An Agent-Based Model of Energy Demand and Emissions from Plug-in Hybrid Electric Vehicle Use

by

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Abstract

An agent-based model, the Driver Vehicle Use Decision (DVUD) model, was developed that uses simple assumptions about travel demand and statistical information on travel by U.S. drivers. From these, and data on the greenhouse gas (GHG) emissions from the fuel supply network and from electric utilities, the electricity and fuel demand and the resulting GHG emissions are estimated.

This model represents a population of drivers as agents, some of whom drive plug-in hybrid electric vehicles (PHEVs). Driver agents make decisions about how frequently to drive trips and when to recharge their PHEV batteries. In deciding whether to take trips, driver agents consider their schedule and travel cost. They also consider cost, location and planned length of time they will stay at a location when deciding whether to recharge their PHEV batteries. This enables the agents to respond to changes in electricity rates and gasoline prices and to constraints on when (time of day) and where (home or both home and work) they can recharge PHEV batteries.

For a fleet penetration of 50% by PHEVs in Michigan, with a total fleet of 7.3 million vehicles, gasoline consumption is projected to decrease from 11.4 million gallons per day to 7.4 million gallons per day. Total fuel-cycle greenhouse gas emissions from the fleet are projected to decrease from 128,000 metric tons CO_2 eq/day to 95,000 metric tons CO_2 eq/day. Peak electricity demand for PHEV charging is projected to reach about 1400 MW. Most PHEV charging is projected to occur overnight, with the peak in charging demand occurring soon after most drivers get home in the evening.

Model results show that PHEV drivers are less sensitive to changes in gasoline prices than drivers of less fuel-efficient conventional vehicles. Response to changes in electricity prices is more complex, with drivers showing little or no response at low electricity rates, but not charging at all at very high electricity rates, depending on the price of gasoline and the efficiency of their vehicle.

Under interruptible electricity service, in which the electric utility shuts off power to PHEV chargers during peak demand hours, nearly all PHEV owners were able to fully charge their vehicles overnight, and there was very little impact on PHEV operating cost, indicating that this may be a feasible approach to managing increased electric demand for PHEV charging.

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Table of Contents

List of Tables

List of Figures

CHAPTER 1

Introduction and background

1.1 Rationale and description of research

Plug-in Hybrid Electric Vehicles (PHEVs) use both an internal combustion engine (ICE) and an electric motor powered by electricity generated on-board or supplied from the grid. PHEVs are more energy-efficient and potentially emit less pollution and greenhouse gases (GHG) than comparable conventional vehicles (EPRI, 2007, 2007a; Stephan and Sullivan, 2008; Bandivadekar et al, 2008). In addition to efficiency, another important factor that influences the overall environmental performance of these vehicles is how they are used by drivers, especially when compared to their conventional counterparts. Toward that end, we model a population of drivers, some of whom drive PHEVs, and investigate how energy demand and resulting emissions change in response to fuel price, electricity rates, electricity availability and driver transportation needs.

The environmental performance of advanced vehicles is dependent on the behavior of both the machine and the driver. For the machine, energy use and emissions attributable to PHEVs can be readily calculated using engineering modeling methods. On the other hand, modeling driver behavior and choices is less straightforward. One approach is to rely on detailed measurements of driving behavior using a fleet of instrumented vehicles. While a few such data sets are available (Gonder et al, 2007, Patil et al, 2009), they are for small populations over brief time intervals and are not sufficient to relate trip patterns and energy demand to conditions that influence driver decisions on when to travel and when to charge their batteries. Without trip-level information on driving and hourly charging demand, assumptions must be made about the fraction of distance vehicles are driven under fuel power vs. electric power and when PHEV drivers are likely to recharge their vehicle batteries. In the absence of adequate detailed data, an alternative approach must be developed for estimating the environmental performance of PHEVs.

Agent-based models (ABMs) are well suited for analyzing the behavior of systems with many decision-makers responding individually (Gilbert, 2008; North and Macal, 2007). In ABMs, agents (e.g., drivers) interact with each other and with their environment, and they take actions based on decision rules and information available to each agent. ABMs can be used to describe systems of distinct, heterogeneous agents, each exhibiting unique behavior. ABMs are also useful in studying formation of patterns in the collective behavior of a population of agents and in determining the sensitivity of outcomes to model input parameters.

Because of the bottom-up approach of ABMs in describing collective agent behavior, this method is applied here to model a population of drivers. Use of an ABM enables investigation of how the collective driving and vehicle charging behavior depend on the attributes of individual drivers, as well as how individual drivers are affected by changes in energy prices or constraints on vehicle charging. In this model, agents represent drivers making trips with realistic distributions of arrival time, speed, distance, interval between trips, and number of trips per day. These distributions are related to driver agents' daily routines, travel needs and travel costs. Driver agents have decision rules for the number of trips to drive and whether to charge vehicle batteries when electricity is available, depending on their needs and preferences and on energy prices. This permits estimation of how driving patterns and energy demand change in response to prices of electricity and fuel and the ability to charge at locations such as home or work and at different times-of-day as determined by "smart" metering or interruptible service. The model, called the Driver Vehicle Use Decision model, or DVUD model, tracks the energy used by vehicles, and calculates the vehicle emissions and upstream emissions. For owners of PHEVs, their satisfaction with the vehicle is tracked with their costs and the availability of electricity for charging.

Taking electricity rate structure, fuel prices, energy supply infrastructure, fleet composition, and basic driver daily routines as given, we use the DVUD model to address the following questions:

1. How does electricity demand for charging as a function of time-of-day, daily fuel demand, and resulting emissions change in response to:
    a. fuel price
    b. electricity rate (constant rate)
    c. time-of-use (TOU) electricity rates
    d. "smart" meter or interruptible electricity service
    e. PHEV market penetration
2. How do the above variables affect the energy savings (operating costs) of a PHEV versus a conventional vehicle, and under what conditions might PHEV drivers opt out of TOU or interruptible electricity service?
3. How do energy demand and emissions change when driving patterns change, such as longer average trip distances or a different distribution of arrival times at work?

4. What combinations of energy prices, ability to charge at home and at work, and demand-side management policies such as interruptible electricity service offer the potential to decrease GHG emissions without impacting PHEV drivers' fuel savings?

The DVUD model was developed to be a simple representation of a population of drivers that enables evaluation of the dependence of driving and vehicle charging behavior on individual driver decisions and attributes. The model is not intended to provide quantitative predictions of the future of PHEV use, but to make projections of driver energy use and emissions under different scenarios and to explore the relationships between drivers' decisions and preferences on 1) driving trips, 2) battery charging, and 3) fuel and electricity use and the resulting emissions from vehicles and energy suppliers. From these projections we draw conclusions about potential benefits of PHEV use under different scenarios and the possible effectiveness of incentives such as pricing or demand-side management for realizing these benefits. This thesis documents the DVUD model, the analyses performed and the conclusions reached.

1.2 Review of previous work

1.2.1 Estimates of electricity demand and emissions from PHEVs

Bradley and Frank (2009) reviewed PHEV design studies and estimates of petroleum savings, emissions reductions and electricity demand resulting from PHEV market penetration. For various PHEV designs operated under different conditions, gasoline demand was projected to decrease by 51 – 88%, and carbon dioxide emissions were projected to decrease by 27 – 67%. The wide ranges reflect the dependence of estimated energy and emissions on many factors which vary between the different studies, but the findings indicate the range of possible improvement achievable by replacing conventional vehicles with PHEVs.

The Electric Power Research Institute (EPRI, 2007; EPRI, 2007a) in collaboration with the Natural Resources Defense Council analyzed scenarios for low, medium and high PHEV penetration (20%, 62%, 80% of the fleet) with electricity supplied by electric power plants having low, medium and high carbon-intensities (97, 199, 412 g CO_2 eq/kWh). These carbon intensities are lower than that of the U.S. electrical grid, which in 2007 averaged 587 g CO_2 eq/kWh (EIA, 2008). Assumptions were made about rate of PHEV market penetration, vehicle miles traveled yearly, electricity demand growth, fleet fuel economy improvements, and the time of day PHEVs were charged. Charging of PHEVs was assumed to be primarily at owners residences, but utilities were assumed to influence charging demand through demand response or electricity rate structures to avoid adding additional demand during peak hours. The charging profile assumed is shown in Figure 1.1.

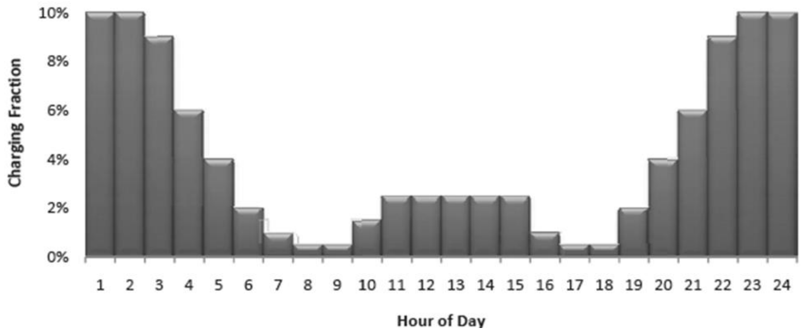

Figure 1.1. PHEV electricity demand as a function of the hour of day assumed in the EPRI (2007) study. Charging fraction is the percent of electricity demand for PHEV charging in a day.

Annual GHG emissions were projected to decrease by 163 to 612 million metric tons annually by the year 2050 under the nine scenarios examined, as shown in Table 1.1. For reference, in 2006, net U.S. GHG emissions were 6,088 million metric tons CO_2 eq, which included 2,445 million metric tons from electricity generation, and 1,995 million metric tons from transportation. Nearly 60% of the 1,995 million metric tons emitted by the transportation sector was from personal vehicle use (EPA, 2010). Emissions reduction predictions for a given PHEV fleet penetration level were found to be sensitive to the carbon intensity of the electric generating sector, as expected.

Table 1.1. Predicted annual GHG emissions reductions from PHEVs in the year 2050

2050 Annual GHG Reduction (million metric tons)		Electric Sector CO_2 Intensity		
		High	Medium	Low
PHEV Fleet Penetration	Low	163	177	193
	Medium	394	468	478
	High	474	517	612

Stephan and Sullivan (2008) estimated and compared energy use by PHEVs, conventional vehicles (CVs) and hybrid-electric vehicles (HEVs), assessed the spare electricity generating capacity available in the U.S. during off-peak hours that could be used for PHEV charging, and estimated potential reductions in GHG upon introduction of the maximum number of PHEVs that could be supported by existing spare capacity. They used published fuel economy values for CVs and HEVs and made estimates of electricity consumption per mile for PHEVs, assuming that PHEVs would be driven in charge-depleting (electric) mode most of the time. Taking an average driving distance of 39 miles per day, they estimated energy used per day by each type of vehicle. From these estimates of capacity and energy requirements, they concluded that capacity exists to charge 74 million PHEVs, or 34% of the U.S. fleet. To estimate GHG emission reductions from substituting PHEVs for this fraction of the fleet, they used estimates of marginal emission rates as a function of power produced for each of the North American Electric Reliability Corporation (NERC) regions. These estimates were based on a study of the variability of power plant emissions with power level by Holland and Mansur (2004). Because GHG emission from generating plants are not proportional to power produced, the emission reduction attributable to PHEVs depends nonlinearly on the number of PHEVs being charged. They estimated the range of emissions for a fleet consisting of 0 to 34% PHEVs and found that emissions per vehicle mile traveled were lower than those of conventional vehicles in all cases. Emissions were lower than those for HEVs in nearly all cases, but were strongly dependent on the PHEV fleet fraction. The nonlinear dependence is due to the change in carbon intensity of the generating plants as plants are dispatched. When greater numbers of PHEVs are being charged, different generating units having different marginal emission rates are dispatched to meet the increasing demand.

Others have made similar estimates of emission reductions achievable from PHEV adoption, but using different assumptions. Samaras and Meisterling (2008) estimated life-cycle GHG emissions from PHEVs, assuming slightly different vehicle characteristics from those used by Stephan and Sullivan (2008), and allocated power plant emissions on the basis of average emissions, not marginal emissions. Samaras and Meisterling assumed that PHEVs were similar to Toyota Prius HEVs in construction and fuel economy (in charge-sustaining mode), but with a larger battery and smaller internal combustion engine. They analyzed cases of PHEVs with charge-depleting ranges of 30, 60 and 90 kilometers and estimated the average distance driven in charge-depleting mode from the distribution of distance driven daily by each driver as reported by the 2001 National Household Travel Survey (2001 NHTS, USFHWA, 2010). From the 2001 NHTS, they determined the fraction of total vehicle-miles traveled per day by vehicles that traveled less than a given distance in a single day. For vehicles traveling less than 30, 60 and 90 km/day, the fraction of vehicle-miles traveled by these vehicles averaged 0.47, 0.68 and 0.76 km, respectively. That is, 47% of the vehicle-miles traveled by the fleet on a single day were traveled by vehicles that traveled 30 km/day or less. Samaras and Meisterling took these fractions to be the fraction of vehicle-miles that could potentially be powered by electricity, that is, the fraction of vehicle-miles traveled electrically in PHEVs. Their estimated values for the fraction of distance driven electrically in PHEVs are shown in Table 1.2 for the three values of charge-depleting range of PHEVs they analyzed.

