicle). For the choice occasion corresponding to the last choice occasion, the alternatives are “not to add a vehicle” or “to add a vehicle” along with vehicle type and usage of the added vehicle. All the models in the evolution module are binary logit models that consider dependency between transaction decisions by including the number of years since an earlier transaction decision as an explanatory variable in the utility specification. The vehicle type and usage of all the replacement /added vehicles are determined using the vehicle type choice model in the vehicle selection module. The vehicle type choice model includes existing vehicle fleet characteristics and the replaced vehicle characteristics as explanatory variables in the utility specification of vehicle type alternatives. This captures dependencies between future vehicle type choices (during evolution) and vehicles already owned and the vehicle getting replaced.
2.2. Forecasting Process

2.2.1 Vehicle Fleet Prediction

We use the entire estimation sample of 6577 households to undertake the forecasting simulations, because these households are sampled to be representative of the population in the State of California. For the base year, the synthetic choice occasions for each household are constructed based on the number of adults in the household. Then, we apply the vehicle selection module to determine the vehicle type (body type, vintage and fuel type of the vehicle) and the associated annual mileage at each of the synthetic choice occasions, updating the vehicle fleet characteristics after each synthetic choice occasion. This process generates the vehicle fleet characteristics of each household in the representative sample for the base year. Next, for each vehicle in the base year, we determine whether the household decides to keep, scrap, or replace the vehicle starting with the oldest vehicle in the vehicle fleet. If there is a scrap decision, the corresponding vehicle is removed from the fleet and the existing vehicle fleet characteristics are updated. Similarly, if there is/are replacement decision(s), then the corresponding vehicle(s) from the vehicle fleet are removed and the vehicle selection module is invoked to determine the characteristics of the new vehicle(s) that replaces(replace) the existing vehicle(s). After determining the transaction decisions of the existing vehicles, the household decision to purchase a new vehicle is simulated. If there is an “add vehicle” decision, then the vehicle selection module is invoked to determine the characteristics of the new vehicle. This evolution procedure is continued year-by-year until the forecast year is reached. During this process, demographic variables are also appropriately evolved. For the analysis of the policy scenarios, the random seeds used in the microsimulation process for each household and for each choice decision occasion over the course of the forecasting period are held fixed at the base case values to ensure that any changes in the vehicle fleet characteristics and associated mileages are attributable to the policy under consideration.

2.2.2 Fuel Consumption and Greenhouse Gas Emissions Calculations

Our simulator predicts annual vehicle usage along with the vehicle type for each vehicle in a household. This enables the estimation of the total annual fuel consumption by dividing the annual mileage with a fuel economy (i.e., mileage in miles per gallon) estimate based on the vehicle type. The average fuel economy value across all makes/models within each vehicle type (as defined by body type, vintage type, and fuel type) is used for the economy estimate for that vehicle type. For hybrid-electric vehicles and plug-in hybrids, we assume that the liquid fuel (which produces GHG emissions) used in the vehicles is gasoline (and not any other fuel such as diesel, flex fuel). For example, if the economy value of a hybrid-electric vehicle is estimated to be 90 miles per gallon, under the assumption we made, it would essentially mean that the vehicle provides a mileage of 90 miles per gallon of gasoline. The fuel economy value estimates of the compressed natural gas (CNG) and fully electric vehicles represent the miles per gallon of gasoline equivalent (MPGe) values. For CNG vehicles, a Gasoline Gallon Equivalent (GGE) factor of 0.51 cubic feet (at 3600 psi, which is the pressure in most CNG cylinders) is used to convert the gallons of gasoline to equivalent volume of CNG with the same energy content. All the fully electric vehicles emit zero GHG emissions and thus are not considered in the GHG
emissions calculation\(^1\). After this step, we obtain the total fuel consumption by gasoline, diesel, flex fuel, and CNG (since the liquid fuel in hybrid-electric and plug-in electric vehicles is assumed to be gasoline, they do not appear separately in the list of fuel types here). Then, the associated CO\(_2\) emissions are estimated using the following equation that EPA uses for all its emissions inventory calculations:

\[
\text{CO}_2 \text{ Emissions/Gallon} = \text{Carbon Content of Fuel} \times \left(\frac{\text{Molecular Weight of CO}_2}{\text{Molecular Weight of Carbon}}\right) \times \text{Oxidation Factor}
\]

\[
= \text{Carbon Content of Fuel} \times \left(\frac{44}{12}\right) \times 0.99
\]