Table 1.2. Fraction of distance driven electrically estimated for PHEVs of different charge-depleting ranges (Meisterling and Samaras, 2008)

Charge-depleting range, km	30	60	90
fraction of distance driven electrically	0.47	0.68	0.76

Samaras and Meisterling determined that use-phase GHG emissions from PHEVs were 38 to 41% lower than those of comparable conventional vehicles, depending on the charge-depleting range. When taking vehicle production into account, they found that battery production contributed 2 to 5% of the PHEVs life-cycle GHG emissions. For the entire life-cycle, they estimated that PHEV GHG emissions were 32% lower than those of comparable conventional vehicles, only slightly lower than those of comparable HEVs, and nearly independent of charge-depleting range. Their estimates depended strongly on assumed power plant carbon intensity, consistent with results of others. For regions with carbon-intensive electricity generation (950 g CO_2 eq/kWh), GHG emissions per distance traveled for PHEVs can be larger by 10 to 15% than those of HEVs. They also estimated GHG emission reductions for cases using E85 (nominally 85 volume% denatured ethanol and gasoline) made from cellulosic ethanol and predicted significant reductions for all vehicles compared with gasoline use, with HEVs and PHEVs emitting slightly less than conventional vehicles.

Kromer and Heywood (2008) estimated potential reductions in fuel use and GHG emissions with adoption of various drive train technologies for near term and for the year 2030, attempting to take into account technological advances in vehicle technology. They compared energy use and emissions estimated for a conventional vehicle, with a naturally aspirated, spark ignition (NA-SI) engine based on current technology, and other vehicles having performance characteristics estimated for the year 2030 performance, including a NA-SI, turbocharged SI, diesel, HEV, PHEV, fuel cell and all-electric vehicles. The PHEV was modeled using the ADVISOR model (AVL, 2010) to optimize the degree of hybridization, battery size, and fuel economy while meeting the acceleration performance of the other vehicles. Fuel use was estimated from the model using estimates of the fraction of miles driven in charge-depleting (electric) mode. This fraction was estimated for PHEVs having different charge-depleting ranges based on the median values of a survey of several different studies of travel patterns in the United States. Values they determined under combined city/highway drive cycles are listed in Table 1.3.

Table 1.3. Fraction of distance driven electrically estimated for PHEVs of different charge-depleting ranges under combined city/highway drive cycles (Kromer and Heywood, 2008)

Charge-depleting range, mi	10	30	60
fraction of distance driven electrically	0.22	0.50	0.70

They found that the conventional NA-SI vehicle with advanced 2030 technology was significantly more fuel-efficient than a current NA-SI vehicle, and that the fuel economies of the HEV and PHEV modeled were higher, as shown in Table 1.4. They found that the life-cycle energy and GHG emissions were lower than those of the current conventional vehicle or projected 2030 conventional vehicle. Emission numbers shown were estimated based on the current carbon emissions of the U.S. electric grid. They found that GHG emissions of PHEVs were sensitive to the assumed carbon-intensity of electricity generation, and this sensitivity was larger for PHEVs having greater charge-depleting ranges.

Table 1.4. Estimated use-phase energy consumption and greenhouse gas emissions of conventional internal-combustion engine (ICE) vehicles of current and projected 2030 performance compared with projected 2030 performance of PHEVs of different charge-depleting ranges (Kromer and Heywood, 2008).

vehicle	2006 ICE	2030 ICE	HEV	PHEV 10	PHEV 30	PHEV 60
Charge-depleting range, mi	0	0	0	10	30	60
use-phase energy, MJ/km	3.35	2.08	1.17	-	1.22	-
use-phase GHG emissions, gCO_2/km	251	157	87	83	85	88

Vyas et al. (2009) examined the distribution of daily driving distances in the 2001 NHTS and estimated the fraction of those miles that could have been traveled under electric power for series and parallel PHEVs. The series PHEV was assumed to use only electricity for its stated electric (or charge-depleting) range, while parallel PHEVs were assumed to operate in “blended“ mode, with power supplied by both the battery and the ICE. A parallel PHEV with a 10 mile charge-depleting range operating in 50% blended mode would deplete its battery in 20 miles, on average, with half the energy coming from the battery. Vyas et al. estimated the maximum fraction of electric-powered vehicle miles traveled by the U.S. fleet, assuming all vehicles were PHEVs. From the fraction, P, of miles traveled on trips of distance less than distance L, the fraction of miles that a PHEV with charge-depleting range, L_{CD}, could travel electrically was estimated to be

$$P(L) = \sum_{L_1}^{L} p(L_i), \quad L \leq L_{CD} \tag{1.1}$$

$$P(L) = \sum_{L_1}^{L_{\mathrm{CD}}} p(L_i) + \sum_{L_{\mathrm{CD}}}^{L_{\max}} p(L_i)\left(\frac{L_{\mathrm{CD}}}{L_i}\right), \quad L > L_{CD} \tag{1.2}$$

where $p(L_i)$ is the number of trips in the i^{th} trip distance bin, i.e. the number of trips of distance between L_{i-1} and L_i.

For series PHEVs charging once per day, this fraction ranged from 22.5% for PHEVs with a 10 mile charge-depleting range to 74.4% for PHEVs with a 60 mile charge-depleting range. For PHEVs with a parallel-configured drivetrain operating in blended (electric/fuel) mode, they assumed that some fuel was consumed during charge-depleting mode. Specifically, they assumed that a parallel-configured PHEV with a given useful battery capacity operating in 50% blended mode would travel twice the distance in charge-depleting mode that a series-configured PHEV with the same useable battery capacity would travel, but it would be powered 50% by electric power. Thus, a parallel, 50% blended PHEV would travel twice as far in charge-depleting mode but use the same electricity over that distance as a series PHEV traveling its charge-depleting rage (with the same useable battery capacity). Their estimates of electric-powered fraction of distance driven in these PHEVs are listed in Table 1.5.

Table 1.5. Fraction of distance driven electrically estimated for series and parallel-blended mode PHEVs of different charge-depleting ranges, charged once per day (Vyas et al., 2009).

Charge-depleting range, mi	10	20	30	40	60
fraction of distance driven electrically, series PHEV	0.225	0.396	0.535	0.620	0.744
fraction of distance driven electrically, parallel-blended PHEV (lower bound)	0.198	0.301	0.372	0.409	0.447

They noted that the actual fraction depends on driving pattern and will be higher if the vehicle is charged more than once per day.

To examine the potential for charging PHEVs a second time during the day, Vyas et al. considered trips in the NHTS database with the longest dwell time for each vehicle between 6:00 am and 6:00 pm. They included only trips by drivers residing in detached, single housing units in a metropolitan statistical area, and excluded trips made by vehicles that made only one trip during the day. Of the remaining vehicles, 36.4% had their longest dwell time at work, 22.6% at home, and 8.5% while shopping. Most of the 36.4% of vehicles at work arrived between 6:00 and 9:00 am, and had a dwell time exceeding 3 hours. Therefore charging these vehicles at the workplace would be feasible and could be completed before noon if charging infrastructure were provided. In most regions, this would not be during the peak electricity demand hours. Of the 22.6% of vehicles at home, only 11.7% arrived home before 9:00am. Since most of these vehicles arrive home after 9:00, charging these vehicles during the day may increase electricity demand during peak load hours.

Vyas et al. noted that accurately estimating petroleum savings due to penetration by PHEVs is complicated by several factors. These include the dependence of fuel consumption rate on speed and aggressiveness of driving, especially for blended PHEVs where the fraction of energy from the battery depends on driving aggressiveness. In addition, Vyas et al. note that the economic advantage of owning a PHEV depends on how well the driver's distribution of trip distances matches the charge-depleting range of the vehicle. Drivers who consistently drive less than the charge-depleting range between recharging do not fully utilize the battery capacity, which represents a significant fraction of the vehicle cost. Drivers who purchase PHEVs may tend to drive trips with a different distance distribution from that of the national driving population. A more thorough analysis would require access to more detailed driving behavior information.

Elgowainy et al (2009, 2009a) used the Powertrain System Analysis Toolkit (PSAT) developed by Argonne National Laboratory (ANL, 2007) to simulate vehicles having different drivetrains including PHEVs of different charge-depleting ranges and using internal combustion engines or fuel cells. They used the GREET model (Greenhouse gases, Regulated Emissions, and Energy use in Transportation), also developed by ANL (ANL, 2009) to analyze the full fuel-cycle energy use and emissions of the vehicles simulated under driving conditions similar to those used by Vyas et al (2009), as described above, including their estimates of the fraction of miles traveled under electric power for series PHEVs. For parallel, blended-mode PHEVs, in which the vehicle could use both electricity and fuel power in charge-depleting mode, they assumed the engine would provide power above a certain threshold. This gave values up to 20% higher for the charge-depleting range, but some fuel was consumed while traveling in charge-depleting mode.

Elgowainy et al. estimated total fuel cycle energy per mile would be reduced from approximately 4,000 Btu/mi for a conventional (internal combustion, spark ignition), gasoline-powered vehicle to between 1,500 and 2,800 Btu/mi for PHEVs with charge-depleting ranges from 10 to 40 miles. For the same PHEVs using cellulosic E85 ethanol, petroleum use was predicted to be between 500 and 1000 Btu/mi. Total fuel-cycle greenhouse gas emissions were predicted to be 200 to 260 g/mi for PHEVs using gasoline or diesel, compared with 370 g/mi for a conventional vehicle on gasoline. For PHEVs using cellulosic E85, GHG emissions were from 100 to 110 g/mi.

In a more recent report, Elgowainy et al. (2010) present results of more refined analysis, using more detailed vehicle models, and accounting explicitly for differences between the efficiency of vehicles in standard fuel economy tests and under more realistic on-road driving and environmental conditions. They also used more sophisticated modeling of electric utilities for some regions of the U.S. Using the PSAT model, they found that most vehicles show lower fuel economy under realistic driving and environmental conditions than under the standard conditions used for EPA fuel economy testing. The efficiency of PHEVs was found to be up to 30% lower under realistic conditions than under standard test conditions. This is due mainly to three limitations of the standard test conditions:

Standard test drive cycles are less aggressive than real-world driving

Standard tests are conducted under controlled (75°F) temperature

No accessories, such as air-conditioning are used in the standard tests.

These factors appear to be more important for high-efficiency vehicles, where accessory loads represent a larger fraction of the energy consumed by the vehicle.

1.2.2 Economic benefits from PHEVs

The potential energy savings and emissions reductions obtainable from PHEVs will depend on the fraction of the fleet they represent. Whether sufficient numbers of drivers will purchase PHEVs for this fraction to be significant depends largely on how economical they will be to own. This depends on whether energy savings are sufficient for an owner to recoup the additional amount spent on a PHEV over the price of a comparable conventional vehicle. Mass-produced PHEVs are just now being released by major automakers. The Chinese battery and auto manufacturer BYD has recently introduced the F3DM PHEV in China, and it is priced at 150,000 Yuan, or approximately $22,000 U.S. (Blanco, 2010). Toyota, General Motors, and other automakers are planning to release PHEVs in

North America in late 2010 to 2012. The Chevrolet Volt, designed with a 40 mile charge-depleting range, may be offered initially for a price near $40,000 (Blanco, 2010a) although General Motors has not yet announced a suggested retail price. Section 205 of the Energy Improvement and Extension Act of 2008 (EIEA, 2008) provides federal tax credit for PHEVs for the first 250,000 vehicles sold. The credit is $2,500 plus $417 for each kWh of battery pack capacity in excess of 4 kWh to $7,500 for 12 kWh or more in passenger cars.

The Committee on Assessment of Resource Needs for Fuel Cell and Hydrogen Technologies estimated that in 2010, PHEVs may cost as much as $18,000 more than an equivalent conventional vehicle (NRC, 2010). A large part of this cost increment depends on the size of the battery, which also determines the charge-depleting range of the vehicle. The estimated cost for a modestly sized battery pack, e.g., one sufficient to provide a PHEV comparable to a Toyota Prius HEV a charge-depleting range of 10 miles, is estimated to cost about $3,300. A larger battery pack sufficient to give a PHEV similar to a Chevrolet Volt a 40 mile charge-depleting range is estimated to cost about $14,000 (NRC, 2010). Battery costs are anticipated to come down as technology matures and production volume increases. The U. S. Advanced Battery Consortium has published goals for PHEV batteries that include the price targets listed in Table 1.6 for production volumes of 100,000 units per year (USABC, 2010).

Table 1.6. U. S. Advanced Battery Consortium goals for PHEV batteries (USABC, 2010)

Reference Equivalent Electric Range, miles	10	40
Available Energy for Charge Depleting Mode, kWh	3.4	11.6
price	$1,700	$3,400

Nemry et al, 2009 have reviewed purchase price projections for PHEVs, and these are listed in Table 1.7 (taken from Nemry et al., table 11). These estimates indicate that purchasing a PHEV will require a significant investment beyond that required for a conventional vehicle or HEV. PHEV owners will need to realize significant energy savings to recoup this additional up-front cost.

Table 1.7. Purchase prices or production costs, and price/cost increments for PHEVs as projected by several researchers (Nemry et al., 2009)

	ICE	HEV	PHEV 10	PHEV 20	PHEV 30	PHEV 40	PHEV 50	PHEV 60	source
Near term									
Price, $	23,392	28,773	34,180	38,935	42,618	45,655	48,162	50,184	Simpson (2006)
Price incr., $			10,788	15,533	19,226	22,263	24,770	26,792	
Prod. cost, $									Kromer & Heywood (2008)
cost incr., $		1,900	3,000		4,300			6,100	
Price, $	22,500	26,520		29,740					Plotkin (2002), Lipman & Delucchi (2006),
Price incr., $		4,020		7,240					
Price, $	18,984	23,042		24,966				29,523	EPRI (2001)
Price incr., $		4,058		5.982				10,539	
Mid-term									
Price, $	18,000								EPRI (2001)
Price incr., $		1,500-4,000		4,000-6,000					
Long-term									
Price, $	23,392								Simpson (2006)
Price incr., $		3,266		8,436				13,289	

Shiau et al. (2009) estimated energy consumption, greenhouse gas emissions, and the operating and total costs of PHEVs having different charge-depleting ranges. They used PSAT (ANL, 2007) to model the performance of each type PHEVs and iterated on battery and motor size to get constant performance and desired charge-depleting range, then calculated the resulting vehicle efficiencies in charge-sustaining and charge-depleting modes. Vehicles were assumed to have the same type and size of internal combustion engine as a 2004 Toyota Prius. They assumed that batteries had a specific energy density of 0.1 kWh/kg, including battery packaging, and cost $1000/kWh (total capacity) and could discharge to a 50% state of charge. Vehicle cost and weight (including additional structural weight to support a larger battery) were determined from the simulations. This allowed them to examine the trade-off between battery size and weight and the resulting impacts on efficiency, emissions and costs.

Shiau et al. found that increasing battery capacity decreased average GHG emissions, and operating costs, but also decreased average energy efficiency of the vehicle and increased the total lifetime cost. They found that PHEVs with shorter charge-depleting ranges (7 to 20 miles) had similar total cost per mile to a comparable hybrid and to a comparable conventional vehicle, but total costs depended on the distance driven between charges. They concluded that for drivers able to charge frequently (only a few miles between charges), an HEV or PHEV with a short charge-depleting range will be most economical, while for drivers who drive farther between charges a PHEV would emit less GHGs, but would not be as economical as an HEV. They noted that decreasing the cost of usable battery capacity or a carbon tax combined with low-carbon electricity would make PHEVs more cost competitive for a wide range of driving distance between charges. They noted that these conclusions are less certain if the distance traveled between charges is variable or if drivers do not consistently charge once per day. They suggested further work to examine driving behavior and effect of availability of charging infrastructure to enable multiple charges per day.

The costs per mile of PHEVs were compared with costs for HEVs and conventional vehicles by Scott et al. (2007). Assuming a real discount rate of 9%, vehicle ownership of 9 years, and not considering battery replacement costs or differences in resale value, Scott et al. compared the life-cycle costs of a PHEV that consumed 0.26 kWh per mile in charge-depleting mode to a conventional Honda Civic with a combined city-highway fuel economy of 35 miles per gallon, with a conventional vehicle with a CAFE standard combined city-highway fuel economy of 27.5 miles per gallon, and with a Toyota Prius HEV with a combined city-highway fuel economy of 56 miles per gallon. They determined the combinations of electricity rates and fuel prices that made the PHEV cost effective in comparison with each of the other three vehicles and calculated the maximum cost premium for the PHEV at which the life-cycle costs of the PHEV were the same as the comparison vehicle. This maximum cost premium is the maximum that a rational purchaser would be willing to pay for a PHEV over the price of the competing vehicle. That is, the maximum cost premium is the present value of the life-cycle savings in fuel minus the life-cycle costs of electricity for powering the PHEV vs. the comparison vehicle. For an electricity rate of $0.12 per kWh and a gasoline price of $2.50 per gallon, the maximum price premium was found to be $2000 when compared with the Honda Civic, $3000 when compared with the 25.7 mpg conventional vehicle, and zero when compared with the Toyota Prius. At lower electricity rates or at higher gasoline prices, higher premiums were calculated, as cost savings of electric-powered travel are higher. Even at electricity rates of $0.083/kWh and a gas price of $3.50/gal, the maximum price premium for the PHEV over the HEV was less than $3,000.

Lemoine et al. (2008) compared the annual cost savings of operating a PHEV with those of an HEV and a conventional vehicle assuming a 16% discount rate over a vehicle lifetime of 12 years. The PHEV was assumed to have a 20 mile charge-depleting range, a gasoline fuel economy of 52.7 miles per gallon and an all-electric efficiency of 4.01 miles per kWh. The HEV was assumed to have a fuel economy of 49.4 miles per gallon, and the conventional vehicle was assumed to have a fuel economy of 37.7 miles per gallon. They assumed vehicles were driven 11,000 miles per year, with the PHEV driving 6,000 of those miles electrically. They compared annual fuel savings and the present value of fuel savings for 12 years for various combinations of electricity rates and gasoline prices. Results were comparable to those of Scott et al (2007). A spreadsheet with their calculations can be accessed on-line at the University of California at Berkeley Transportation Sustainability Research Center website (TSRC, 2009). Lemoine et al. also estimated costs per mile for operating PHEVs and compared these costs with HEV and conventional vehicle operating costs for a range of electricity and fuel prices. They determined the price of gas at which the cost per mile for gasoline-powered PHEV travel was the same as electric-powered travel. Under their assumptions, gasoline at $2.50 per gallon would be equivalent to electricity at $0.190 per kWh, making electric-powered travel cheaper than gasoline-powered travel at electric rates lower than this.

Lemoine et al. made similar estimates for the residential time-of-use rates charged in May 2006 by the Pacific Gas and Electric Company. They found that for a consumer with a high electricity demand, charging a vehicle during peak hours when the electricity rate is up to $0.543 per kWh, the equivalent cost for gasoline was as high as $6.88 per gallon. Costs were significantly less if the vehicle were charged during the off-peak period. Depending on electricity rates and fuel prices, a PHEV costing more than a few thousand dollars more than a comparable conventional vehicle or more than about one thousand dollars more than a comparable HEV may not be economical. PHEV owners will find it more economical to travel electrically, that is, they should charge their batteries when electricity is available, but if electricity rates are very high and gasoline is very inexpensive, PHEV owners might find it more economical not to charge their vehicle batteries, in which case, they would be better off with a less expensive conventional vehicle or HEV. If PHEV owners pay a higher rate for electricity during peak hours, they may choose to charge their vehicles during off-peak hours, but depending on the price of fuel, it may still be cheaper to operate the vehicle electrically even when paying peak electricity rates.

Stephan and Sullivan (2005) used an agent-based model of a population of drivers to examine market penetration of hybrid electric vehicles and driver behavior in response to fuel and vehicle price changes. Stephan and Sullivan examined the effects of consumer product preferences and sensitivity to fuel prices as well as policies such as carbon taxes and changes in fuel taxes and CAFE standards. They demonstrated that a population of vehicle owners can be modeled as a population of agents, interacting with other agents representing fuel suppliers and automobile manufacturers, and their model showed realistic responses by driver agents to changes in fuel prices and vehicle prices. Vehicle owner agents responded to an increase in fuel price over time scales of 1 to 3 months by decreasing the number of miles they drove. Over longer time scales, some agents responded by trading in their vehicles for more fuel-efficient models.

Sullivan et al. (2009) developed a similar model projecting market penetration of PHEVs to examine the effects of consumer preferences, vehicle prices, and fuel price on driving behavior and vehicle sales. They modeled scenarios with tax rebates to vehicle purchasers, sales tax exemptions, subsidies to vehicle manufacturers, and increased gas tax. The model included agents representing consumers, vehicle providers, energy (fuel and electricity) providers, and government. Consumers were represented as agents having transportation needs and budgets who purchase used or new automobiles according to their needs, budgets and preferences. Vehicle provider agents offered new and used automobiles for sale and would adjust prices for used cars in response to demand. Several vehicle models, including HEVs and PHEVs were included with different prices, performance levels and other attributes. The tax rebates to purchasers considered were in the amounts consistent with the EIEA tax credits for PHEVs (EIEA, 2008), which were taken to be $2,780, $7,100 and $7,500 for PHEVs with charge-depleting ranges of 10, 20 and 40 mi, respectively. The subsidies to vehicle manufacturers considered were taken to be of magnitude to reduce the purchase prices by $1,500, $3,000, and $6,000 for PHEVs with charge-depleting ranges of 10, 20 and 40 mi, respectively. The model tracked automobiles bought and sold by model, automobile prices, vehicle provider profits, vehicle miles driven, fuel and electricity used, and emissions resulting from energy production and use. They found that PHEV fleet penetration of around 18% would reduce gasoline consumption by over 20% and decrease fossil carbon emissions by about the same amount. They projected that by 2020, sales could reach around 4 to 5 percent with fleet penetration reaching a little more than 2%, but that adequate subsidies were critical. Without subsides, fleet penetration was projected to be less than 1% in ten years.

Another market penetration analysis performed by Vyas et al (2009) estimated the maximum PHEV market based on the assumption that drivers purchasing PHEVs will likely be residents of single detached houses with a garage or carport. According to the U.S. from the National Housing Survey (USHUD, 2006) 51.5% of residences in the U.S. were single detached units having a garage or carport in 2005, however, 92.4% of detached single units built during 2000 – 2005 have a garage or carport. As an indicator of the time required for market penetration, they presented a projection of HEV sales based on a logit model fitted to the available HEV sales data. This shows that HEVs could reach their ultimate sales share of around 30% in approximately 25 years. They noted that long times (decades) are typically required for significant market penetration of new vehicle drivetrain technologies.

1.2.3. Personal vehicle travel patterns

In estimating potential energy and emissions reductions and cost savings of PHEVs, many have noted the importance of the distance driven between vehicle battery charging. Better understanding of the distribution of trip distances and distances driven per day would enable better assessment of potential energy consumption, emissions and costs of PHEV use. Information on times of day when PHEV drivers arrive at locations where electricity is available for charging and the distance they have driven since their previous charge is needed to estimate the electricity demand for charging as a function of time of day. This requires travel demand modeling or, with the assumption that PHEV drivers will drive similarly to current drivers of conventional vehicles, statistical analysis of travel survey results.

Traditional travel demand modeling is based on a four-step method (TRB, 2007), consisting of:

1. Trip generation (the number of daily trips is estimated)
2. Trip distribution (trip origins are matched to destinations)
3. Mode choice analysis (the proportion of trips taken via each mode is estimated)
4. Route assignment (the number of trips between origin/destination pairs is estimated by mode)

The four-step method has been used by metropolitan planning organizations for development of regional transportation plans and programs. Models typically deal with transportation at neighborhood or regional spatial scales, and at long time scales, that are relevant for development planning (although congestion patterns are sometimes modeled by time of day). Aggregate statistics on traffic flows by route or planning zone are modeled, not individual trips. These models are too coarse to use for projecting arrival time distributions of PHEV drivers at charging locations.

One alternative to using traditional travel demand modeling is to use data from surveys of driver populations to project how vehicles (including vehicles different from those the surveyed population drives) would be driven under conditions similar to those of the surveyed population. Axsen and Kurani (2010) conducted a survey of drivers in California who had recently purchased a new vehicle which they drove. This included purchasers of any type of light-duty vehicle, in order to select a population of drivers who had recently made decisions regarding a new vehicle purchase. Driving patterns and recharge potential data were collected from respondents who recorded all trips driven and all opportunities for charging a vehicle battery on one day in a travel diary. Survey respondents also participated in a PHEV design exercise designed to identify the next conventional vehicle they expected to purchase and to elicit their preferences for and willingness to pay for a PHEV with various attributes. These PHEV attributes included different values of recharge time, fuel economy in charge-depleting mode and in charge-sustaining mode, and charge-depleting range. Survey respondents then chose their preferred vehicle, either the base PHEV, a PHEV with upgraded attributes, or a conventional vehicle.

From the respondents' travel diaries and assumed vehicle characteristics, Axsen and Kurani calculated fuel and electricity use under four scenarios:

A) No PHEVs: fuel use was estimated based on all drivers driving their anticipated next conventional vehicle,

B) Plug and play: fuel and electricity consumption were estimated based on all drivers driving their chosen PHEV, and drivers were assumed to charge when parked near an outlet,

C) Enhanced workplace access: same as Plug and play, with the additional opportunity to charge when parked at work, and

D) Off-peak only: same as Plug and play, but no vehicle charging between 6:00 am and 8:00 pm, and load perfectly balanced during off-peak hours.

Axsen and Kurani estimated fuel consumption and electricity demand throughout the day in 15-minute increments for the four scenarios. These are shown in Figure 1.2. Axsen and Kurani found that in all scenarios with PHEVs, gasoline consumption was close to half of that with no PHEVs. They attributed the lack of sensitivity of fuel consumption to scenario conditions to the assumption that all PHEVs operated in blended mode and consumed some fuel even for trips shorter than the charge-depleting distance. They noted that the projected demand as a function of time differed significantly from the assumed charging profile assumed in most studies, which is the same or similar to the profile used in the EPRI study (Figure 1.1, above). Charging demand is significant throughout the day, due to heterogeneity in driving and parking behavior and in PHEV design. This suggests that further work in predicting charging profiles from realistic travel patterns may be valuable in assessing charging demand as a function of time of day.