The oxidation factor accounts for the fact that some percentage of carbon remains un-oxidized. EPA suggests using an oxidation factor of 0.99. Also, EPA uses 2,421 and 2,778 grams as the carbon content in gasoline and diesel vehicles [3]. We assume that all the flex fuel vehicles use E85 blend which contains 85% ethanol and 15% gasoline. So, the carbon content of flex fuel is obtained as 2,421*0.15 = 363.15. The CO\(_2\) emissions from CNG vehicles are computed using a carbon content value of 490 grams of carbon per cubic meter of CNG. This value is obtained from Bio-energy Feedstock Information Network (BFIN) website [4]. All the non-CO\(_2\) GHG emissions including \(N_2O\), \(CH_4\), and \(HFC\) (hydrofluorocarbons) usually constitute 5% of total GHG emissions, so the total CO\(_2\) emissions is multiplied by a factor of \(\frac{100}{95}\) to obtain the total GHG emissions [3].

3. POLICIES CONSIDERED AND EXPECTED MAJOR RESULTS

State agencies across the U.S. are currently implementing several GHG emissions control policies/strategies. These include HOV lane exemption for fuel efficient vehicles, parking incentives (such as allowing an individual to park an Alternate Fuel Vehicle (AFV) in areas designated for carpool operators), free parking on city streets for qualified AFVs and Hybrid Electric Vehicles (HEVs), reduced rental surcharges for electric vehicles, real property tax exemptions for electric vehicle charging systems, tax credits for costs of installing electric charging stations, alternate fuel equipment tax credit, rebate on HEV/AFV purchases, vehicle registration fee reduction/exemption, and reduced/exempted alternate vehicle fuel taxes. A detailed list of policies that are currently implemented in different states of the U.S. is available at: http://www.ncsl.org/default.aspx?TabId=19324. In addition to the typical socio-demographic variables, the vehicle fleet simulator being developed in this study is sensitive to many of the policies just identified, making it an effective tool for comprehensive policy analysis.

The scenarios that will be evaluated in the current paper using the proposed vehicle fleet simulator may be grouped into three broad categories- (1) Incentive based policies, (2) Future market conditions, and (3) Technological innovation based scenarios. The incentive-based policies for non-gasoline (CNG, hybrid-electric, plug-in hybrid, and fully electric) vehicle use will include (a) HOV lane access, (b) Free parking in certain designated spots, (c) $1,000 annual

\(^1\) In the current study, we consider only the tailpipe emissions that occur due to vehicle usage but not life-cycle emissions which include production and distribution emissions associated with the fuel.
income tax credit, (d) 50% reduced tolls, and (e) $1,000 reduced vehicle price. Future market conditions will include changes in the vehicle purchase price, maintenance cost, fuel cost, and fuel availability. Lastly, technological innovations will include the development of (a) powerful vehicles that have lower acceleration times, (b) AFV/EV vehicles with increased driving range, and (c) vehicles with better fuel economy (miles per gallon). Specific selected combination scenarios will also be considered in our analysis. The impact of the policies on the total number of vehicles owned, consumption levels of different fuels, and the associated GHG emissions in the next 5, 10, 15, and 20 years will be estimated.

4. IMPLICATIONS FOR THE SCIENCE AND PRACTICE OF TRAVEL MODELING

This study contributes in important methodological ways to the science of travel modeling. Specifically, it develops a methodology to model the entire household fleet of households by vehicle type and usage. This is a substantial improvement over earlier studies that have focused on vehicle type modeling for a single vehicle in the household and used rather aggregate characterizations of vehicle body type (such as cars and non-cars). Another important contribution of the proposed research is that it uses a unique data set obtained from the California Energy Commission (CEC) that enables the modeling of purchase decisions of alternative fuel and electric vehicle types that are only recently beginning to “hit” the market. This is because the CEC data collects prospective stated intentions data about purchase of vehicles in the near future as well as stated preference data on the choice of a vehicle type from carefully designed experimental scenarios. By using all the information from the CEC data, a microsimulation methodology to “evolve” vehicles over time is proposed, which is sensitive to non-gasoline vehicle incentive-based policies, future market conditions, and technological innovation-based scenarios. The research also contributes to the practice of travel modeling by applying the microsimulation platform to examine the effects of a suite of GHG control policies. The results from this study will contribute to identifying effective strategies at the regional, state, and national levels to increase the penetration of alternative-fuel vehicles and fuel-efficient vehicles, reduce energy consumption, and reduce greenhouse gas emissions.

REFERENCES