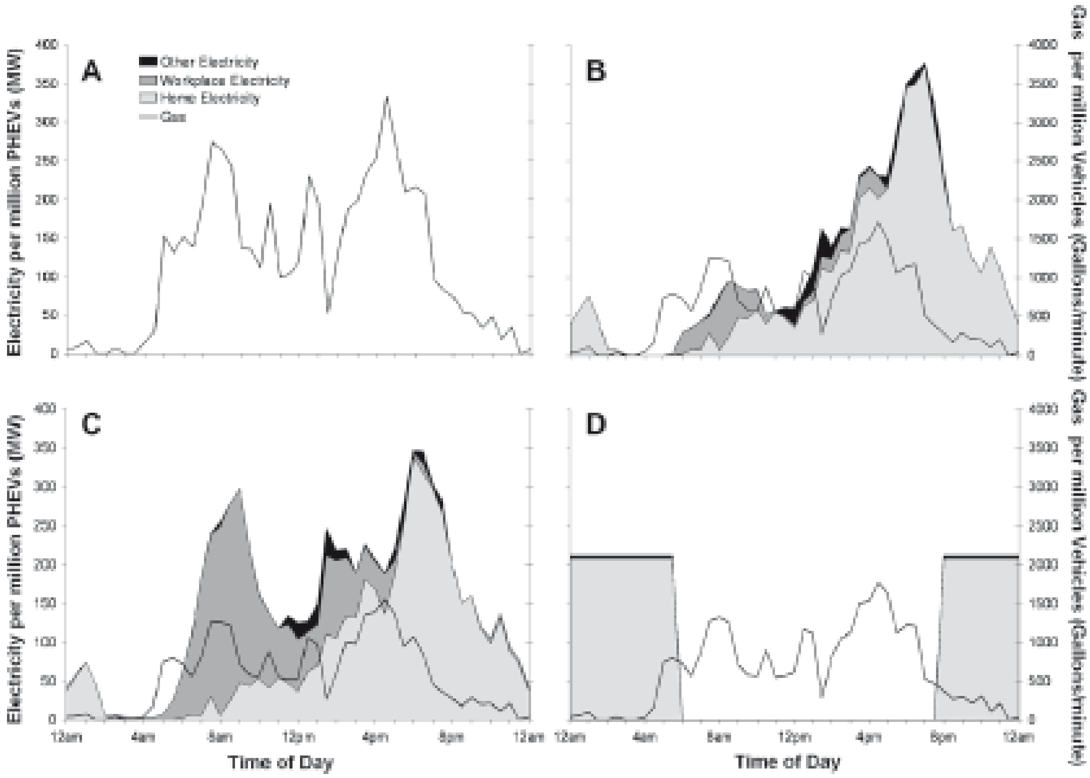

Figure 1.2. PHEV electricity demand and gasoline consumption as a function of time of day estimated by Axsen and Kurani (2010) from travel survey of California drivers likely to purchase a PHEV. A: no PHEVs, B: All PHEVs and charging when parked near an outlet (not at work) C; Same as B plus charging at work. D: Same as B but no charging between 6:00 am and8:00 pm.

Keoleian at al., (2009) used trip data from the 2001 NHTS to estimate how vehicles are driven, assuming a fraction of vehicles are PHEVs. Conventional vehicles were assumed to have characteristics similar to those of the U.S. fleet, and some vehicles were assumed to be PHEVs with given fuel economies and electric efficiency, depending on the class of the vehicle. A simulation was developed in which trips were drawn from the NHTS trip data set, and for each trip, energy use was calculated from average speed and distance, depending vehicle characteristics. PHEV charging demand was predicted as a function of time of day. Power plant emissions were estimated using data available on Michigan power plants and a dispatch model, as described in Section 1.2.4 and using their projections of future electrical generating capacity in Michigan. Keoleian et al. made projections of vehicle-miles traveled, electricity and fuel consumption, and emissions from vehicles, power plants, and upstream fuel production for the personal vehicle fleet in Michigan for years 2010 to 2030 under different PHEV fleet penetration rates.

Kang and Recker (2009) used data from the California Statewide Household Travel Survey (Caltrans, 2002) to assess the potential electricity demand for charging a fleet of PHEV being driven in patterns typical of California drivers. Using data from travel diaries of survey respondents, Kang and Recker constructed trip/activity chains for one day. They then estimated energy use by drivers driving these trips in PHEVs. They made projections of electricity demand for PHEV charging for four scenarios:

1) End-of-day recharging
2) Charging at home, uncontrolled,
3) Charging allowed only between 10:00 pm and noon the next day, and
4) Publicly available charging.

For scenarios 1) and 2), the resulting charging demand as a function of time of day showed a peak at about 6:00 or 7:00 pm. Under controlled charging scenario, the peak charging demand was just after 10:00 pm and was very sharp, with power levels approximate four times that of the peak projected for uncontrolled charging. Scenario 4) showed a peak at 6:00 to 7:00 pm as in the first two scenarios, but also showed a smaller peak near 8:00 to 9:00 am, and somewhat greater demand in the middle of the day.

Kang and Recker also estimated the number of trips that could be completed in charge-depleting mode by PHEVs with charge-depleting ranges of 20 or 40 miles. They noted that the fraction of trips driven electrically increased with publicly available charging. They also analyzed engine status for trips, to estimate the number of cold starts vs. hot starts. If a trip was followed by another trip within 60 minutes, the second trip was considered a hot start; otherwise it was considered a cold start. Emissions from cold starts are higher than from hot starts. Although they did not estimate emissions from vehicles, they noted that a fleet of PHEV can complete the same trips with fewer engine starts and with fewer hot starts than a fleet of conventional vehicles. If PHEVs are charged only at the end of the day (scenario 1), the number of engine starts was seen to increase during the day, as PHEV batteries are depleted. PHEVs with longer charge-depleting ranges reduce the number of engine starts more, since they can complete more trips electrically.

Another alternative to using traditional travel demand modeling is to use a microsimulation of a driver population, such as that used in the Transportation Analysis and Simulation System

(TRANSIMS) model (Hobeika, 2005). TRANSIMS is an integrated suite of travel forecasting models. It consists of a population synthesizer, an activity generator, a route planner, a microsimulator and a feedback controller. The population synthesizer creates synthetic households with the desired demographic characteristics and locates each household in a spatial representation of the zone or region being analyzed. The activity generator generates an activity list for each individual based on household characteristics and survey data on households. The route planner chooses a travel mode and a route for each trip, based on decision criteria, the route network and travel data. The microsimulator simulates travel by each traveler and computes the operating status, including locations, speeds, and acceleration or deceleration of all vehicles, second by second. Depending interaction between vehicles, travel times, household activity decision criteria, capacities of routes, the feedback controller can rerun microsimulations to change travel mode decisions, routes, or travel times to arrive at travel patterns that are consistent with the travel capacities of routes and other criteria. From the resulting microsimulation, vehicle emissions and energy consumption can be estimated from vehicle characteristics and details of travel by each vehicle.

The TRANSIMS model requires a large volume of detailed input data on households, their vehicles, routes, and land use. These data are available for many metropolitan areas, and some metropolitan planning organizations have begun using TRANSIMS; several are members of the model user group. However, the data requirements and level of detail make TRANSIMS difficult to use for statewide or regional simulations or for idealized scenarios designed to examine specific factors. For assessing potential impacts from new vehicle technologies, a simpler approach would be more efficient.

More idealized scenarios of travel and vehicle use have been modeled using agent-based models. Two issues of the journal *Transportation Research Part C* were devoted to the use of agent-based modeling in traffic and transportation modeling and analysis. Most of these models were developed to study congestion and various traffic management approaches (Schleiffer, 2002; Ossowski, 2005). Potential benefits of new information and communication technologies were analyzed. These included scenarios involving novel algorithms for on-ramp metering or traffic signal programming using real-time traffic information, and other scenarios in which drivers could access real-time information or could even share control of vehicles to permit closer vehicle spacing on highways.

Apart from these papers, few applications of agent-based models to analyze driver behavior and vehicle use have been documented, particularly the use of vehicles with alternative drive train technologies. Sullivan and Stephan (2004) used an agent-based model with agents representing drivers and fuel station operators to model the transition to a hydrogen-based transportation system. They were able to model the interaction between drivers of hydrogen powered vehicles and fuel suppliers. Drivers would plan routes based in part on the location of fueling stations that provided hydrogen, and fuel suppliers would decide whether to offer hydrogen (with a significant investment in equipment), depending on the local traffic Driver agents would also choose between a conventional or hydrogen-powered vehicle. Stephan and Sullivan modeled the penetration of hydrogen-powered vehicles into the fleet. They found that the relative cost of hydrogen-powered vehicles vs. conventional vehicles and the density of hydrogen fueling stations were important in determining fleet penetration and whether the numbers of hydrogen-powered vehicles and fueling stations were stable or decayed to zero. Thus the viability of hydrogen-fueled transportation and the supporting infrastructure could be related to decisions of individuals.

1.2.4. PHEV charging and electric utilities

The potential operational and economic impacts on electricity utilities of increasing numbers of PHEVs have been examined. If PHEVs are charged at low-demand hours, the demand can be met by current infrastructure capacity, assuming that generating plants and transmission and distribution systems can be operated at higher duty factors. Operating capital equipment for a greater fraction of the time is generally economically favorable, however higher demand decreases the generating assets available for services such as reserve capacity and frequency regulation, and longer duty cycles may shorten the service life of some equipment. Scott et al. (2005) performed an economic analysis of a large PHEV market penetration, and determined that a utility with low marginal generation costs, high fixed costs, and a large difference between peak and off-peak demand can benefit from market penetration by PHEVs.

Blumsack et al. (2008) investigated capacity constraints to PHEV charging due to local transmission equipment, specifically oil-cooled substation transformers. These transformers are designed to cool off at night when power throughput is low. Charging many PHEVs overnight during the low base load demand period would not allow transformers to cool as much, which may shorten their useful service life. Using a simple heat transfer model and an assumed temperature dependence of the rate of degradation of transformer insulation, they proposed expressions relating transformer operating temperatures to the maximum power throughput that could be allowed without degrading transformer service life. Using demand data for the PJM interconnection (a mid-Atlantic regional transmission organization), they calculated the charging capacity as constrained by the estimated maximum transformer power throughput. This shows that regional or local distribution constraints may require management of demand for charging large numbers of PHEVs or upgrading of distribution equipment.

Power system management with significant numbers of PHEVs charging has been investigated by Galus and Andersson (2008) who developed an agent-based model of a regional integrated energy system supplying heat, natural gas and electricity, including electricity for charging PHEVs. The agents in the model included an energy hub agent, a PHEV manager agent, and individual PHEV agents. The energy hub agent represents a multi-energy carrier system that tracked electricity, gas and heat demand and dispatches energy sources, depending on demand. Demand included a baseline load plus the load for charging PHEVs. A number of generators, including combined heat and power sources, were assumed with known marginal costs. The energy hub agent optimally dispatched energy sources to minimize total energy costs while supplying the load and keeping the total power of the hub within generation capacity. The PHEV manager agent tracked PHEV electricity demand and distributed electricity for charging PHEVs so that PHEV driver utility was maximized, subject to distribution capacity constraints and the maximum allowable state of charge of PHEV batteries. The PHEV manager agent could adjust the electricity price to incentivize PHEV drivers to decrease demand during peak load times. The individual PHEV agents would leave on trips and arrive with a given probability distribution and had a utility function that determined their willingness to pay for electricity. The utility function depends on the PHEV battery state of charge upon arrival, the desired battery state of charge at departure, and the time remaining to departure. At a given electricity price, the total demand for PHEV charging could be calculated from the arrival time distribution, the state of charge of PHEV batteries, and the driver agents' willingness to pay. Simulation runs showed that at low number of PHEVs, demand could be met without adjusting electricity prices. With a large number of PHEVs, the hub agent reallocated heat loads to increase combined heat and power to increase electricity generation, and the PHEV manager agent increased the price of electricity. This reshaped the PHEV charging demand curve and kept demand from exceeding capacity. This shows the potential for managing demand for PHEV charging if PHEV drivers are responsive to electricity rates. It also shows how issues of integrating large numbers of PHEVs with electric utilities can be studied using agent-based models. In the Galus and Andersson model, details of energy flows, consumer demand and utility, and electricity rates could be followed for different power management strategies, pricing schemes and driver willingness to pay. An agent-based model permits linking system behavior to individual consumer behavior.

Potential impacts of PHEV charging on local electricity distribution networks in the Pacific Northwest was examined by Schneider et al. (2008) who performed load flow analyses for two regions, the eastern Pacific Northwest, and the western Pacific Northwest. They used residential baseline load profiles (with no PHEVs) and for each region analyzed power flows for two PHEV load profiles: i) the profile used in the EPRI 2007 study (shown in Figure 1.1, above), or ii) a rapid charge profile with the same energy delivered in the three hours between 5:00 and 8:00 pm. In both regions, they found that the local distribution system was adequate to serve the demand at a PHEV penetration as high as 0.5 PHEVs per household (21.6% of the light-duty fleet in Washington State) when PHEVs were charged according to the EPRI load profile. This penetration is higher than the generating capacity estimated by Kintner-Meyer et al (2007). However, for the rapid charging load profile, local distribution equipment would be overloaded at much lower PHEV market penetration. The hours of high demand in the rapid charging profile assumed coincides with the current peak load hours in the Pacific Northwest region. Schneider et al. recommended that “smart charging”, utilizing demand management, would be necessary to support high PHEV penetration levels due to local distribution constraints.

The emissions from electricity generation for PHEV battery charging depend on the type and efficiency of the generating plants that are dispatched in response to the increase in electric power demand. The Oak Ridge Completive Electrical Dispatch (ORCED) model has been used to assess impacts of PHEV charging demand on the electricity supply and emissions from power plants (Hadley and Tsvetkova, 2008, 2009). In this model, power plants are classified by technology, fuel type, variable cost, and region of the country. Within each region, plants are binned with other similar plants to provide a manageable number of notional plants representing the actual plants in each region. Hadley and Tsvetkova modeled dispatching of these notional plants by assuming that they are dispatched in the order of decreasing load duration, or fraction of the year a plant operates. In addition, hydropower was assumed to be used for peaking, and power generated by some randomly selected plants was de-rated to account for outages. With the increased demand for PHEV charging, if the demand exceeded the predicted power output of all plants in the region, the cost to meet the unserved demand was estimated from the operating cost of the last plant dispatched and an elasticity factor. It is not clear how marginal emissions at these high power levels are estimated. From the order of dispatch, the notional plants that supply power at any given total power level were determined, and their costs and emissions could be estimated.

Assuming various PHEV penetration levels, and assuming the PHEV would be plugged in at either 5:00 to 6:00 pm or from 10:00 to 11:00 pm, Harley and Tsvetkova estimated demand and emissions for the thirteen North American Electric Reliability Council (NERC) regions. Emissions were sensitive to the type of generating plants used to serve PHEV charging demand, with emissions increasing more for coal-intensive regions (e.g., ECAR in the mid-west and SERC in the southeast) than for regions served more by gas-fired power plants (e.g., ERCOT, Texas and SPP, Oklahoma and Kansas), however this was somewhat dependent on the time assumed for PHEV charging. This was because the plants dispatched to meet the PHEV charging demand would depend on the power level when the PHEVs were plugged in, which was different at different times of day.

Kelly and Keoleian (2010) compared two approaches to modeling the dispatch of electricity generating plants. One approach was an economic dispatch model, which used fuel price data to estimate the relative operating costs of electrical plants and assumed that plants are dispatched in order of increasing operating cost. The other approach used reported plant capacity factor and yearly energy data to predict each plant's dispatch order, annual average operating power, and total annual hours of operation. In the capacity factor approach, it was assumed that plants were dispatched in the order of decreasing capacity factor, except for nuclear power plants, which were assumed to be dispatched first, regardless of their capacity factor. Both models could be used to predict, on average, which plants would be operating at a given power level. In both models, hydropower plants were assumed to operate as peaking plants, and wind power was assumed to be dispatched when available (must-run) and was treated as negative load.

With emissions factors for each plant, Kelly and Keoleian could predict emissions at the plant level as a function of total power level. They compared the accuracy of the two models in predicting the fraction of time in a year that a set of electrical plants operated based on demand data from a different year and found that the capacity factor model gave more accurate predictions in cases in which the relative operating costs of plants did not change significantly. For example, in cases in which a carbon tax was imposed, which changed the relative costs of fuels, the economic dispatch model performed better. For scenarios involving changes in electric power demand over short time scales (weeks to months) in which fuel prices and generating assets do not change significantly, the capacity factor approach performed well and is appropriate for predicting dispatch order. With emissions factors for each plant, or for each type of plant, the capacity factor approach is valuable for estimating changes in emissions from power plants due to the demand for PHEV charging, with other conditions (generating assets, other electricity demand) remaining constant.

Keoleian et al. (2009) modeled PHEV charging demand and resulting GHG emissions in Michigan for various projected PHEV market penetration rates, as discussed in Section 1.2.3. They predicted electricity generating capacity over several decades, based on planning projections, and they used a dispatch modeling approach similar to that of Kelly and Keoleian (2010), with the assumption that capacity factors were de-rated slightly each year due to aging of power plants. They also assumed that at high power levels, once all power plants had been dispatched, unmet demand was assumed to be satisfied by electricity imported from outside the state. They projected PHEV charging demand, fuel use and emissions from fuel combustion in both vehicles and power plants and from fuel production. They found that the fuel mix of electric power plants supplying power for PHEV charging depend on the number of PHEVs in the state, and therefore, so do the emissions. They estimated that total GHG emissions will decrease with increasing PHEV penetration.

1.2.5. Summary of previous work

Work reviewed suggests that PHEVs can significantly reduce petroleum consumption and may reduce GHG emissions if electricity is generated from low-carbon-intensity resources. Emissions will depend on vehicle efficiency and on how power plants are dispatched to meet the electricity demand for PHEV charging. Improved models for electric power plant dispatching would enable more robust assessments of potential benefits achievable from PHEVs, but the capacity factor dispatch modeling approach of Kelly and Keoleian (2010) is useful for predicting emissions from electricity generation due to PHEV charging, especially for time scales over which generating assets do not change significantly.

Management of electricity demand may be necessary to manage peak loads, but if vehicles are charged during off-peak hours, existing capacity is sufficient for the levels of automotive fleet penetration projected for the near future. However, projections made about when PHEV drivers will charge vehicle batteries are uncertain, and some projections of PHEV charging as a function of time of day differ significantly from charging profiles that have been commonly assumed. This uncertainty is largely due to the diversity of driving and charging behavior by drivers and to the expected heterogeneity of PHEV characteristics within a fleet. Variability of driving behavior also limits the confidence in predicted energy and emissions reductions, since this is important in determining the fraction of vehicle-miles that can be traveled electrically by PHEVs. Better methods to estimate energy and emissions from PHEVs under more realistic driving patterns would enhance the existing capability to assess potential economic and environmental benefits of PHEVs.

Another important question is how drivers might respond to incentives to charge vehicles at times other than when they would naturally tend to, such as time-of-use electricity rates, and how use of PHEVs might be impacted by demand-side management of PHEV charging loads such as load control or interruptible service. Most of the work to date evaluating potential energy savings and emission reductions by PHEVs has been based on assumed PHEV charging profiles and driving patterns. There is a need for methods to relate the charging decisions by PHEV owners to incentives or demand-side management.

Agent-based modeling affords an approach to model driver decisions regarding vehicle use and battery charging, to relate these to aggregate driving patterns and energy use of the driver population, and to permit estimation of the resulting emissions. ABM has not been used extensively to model driver behavior and energy use. Apart from Galus and Andersson (2008) modeling PHEV drivers' response to electric price, few efforts to date have examined how charging profiles arise from driver's decisions when to charge and vehicle and charging infrastructure characteristics. The work by Galus and Andersson (2008), as well as agent-based models of consumer choices and energy demands by Sullivan et al. (2008) and Ehlen et al (2007) show that agent-based modeling is a promising approach for exploring these questions.

More specifically, to examine the potential effects of fuel price, electricity rates, multiple vehicle charging locations, and interruptible electricity service on the energy demands from PHEV drivers, a model relating vehicle use to individual driver decisions is needed, Vehicle use depends on drivers' transportation needs, time constraints and sensitivity to travel costs. Explicit representation of drivers, their transportation needs, schedules and sensitivity to vehicle operating costs enables evaluation of how driver decisions on the number of trips and when to recharge batteries might change in response to energy prices and constraints on when and where charging is possible. In addition, evaluation of energy use at the trip-by-trip and vehicle-by-vehicle level rather than at an aggregate fleet level permits examination of the distribution of energy use across the fleet and enables estimation of correlations between vehicle energy use and trip-level driving statistics. These can reveal additional insights into how segments of a heterogeneous driver population are impacted by constraints on when and where they can charge their vehicles. Tracking vehicle use by individual vehicle and by trip permits accurate estimation of energy and emissions without having to assume a value for the fraction of distance that PHEVs travel under electric power. The model developed here is based on a simple representation of a population of drivers having a small number of decision criteria that are relevant to driver energy use and that serve as the focus of the interactions between drivers, transportation needs, and energy markets.

1.3 Organization of this thesis

The remainder of this thesis is organized as follows. Chapter 2 describes the model developed including the attributes and actions of the agents in the model. Chapter 2 also describes the model parameters and input data and the basis for choosing the values used. Chapter 3 describes the scenarios modeled and presents the results obtained. In chapter 4, these results are discussed, and conclusions are drawn.

CHAPTER 2

Description of the model

2.1 Model overview

To better characterize the energy demands and the environmental performance of a population driving PHEVs, it is necessary to obtain sufficient information on driving behavior. The Driver Vehicle Use Decision (DVUD) agent-based model has been developed to meet this need. The model represents a population of drivers by a set of agents. There are two additional agents, an electricity supplier agent and a fuel supplier agent.

Driver agents each have a vehicle, and they drive trips to destinations they choose each day. As with real drivers, there are times when driver agents do not drive because driving is precluded by other activities. In the model, there are blocks of time for each driver when he does not drive. Driver agents, as do real drivers, value travel depending on trip purpose. For simplicity, driver agents who drive to work place a very high value on commuting trips, and always drive these trips, and they place a smaller value on all other trips which are driven depending on their schedule and sensitivity to travel costs. Driver agents who drive PHEVs decide whether to charge their vehicle batteries depending on availability of electricity, planned length of stay at their current location, and spending preferences, as described in more detail in Section 2.2.1 below.

The electricity supplier agent sets electric rates, controls electricity availability at controllable meters, and tracks electricity demand. A fuel supplier agent sets the fuel price.

A high-level schematic of the model is shown in Figure 2.1. Input data are shown in red, and output is shown in green. Input defining driver transportation needs includes distributions of arrival times, distances and dwell times for trips, and driver income. Other inputs include vehicle design parameters (described in more detail in Section 2.3.3, below), the distribution of vehicle types (models) and the fraction of vehicles that are PHEVs. Input describing the electricity supply includes a list of power plants, each with a capacity factor, annual average power level, and emissions factors. The power plant data are described in more detail in Sections 2.2.2.1 and 2.3.4.1, below.

The model output includes vehicle-miles driven per week, vehicle-miles driven per week on electricity and on fuel by PHEV drivers, electricity demand by hour, and fuel use by day and by week, and the resulting total fuel cycle greenhouse gas emissions from electricity and fuel consumption. Output also includes driver operating costs for their vehicle, and for PHEV owners, cost savings and a measure of their satisfaction with their PHEV. More detailed flowcharts are shown in Appendix A. Appendix B includes instructions for installing and running the program, which is written in Java, using the RepastJ system (North et al., 2006).

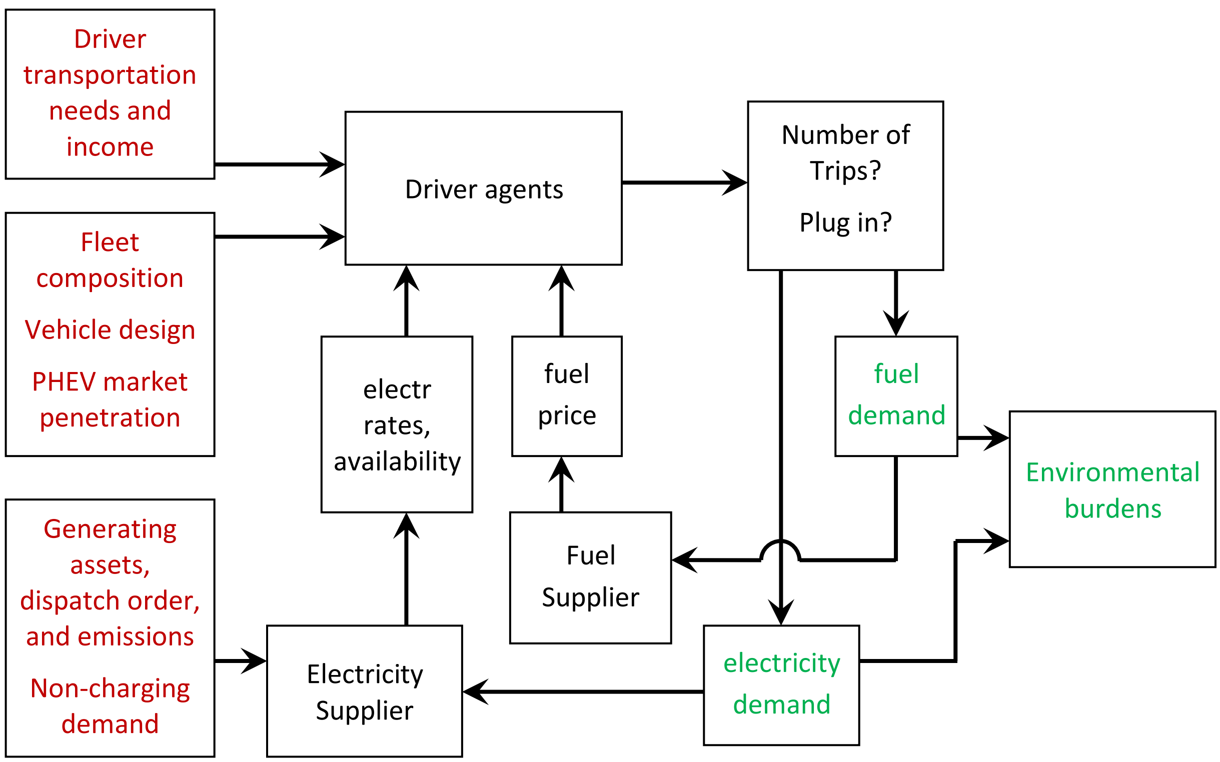

Figure 2.1. Schematic of agent-based model. Inputs are shown in read, and outputs are shown in green.

2.2 <u>Agent attributes and actions</u>

2.2.1 Driver agent attributes and actions

Drivers possess attributes that influence their actions. Their actions are to select a number of trips to drive each day, drive these trips, and, for drivers of PHEVs, decide whether to recharge the vehicle batteries. Driver attributes and actions are described below.

2.2.1.1 <u>Driver attributes</u>

Drivers each have the following:

a vehicle,

an income,

a location,

a list of routine trips for each day of the week

a list of all trips scheduled for one day

a baseline number of optional trips the driver tends to drive on an average workday, $N^0_{opt,work}$

a baseline number of optional trips the driver tends to drive on an average day off, $N^0_{opt,off}$,

and

a parameter describing his sensitivity to fuel and electricity costs.

Each driver has one vehicle, with attributes assigned at the beginning of the simulation. Vehicles can be conventional vehicles or PHEVs with the attributes described in Section 2.3.2 below. The type of vehicle a driver agent drives is correlated with his income.

A driver's income represents the annual pre-tax income of the driver's household. Although it is assumed that drivers belong to households, households are not modeled explicitly, and whether drivers belong to the same household is not considered. Incomes are initialized at the beginning of the simulation and are distributed as described in section 2.3.2.1

A driver's location is the destination of that driver's most recent trip. When the model is initialized, time starts at midnight on a Sunday morning, and the location of each driver is home, unless the driver works Saturday nights past midnight, in which case the location is work. All other locations are designated "other", which represents multiple locations that drivers may travel to other than work and home. Trips driven by drivers are described in section 2.2.1.3.

A driver's list of routine trips is used to define the blocks of time when the driver does not travel, and the driver's location, either home or work, during each of these time blocks. For drivers who drive to work, this list contains the hours the driver is routinely at work as well as the hours the driver is routinely at home. For drivers who do not drive to work or for days off, the list defines the hours the driver is routinely at home. As described in Section 2.2.1.2, below, when the driver decides to drive optional trips, none of these optional trips are scheduled to take place during the blocks of time when drivers are routinely at home or at work. Drivers are not precluded from spending additional time at home; the routine trip list defines the hours when the driver is always at home. Only trips made by drivers in their vehicles are modeled; travel by other modes is not considered.

The driver's list of trips scheduled for one day includes his routine trips as well as any additional trips, i.e., optional trips he decides to take that day. The optional trips, in contrast to routine trips, are different from day to day. The number of optional trips a driver tends to take on average depends on whether it is a workday or a day off. The number a driver actually chooses to take on a given day also depends on the driver's spending rate on fuel (and electricity if he drives a PHEV), as described in section 2.2.1.2, below.

The list of trips scheduled for one day is updated each day 24 hours in advance, as described in Section 2.2.1.3, below. Once a driver decides on a number of trips to take on a given day, these trips are generated and put on this list, along with any routine trips for that day. Driver agents always take their routine trips, but any additional trips are optional, depending on the driver's travel needs (the baseline number of optional trips that he tends to drive on a given day) and average spending rate. If a driver does not work on a given day, and his only routine trip is to home, and no optional trips are taken that day, he stays home all day. In this case his routine trip is assigned a zero duration and zero distance, and his location remains "home". Otherwise, each driver agent drives each trip on his list of trips scheduled for the day. The actions that occur when driver agents drive trips are described in Section 2.2.1.3 below.

If fuel or electricity costs change, driver agents respond to changes in their rate of spending on travel (their vehicle operating cost per mile) by changing the number of optional trips they choose to take. The parameter describing a driver's sensitivity to fuel and electricity costs is a constant that relates a driver's travel demand to operating costs. This parameter is initialized as described in Section 2.2.1.2 below to represent driver's tendencies to drive under little or no cost constraint, i.e. when operating costs for driving are low. These represent a baseline preference for travel.

2.2.1.2 <u>Driver decision on number of trips</u>

Driver agents decide what trips to drive each day. This mimics real drivers who come up with a list of places they need to travel to and when they need to be at each place. In the model, drivers do not decide on the quantity of fuel or electricity to use for travel, their decision is simply the number of trips to take in addition to their routine trips (which they always take). The decision on the number of trips depends on their spending on fuel and electricity, so this is how driver agents respond to energy costs if these change.

During the simulation, at midnight of each day after the first day, each driver schedules a number of trips to take on the day starting 24 hours later. On the first day, the driver schedules the first two days of trips. When scheduling a day's trips, the driver first schedules his routine trips, which are commutes, if it is a workday. If a driver works nights, he schedules a trip home on a day following a workday. The driver then chooses a number of additional trips to add to the day's schedule. This number depends on the driver's baseline number $N^0_{opt,work}$ or $N^0_{opt,off}$, of optional trips that he tends to drive daily and the driver's weekly spending rate on transportation energy (fuel consumed per week, and for PHEV drivers, electricity per week for vehicle charging). For the first six days of simulation time, drivers estimate their spending based on an assumed average number of miles driven and their vehicle's fuel economy and electricity consumption per mile in charge-depleting mode. After six days, they estimate their spending based on their fuel and electricity consumption for the previous seven days. Each driver compares his weekly transportation energy spending rate to his baseline spending rate. The baseline spending rate is the amount a driver would spend on average driving his vehicle for his routine trips plus his baseline number of optional trips. The baseline spending rate for drivers is a constant determined when the model is initialized and stays constant throughout the simulation. It is correlated with the driver's household income, as described in section 2.3.2.1 below.

The number of trips a driver schedules in addition to commute trips (if any) is a random number picked from a triangular distribution with mean $\overline{N_{nr}}$, and width $min[12, max(1, \overline{N_{nr}}/2)]$, where this mean was related to the driver's spending and budget as follows.

$$\overline{N_{nr}} = N^0_{opt,work} R^{\varepsilon_{nr}}, \text{ workday} \tag{2.1}$$

$$\overline{N_{nr}} = N^0_{opt,woff} R^{\varepsilon_{nr}}, \text{ day off} \tag{2.2}$$

$$R = \frac{spending}{baseline}, \text{ and} \tag{2.3}$$

$$\varepsilon_{nr} = -K(income)^{\alpha} \tag{2.4}$$

This distribution was chosen to give some variability in the number of trips from day to day in the number of trips while ensuring that the number did not go negative. Here, *baseline* is a monetized value of travel the driver compares his spending to. It is initialized at the start of the simulation at a value approximating a driver's spending on energy if he drives his routine trips and his baseline number of additional trips, given the fuel efficiency and electricity consumption of his vehicle. It does not represent a budget the driver adheres to. Drivers who spend faster than their target spending rate do not, in general, curtail their trips to bring their spending to the target rate. It is assumed that drivers make some adjustment in the amount of their driving if they spend faster than their baseline spending rate, but can also adjust their spending on other activities. Here, households are not modeled explicitly; equations (2.1 – 2.4) represent the net effect on driving from all household adjustments in response to changes in fuel and electricity costs.

Each driver maintains a list of trips scheduled for one day that is updated at midnight for the day starting 24 hours later (e.g., Tuesday's trips are scheduled at midnight Monday morning). First, routine trips are put on the list. On a workday, driver agents who work will have two routine trips, their two commutes. Driver agents who have the day off, or who don't work, will have one routine trip to home, which defines the hours he is at home. Each driver chooses a number of optional trips to take that day, in addition to the routine trips. Once the number of optional trips is chosen, a trip is generated, and if it can be completed in the interval between the earlier or later trip already on the list (if any), the new trip is added to the list. This is repeated until the driver has the desired number of trips on the list or cannot fit any more in the time available that day.

Optional trips are generated to destinations "home" or "other" with arrival times distributed randomly, with trips arriving at noon or after work (on workdays) being more likely. Then arrival times are adjusted so that trips start (driver departs) when the next earlier trip ends (when the driver finishes his dwell at the previous trip destination) or the trip ends just in time for the driver to depart on the next later trip on the list. This assumes drivers tend to drive optional trips just before or just after trips to work or to home or tend to do some amount of trip chaining. The dwell times of optional trips are chosen randomly from a distribution skewed to shorter times. Distributions of trip arrival times, distances and dwell times were chosen to reflect realistic driving, as described in Section 2.3.2.2.

The trip generation process used by driver agents mimics drivers who come up with a list of locations they must or desire to travel to and times they need to be at each location during the upcoming day. Trips are generated as the driver comes up with another destination and arrival time. These are not generated in chronological order, so new trips are often scheduled between trips already on the list. The distance associated with given trip is the distance the driver must travel from the destination of the previous trip to get to the destination of the given trip.

For example, consider a driver with two routine trips on his list, as shown in Table 2.1. The commute distance is the same for both trips, since they are between the same two destinations.

Table 2.1. A hypothetical list of routine trips for a driver for one day. (Trips also include departure time, travel time and dwell time, which are not shown, for clarity).

destination	arrival time [24 hr clock]	distance [mi]
work	08:00	10
home	18:00	10

If the driver adds a trip after work to the destination "other", located 5 miles from work, the distance from "other" to home must be between 5 and 15 miles. Table 2.2 shows a hypothetical case in which the trip from "other" to home has a distance of 8.923 miles.

Table 2.2. The list from Table 2.1, updated with a new trip that a driver has added.

destination	arrival time [24 hr clock]	distance [mi]
work	08:00	10
other	17:30	5
home	18:00	8.923

As each optional trip is added to the list of trips scheduled for one day, the distance from the destination of the trip just added to the destination of the following trip is adjusted to reflect the distance between these two destinations. Since trip routes and destinations are not mapped in a 2-D space, the distance between these two destinations is not well-defined. However, it is constrained to be no less than the minimum possible distance and no greater than the maximum possible distance. The minimum possible distance is simply the difference between the distance of the new trip and the original distance of the trip after the new trip. This corresponds to the case when destination of the new trip is along the way to the following destination. The maximum possible distance is their sum (the case when the destination of the new trip is exactly in the opposite direction of the following trip). In the model, a number is chosen randomly between these two limits.

Mathematically, if the original distance between destinations 1 and 2 is *dist12*, then when a trip with a distance *dist13* between destinations 1 and 3 is added, the distance from destination 3 to destination 2, *dist32* is a assigned a value

$$dist32 = U \min(dist13, dist12) + \max(dist13, dist12) \tag{2.5}$$

where U = a uniform random number between –1 and 1.

This distance, $dist32$, is the distance associated with the trip to destination 2. This trip is already on the list with distance $dist12$, but its distance is reassigned to the value $dist32$. This results in plausible distances for trips as new trips are added.

This reassignment is not done if a new trip is added to “home”, and the following trip is to “work”, in which case, the distance to “work” is assigned that driver’s commute distance. Likewise, if a trip to “home” is added just after a trip to “work”, the distance of the trip to “home” is assigned the commute distance.

After the trips have been added to the driver’s list for the next day, any consecutive trips to “home” are consolidated into a single trip. Consecutive trips to “other” are assumed to be to distinct locations.

2.2.1.3 Driver actions during trips

Each trip has a destination, arrival time, travel time, distance and dwell time. Destinations and routes are not represented spatially. Destinations include “home”, “work” and “other”. The destination “other” is used to represent multiple locations, but “work” and “home” represent unique locations, i.e., each driver has one home, and each driver who works has one workplace separated by a fixed commuting distance from home. The distributions used for trip arrival times, distances and dwell times are described in Sections 2.3.2.2.

At the start of each trip the driver, if he has a PHEV and it is plugged in, unplugs the PHEV. Electricity consumed during the last hour is recorded. The driver departs and upon arrival, the fuel consumed by the vehicle is estimated. For PHEVs, the electricity used during the trip is estimated from the trip distance and the vehicle’s electricity consumption rate. Electricity consumption rates were assumed to be constant. Values used for PHEVs in the model are given in Section 2.3.3. Fuel consumption by conventional vehicles and during the gasoline-powered portion of PHEV trips is estimated using the average speed for each trip and the effective fuel consumption, $F_{c,eff}$, which was taken to be a combination of the city and highway values:

$$F_{c,eff} = (1 - s)F_{c,city} + sF_{c,hwy} \tag{2.6}$$

where

$$s = \begin{cases} 0, & avg\ speed \leq 20 \text{ mi/hr} \\ \frac{avg\ speed - 20}{60 - 20}, & 0 < avg\ speed \leq 60 \text{ mi/hr} \\ 1, & 60 \text{ mi/hr} < avg\ speed \end{cases} \tag{2.7}$$

Values used for city and highway fuel economy of vehicles are given in Section 2.3.3. No adjustment was made to account for differences in standard city and highway fuel economy values and fuel economy under real-world driving conditions. Distances driven electrically and on liquid fuel are recorded, and tailpipe and total fuel cycle emissions from gasoline consumption are recorded. The driver's location is set to the trip destination.

For PHEV drivers, the estimated difference between his operating cost and the estimated operating cost of an equivalent conventional vehicle traveling the same distance with a combined 50/50 city/highway fuel consumption was recorded. A 50/50 weighted average was used, since it lies between the 55 percent city and 45 percent highway weighting used by the National Highway Travel Safety Administration in administering Corporate Average Fuel Economy (CAFE) ratings (CFR, 2000) and the 43/57 weighting considered by the EPA as more representative of recent U.S. driving (EPA, 2006). A 50/50 weighting was also considered more likely to be used by a typical driver than unequal weights. Values of fuel economy and other vehicle characteristics were set as described in section 2.3.3. The difference in operating costs equals the fuel savings minus the cost of electricity. Differences between the purchase prices of PHEVs and comparable conventional vehicles are not tracked during the simulation, since this difference is constant for a given PHEV and comparable vehicle. Although financing implications may vary over time, in this model PHEV driver agents do not purchase or trade in vehicles, and PHEV driver decisions on the average number of trips are assumed to depend on operating costs, not on purchase prices. Total cost of ownership does depend on purchase price, and this was considered in analyses performed after simulations were run, as discussed in Section 3.3.

For PHEV drivers, the driver's satisfaction with the vehicle is tracked. This is a measure of his satisfaction with his vehicle in comparison with a comparable conventional vehicle. Satisfaction is the sum of a driver's operating cost savings (in comparison with a comparable conventional vehicle) and two other factors that represent the monetized value of a driver's negative experiences with his vehicle. One type of negative experience is having less than a full charge despite having plugged the vehicle in for the nominal time required to fully charge the battery. This can occur if the driver's charger is on interruptible electricity service, in which the utility (the electricity supplier agent) can shut off power during peak hours. The other type of negative experience represents the inconvenience of plugging the vehicle in or unplugging it, since these actions take time and effort that are not required with conventional vehicles. For each negative experience, a small amount is subtracted from a running total of the driver's cost savings. The increment subtracted for each negative experience varies from agent to agent, assuming some drivers will be less inconvenienced or annoyed by plugging in or unplugging their vehicle or by having less than a full charge. The satisfaction per mile or per unit time is taken to be representative of how satisfied the driver is with his PHEV vs. a comparable conventional vehicle and indicative of whether he would be likely to choose a PHEV the next time he purchases a vehicle. Vehicle purchasing is not modeled.

2.2.1.4 PHEV driver decision whether to charge the vehicle batteries

Upon arriving at a destination, a driver of a PHEV determines whether electricity is available at that location. In most scenarios, electricity is available only at home, but in some scenarios, drivers can also charge at work. If electricity is available, the driver considers the length of time that he plans to stay at the destination (dwell time) and the cost of electricity per mile in comparison with the cost of fuel per mile for his vehicle–a 50/50-weighted average of city and highway fuel consumption values. A 50/50 weighted average was used, since it lies between the 55 percent city and 45 percent highway weighting used by the National Highway Travel Safety Administration in administering Corporate Average Fuel Economy (CAFE) ratings (CFR, 2000) and the 43/57 weighting considered by the EPA as more representative of recent U.S. driving (EPA, 2006). A 50/50 weighting was also considered more likely to be used by a typical driver than unequal weights. Most drivers are aware of the fuel economy ratings of their vehicles, but not familiar with the harmonic mean formula or values of weights used in combining highway and city fuel economy ratings. A 50/50 weighting was used simply to represent the approximate fuel economy that a PHEV owner might expect if he were to drive a comparable conventional vehicle instead of the PHEV.

A minimum dwell time of 2 hours was used unless otherwise noted. That is, a driver would plug in if the planned dwell time at that destination was greater than 2 hours. In comparing costs per mile, drivers could exhibit a bias, that is, the driver was not necessarily indifferent to charging if costs per mile were equal. A driver may be biased if he considers plugging in to be an inconvenience with an associated cost (assuming he values his time), or if he prefers to use electricity instead of gasoline for environmental or other reasons. This bias was represented as a constant added to the cost per mile of electric-powered travel, but could be positive (bias against electricity) or negative (bias against gasoline). That is, the driver would plug in if the following criteria were met:

1. Electricity available at trip destination
2. Dwell time > 2 hours
3. Electricity cost per mile ≤ gasoline cost per mile + bias

Unless otherwise indicated, zero bias was used in the scenarios presented below.

In scenarios in which the electricity rate varies with time, the current rate is used in comparing operating costs per mile. It is assumed that PHEV chargers are programmable with a timer (assuming the person setting the timer knows the times when the electricity rate changes) or that chargers have some communication capability with utilities and can be programmed to charge the battery when the electricity rate is lower than a given value, set by the user (e.g., PHEV driver).

Thus if a driver's criteria for plugging in is not met at the time of his arrival but is met at a later hour while he is at the same location, charging can start at this later hour.

2.2.2 Electricity supplier agent attributes and actions

2.2.2.1 Electricity supplier agent attributes

The electricity supplier agent has attributes set at model initialization that determine electricity rates, including flat, peak and off-peak rates, and peak hours. The electricity supplier agent also has a number of power plants, each having a power band, defined here as the power the plant produces averaged over one calendar year, a capacity factor, defined as the ratio of the annual average power to the nameplate capacity, and emission factors that give the emissions due to generation and fuel production as a linear function of power.

Data for 181 power plants in Michigan were used in scenarios modeled. These data and the sources from which they were obtained are described in Section 2.3.4, below.

2.2.2.2 Electricity supplier agent actions

The electricity supplier agent sets the electricity rate according to values set at model initialization. The rate may vary with time, as in cases where there are time-of-use rates (different rates during peak and off-peak hours). Costs of generation and transmission were not considered; it was assumed that retail electricity rates are regulated and do not reflect the real-time price.

The electricity supplier agent also tracks demand by driver agents, as well as baseline (non-PHEV charging) demand. The electricity supplier can limit or shut off power to PHEV chargers if drivers have interruptible service to their chargers. Electricity demand, both total demand and demand for PHEV charging, is tracked hourly. The electricity supplier agent dispatches power plants to meet overall electricity demand each hour, and calculates emissions from power plants and upstream fuel supply.

Power plants were assumed to be dispatched in the order of decreasing capacity factor. For scenarios in which the PHEV charging demand was high enough that the total demand exceeded the sum of the annual average power of all the electricity supplier agent's plants, capacity factors of some plants were adjusted using the approach of Kelly and Keoleian (2010). The power plants were listed in order of decreasing capacity factor, and the sum of the annual average power produced by all plants having a capacity factor less than a value *CF* was tabulated against *CF*, so that each plant was associated with a total power level. For each scenario, the minimum and maximum electric power demand with no PHEV charging, $D_{min}^{no\,PHEV}$, and $D_{max}^{no\,PHEV}$, were determined, and the minimum and maximum total power demand (including PHEV charging), D_{min}^{Tot} and D_{max}^{Tot}, were determined. The capacity factors of those plants associated with power levels greater than D_{min}^{Tot} were increased by a factor η, where

$$\eta = \frac{D_{max}^{Tot} - D_{min}^{Tot}}{D_{max}^{no\,PHEV} - D_{min}^{Tot}} \qquad (2.8)$$

This is consistent with the assumptions that no new power plants are constructed during the simulation, and that the additional demand from PHEV charging is met by existing plants that run for a greater fraction of the time.

The non-PHEV demand was taken to be the electricity supplied by the 181 power plants in Michigan mentioned above, for the year 2008. These data and the sources from which they were obtained are described in Section 2.3.4.2, below. Non-PHEV demand was assumed to be independent of the additional demand from PHEV charging and not responsive to electricity rate changes.

2.2.3 Fuel supplier agent attributes and actions

The fuel supplier agent sets the fuel price. Fuel use and emissions from fuel use are tracked for each trip that drivers take, depending on vehicle efficiency, trip distance and average speed.

2.3 Model parameters

Values for agent attributes and other parameters were set in order to achieve realistic, or at least plausible, agent behavior and vehicle performance. Where relevant data were available, these were used to guide choices for parameter values, otherwise, values were chosen that gave reasonable behavior. Data from the 2001 National Household Travel Survey (2001 NHTS) were used to determine distributions of trip distance, arrival times, dwell times and travel speeds. Development of these distributions is described below.

2.3.1 Summary personal travel statistics from the 2001 NHTS

The 2001 National Household Travel Survey (2001 NHTS) was conducted in 2001 by the U.S. Federal Highway Administration to collect detailed data on personal travel in the U.S. Data obtained from the survey are described by Hu et al. (2004) who also give a broad analysis of the data. Data from the survey are available from the Department of Transportation (USFHWA, 2010) in comma-space-value (csv) format files and in other formats, as well. The day trip file, DAYPUB.csv contains records of day trips made via all travel modes and includes trips by passengers as well as drivers. Data on vehicles driven by survey respondents are contained in the file VEHPUB.csv. Several subsets of these data files were selected containing only records for trips driven in cars, vans, pickup trucks or SUVs, and for different trip purposes. Fields in the NHTS used to identify records in the DAYPUB.csv file are listed in Table 2.3. This is only a partial listing; the data file contains many more fields.

Table 2.3. Fields in the 2001 NHTS trip data file DAYPUB.csv.

variable	values and significance
TRPTRANS	travel mode, 1 = car, 2 = van, 3 = SUV, 4 = pickup truck
DRVR_FLG	record for driver, 1 = yes, 2 = no
WHYTRP01	1 = to home, 11 = to work (first time that day), 12 = return to work
ENDHOUR	hour of arrival (0 = between 00:00h and 01:00h, 24-hour clock)
TRPMILES	trip distance in miles
DWELTIME	time at destination in decimal hours
WTTRDFIN	travel day person weight for full sample

The files contain weights which are required to correct for sampling error (non-uniform representation of households), and the proper weights must be used to make estimates for the entire U.S. population. Two sets of weights are provided, one for the national sample, and one for the full sample. The full sample included the national sample plus add-on samples. For the full sample, use of the weight WTTRDFIN with each trip record permits estimating vehicle trips and miles for the U.S. population.

A subset of the DAYPUB.csv data was selected for which DRVR_FLG was 1, TRPTRANS was 1, 2, 3 or 4 (light-duty vehicles), and TRPMILES was greater than zero (a valid trip distance recorded). This contained 377,115 trip records. The weighted sum (the sum of WTTRDFIN) for these records was 2.27638×10^{11} which represents an estimate of the number of vehicle trips made in the U.S. 2001 in light-duty vehicles. The sum of the product of the weight WTTRDFIN and the trip distance TRPMILES gave an estimate of 2.201792×10^{12} vehicle-miles traveled in light-duty vehicles in the U.S. in 2001.

In the file VEHPUB.csv, 132,920 records were for vehicles of type car, van, SUV or pickup truck. The total of the household weight for the full sample, WTHHFIN for these records is 194,407,511, which is an estimate of the number of light-duty vehicles driven in the U.S. in 2001.

From these estimates, averages for the U.S. 2001 light-duty fleet were made. These are listed in Table 2.4 and compared with similar estimates made from the 2001 NHTS by Hu et al. (2004) and by another analysis of the 2001 NHTS data by the Energy Information Agency (EIA, 2005). The other estimates differ somewhat from the estimates made here. This may be due in part to the other estimates being for a slightly different selection of records.

Table 2.4. Personal vehicle travel statistics from the 2001 NHTS from different sources.

statistic	This study	Hu et al (2004)	EIA (2005)
vehicles in U.S. fleet	1.944×10^8	2.02586×10^8	1.91×10^8
vehicle miles traveled per year	2.202×10^{12}	2.274797×10^{12}	2.287×10^{12}
vehicle trips per year	2.276×10^{11}	2.33040×10^{11}	-
vehicle miles per vehicle per year	11,330	11,078	12,000
miles per vehicle trip	9.67	9.87	-
vehicle trips per day per vehicle	3.208	3.35	-

Additional analysis of the 2001 NHTS data to develop distributions for choosing driver agent parameters is described below.

2.3.2 Driver agent parameters

2.3.2.1 Driver income distribution and price sensitivity

Driver incomes were distributed approximately the same as U.S. household annual incomes in the 2001 National Household Travel Survey, obtained using the NHTS Online Table Designer (NHTS, 2001). Driver incomes were chosen as

$$income = 0.3825u^3 - 37.996u^2 + 1667.1u \tag{2.9}$$

where u is a uniformly distributed random number between 0 and 100.

This income distribution is compared with the income distribution for drivers in the 2001 NHTS in Figure 2.2. Although households were not modeled, drivers were assumed to belong to households having incomes distributed as shown.

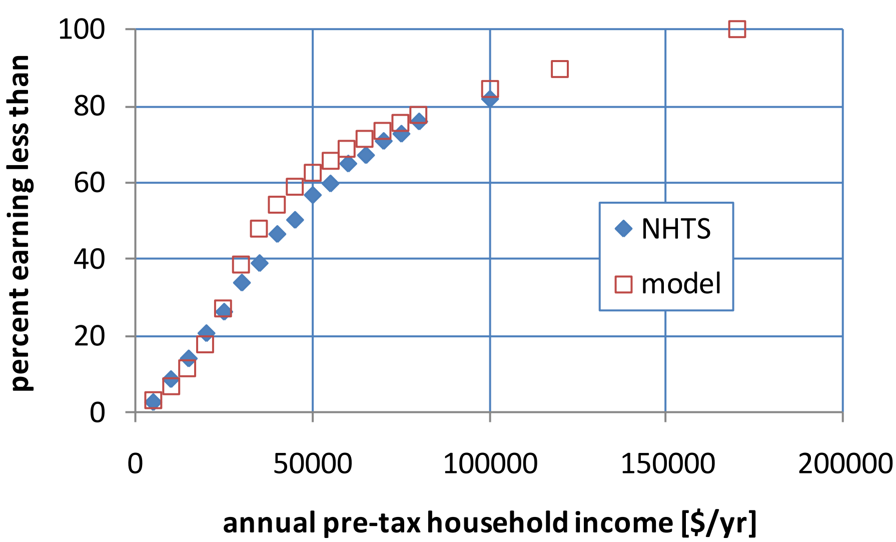

Figure 2.2. Cumulative distribution of annual, pre-tax, household income assumed in the model compared with the distribution of household incomes of drivers survey in the 2001 NHTS.

Parameters governing the drivers' choice of the number of optional trips to take in a day (see equations (2.1 – 2.4) in Section 2.2.1.2, above) are set by each driver agent at model initiation based on the estimated operating cost per mile for his vehicle. For PHEV owners, this depends on the fraction of miles driven electrically, f_{elec}, which was roughly estimated as the charge-depleting range in miles divided by 60. This estimate of this fraction was not used elsewhere in the model. The cost per mile, C_{est} is a linear combination of the cost per mile of electric-powered travel C_{elec}, and the cost per mile of electric-powered travel C_{fuel}.

$$C_{est} = f_{elec}C_{elec} + (1 - f_{elec})C_{fuel} \tag{2.10}$$

$$baseline = r(12558 + 0.05638income)C_{est} \tag{2.11}$$

where *baseline* is in \$/year and *r* is a random number chosen from a normal distribution with mean 1.0 and standard deviation 0.25 truncated to be between 0.5 and 2.0. This random factor is applied to make *baseline* variable from agent to agent.

The parameter *baseline* in eq (2.11) is a baseline spending rate corresponding to the amount of travel when vehicle operating costs are low, i.e., when constraints other than operating cost, such as time available for travel, limit the amount of travel. The income dependence in eq (2.11) results in higher-income driver agents driving more trips per year, consistent with observation, as discussed below. The estimated cost per mile, C_{est} was used only at model initiation for setting the parameter *baseline*, not for tracking individual drivers' actual costs.

An average cost per trip was estimated

$$avg\ cost\ per\ trip = 9C_{est} \tag{2.12}$$

where an average trip distance of 9 miles was assumed, which is consistent with Table 2.4 and the trip distance distribution determined for this population, as described in Section 2.3.2.2 below. From the baseline spending rate and estimated average cost per trip, the baseline number of optional trips on an average workday was set to

$$N^0_{opt,work} = \frac{baseline/365}{avg\ cost\ per\ trip} - 2 \tag{2.13}$$

or, $$N^0_{opt,work} = r(12558 + 0.05638income) - 2 \quad (2.14)$$

where 2 is subtracted for the 2 routine trips (commutes) driver agents take on workdays. This number, $N^0_{opt,work}$, is never negative. The baseline number of optional trips on an average day off was set to

$$N^0_{opt,off} = \frac{baseline/365}{avg\ cost\ per\ trip} - 1 \quad (2.15)$$

or, $$N^0_{opt,off} = r(12558 + 0.05638income) - 1 \quad (2.16)$$

where 1 is subtracted for the one routine trip driver agents take on days off. This number is never negative.

At the 2001 U.S. national average gasoline price of $1.33, U.S. drivers drove on average between 11,000 and 12,000 mi in the year, and between 3.2 and 3.35 trips per day, as listed in Table 2.4. For a population of driver agents driving all conventional vehicles, the above parameters resulted in driver agents driving an average of 3.68 vehicle trips per day. The vehicle fleet was composed of a mix of different vehicle models as described in Section 2.3.3, below. The trip distance distribution, as described in Section 2.3.2.2.6 below, gave an average trip distance of 8.40 mi, so at 3.68 trips per day, drivers averaged 31.1 mi/day, or 11,350 mi/yr.

Using eq (2.11) for *baseline* for a population of agents driving all conventional vehicles, as described in Section 2.3.2 below, resulted in higher-income agents driving more vehicle miles than lower-income agents. This is consistent with analysis of driving as a function of household income reported by EIA (2005), based on the 2001 NHTS. Table 2.5 gives the reported vehicle miles traveled per vehicle per year, fuel consumed per vehicle per year and expenditures on fuel per vehicle per year for 2001. Table 2.6 lists the results from the model, for a population of drivers driving only conventional vehicles at a fuel price of $1.33/gal.

In the model, it is assumed that each driver agent has one vehicle, so the fraction of vehicles for each household income bracket is the same as the fraction of drivers in each income bracket. This is not necessarily true for the actual U.S. population, and there is some discrepancy between the model and observation in the fraction of vehicles in the upper income brackets. This is because in higher income households, the ratio of the number of vehicles to drivers is higher than in lower income households.

However the model qualitatively mimics the increasing vehicle-miles traveled and fuel consumption with increasing income.

Table 2.5. Income dependence of vehicle-miles traveled, fuel consumption and fuel expenditures from the 2001 NHTS (EIA, 2005).

income	number of vehicles [millions]	fraction of vehicles [%]	vehicle miles traveled per vehicle [mi/yr]	fuel consumed per vehicle [gal/yr]	expenditures on fuel [$/yr]
0 – 5,000	2.4	1.3%	9,400	438	578
5,000 – 9,999	5.6	2.9%	9,900	472	627
10,000 – 14,999	6.7	3.5%	9,400	455	605
15,000 – 19,999	9.6	5.1%	10,600	510	674
20,000 – 24,999	9.0	4.7%	10,300	502	661
25,000 – 34,999	23.0	12.0%	11,100	542	718
35,000 – 49,999	37.3	19.5%	12,100	598	793
50,000 – 74,999	36.9	19.4%	13,100	650	865
75,000 or more	50.9	26.6%	13,100	652	870
don't know	9.6	5.0%	10,700	538	718

Table 2.6. Income dependence of vehicle-miles traveled, fuel consumption and fuel expenditures predicted by the model for a population of drivers driving all conventional vehicles.

income	fraction of vehicles [%]	vehicle miles traveled per vehicle [mi/yr]	fuel consumed [gal/yr]	expenditures on fuel [$/yr]
0 – 5,000	3.2%	11,103	462.7	615.4
5,000 – 9,999	3.7%	10,717	446.2	593.5
10,000 – 14,999	4.7%	10,771	449.4	597.7
15,000 – 19,999	6.3%	10,840	451.4	600.4
20,000 – 24,999	9.2%	10,705	447.3	595.0
25,000 – 34,999	20.7%	10,797	513.1	682.5
35,000 – 49,999	14.8%	11,031	529.9	704.8
50,000 – 74,999	13.1%	11,396	549.4	730.7
75,000 or more	24.3%	12,507	631.5	839.9

Constants for drivers' sensitivity to price (K and α in eq (2.4) in Section 2.2.1.2., above) were chosen to give a realistic value for price elasticity of demand for gasoline, with a reasonable income dependence, such as that reported by Small and van Dender (2007). Averages of several runs with

10,000 agents, all driving conventional vehicles, at a gasoline price of \$1.33/gal, gives an income dependence of the fuel price sensitivity of the number of trips, d ln(N_{tr})/d ln(P_{fuel}), and is shown in Figure 2.3. Ten thousand agents were used since this was sufficient to give at least a few hundred drivers in each income bin.

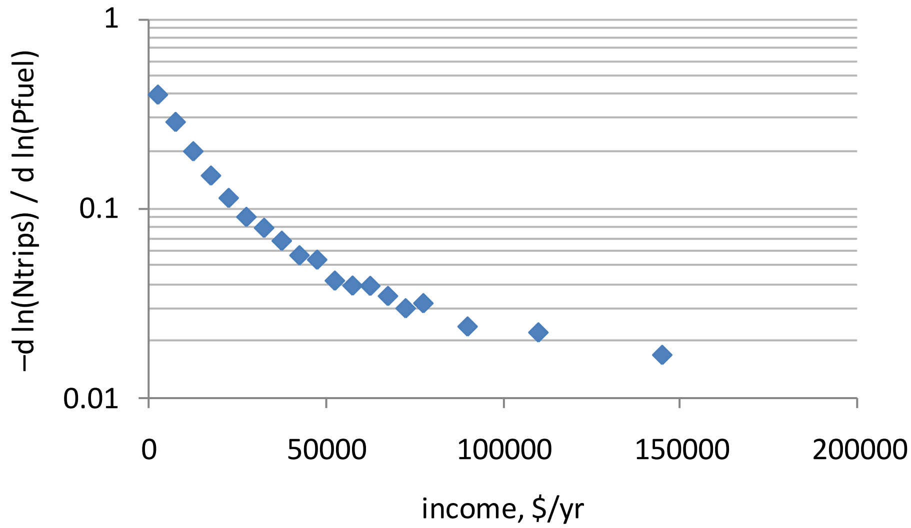

Figure 2.3. Price sensitivity of the number of trips per day by driver agent driving conventional vehicles at a gas price of \$1.33/gal.

As expected (see Figure 2.3), after a change in fuel price, higher-income drivers change their trip frequency less than lower-income drivers do. The resulting dependence of the fuel price elasticity of demand for gasoline for the same population of driver agents is shown in Figure 2.4. In general, higher-income drivers have a lower fuel price elasticity of demand, as expected, however there is somewhat more scatter in the price elasticity (Figure 2.4) than in the fuel price sensitivity of the number of trips (Figure 2.3). This is due to the fact that driver agents make decisions on the number of trips, not the number of miles to drive. Even if the number of trips were to decrease smoothly with increasing gasoline price, agent-to-agent variability in distance driven, average speed, and vehicle fuel economy increases the variability of the resulting change in fuel consumed. Additionally, higher-income driver agents drive vehicles having lower fuel economy on average, and see a larger increase in cost per increase in vehicle miles traveled, than do lower- or middle-income drivers. However, because the magnitude of the elasticity is low for high-income drivers, this increase has very little effect on the response of high-income drivers to fuel price changes.

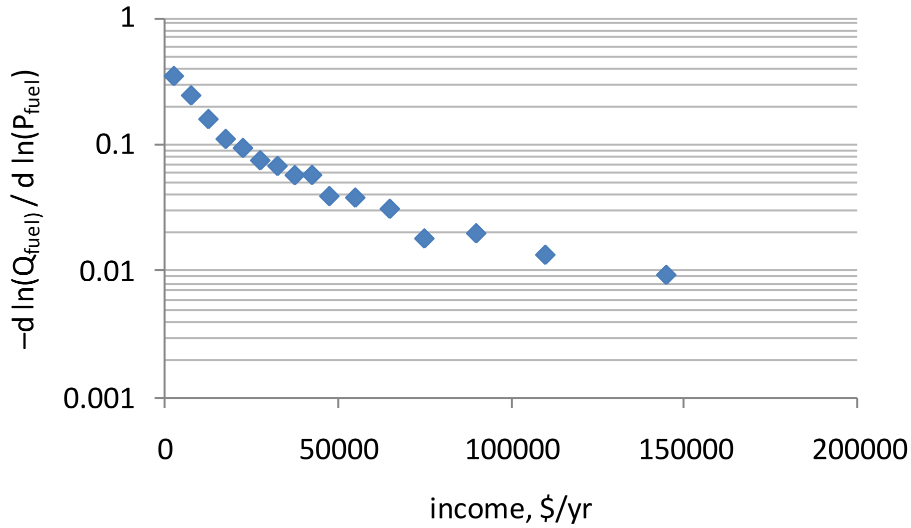

Figure 2.4. Price sensitivity of the volume of gasoline consumed per day by driver agent driving conventional vehicles at a gas price of $1.33/gal.

2.3.2.2 Trip distributions

Trips each have an arrival time, destination, distance, travel duration, and a dwell time. In the model, as trips are generated, values for these quantities are drawn by random from appropriate distributions. The distributions of arrival time, distance, travel duration and dwell time were based on subsets of data on light-duty vehicle trips from the 2001 National Household Travel Survey (USFHWA, 2010) contained in the data file DAYPUB.csv. These distributions were estimated as described below.

2.3.2.2.1 Relative numbers of trips by purpose

For estimating numbers of trips by purpose (to work, to home or other), and to estimate arrival time distributions, a subset of trip records for light-duty vehicles was selected from the 2001 NHTS file DAYPUB.csv. This subset consisted of 376,885 records for which

DRVR_FLG = 1,

TRPTRANS = 1, 2, 3 or 4,

STRTHR >=0,

ENDHR >=0 and

TRPMILES > 0.

Trips to home, to work (first arrival of the day) and returning to work (not the first trip to work that day) in the dataset are identified by the field WHYTRP01, as listed in Table 2.3. The distribution of arrival times for all trip records, weighted by WTTRDFIN, is shown in Figure 2.5. The total number of arrivals (vehicle trips by LDVs) in 2001 is estimated to be 2.275 x 10^{11} trips for the year. The arrival time distributions for trips to home, to work for the first time in the day, and for subsequent returns to work are shown in Figure 2.5. The weighted number of vehicle trips to work, trips back to work, trips to home and all trips are listed in Table 2.7.

Table 2.7. Numbers of vehicle trips in 2001for trips of different purposes, in light-duty vehicles, as estimated from the 2001 NHTS.

WHYTRP01	number of vehicle trips in 2001	fraction of vehicle trips
1 = to home	7.71 x 10^{10}	0.339
11 = to work (first time that day)	2.44 x 10^{10}	0.107
12 = return to work	5.63 x 10^{9}	0.025
all trips	2.28 x 10^{11}	1.0

These numbers were used to set several parameters in the model that govern numbers of trips. The fraction of driver agents who work was set to 0.7 to give a fraction of trips to work of about 0.12, and the fraction of workers who could travel at lunch hour was set to 0.5 to result in a fraction of trips returning to work close to 0.015.

The fraction of optional trips generated that were to home was set to 0.3 to give a fraction of the total trips driven by agents to home close to 0.33. Not all optional trips generated to home are taken by driver agents, since if a driver adds an optional trip to home to his list for the day immediately before or after another trip to home, then the two trips are consolidated into one trip with a dwell time set to the combined dwell times of the two trips. That is, the driver is assumed to remain at home for the total time of the two trips to home. Also, if an agent adds no optional trips and has only a trip to home on his routine trip list, then it is assumed that the agent stayed home all day, and his one trip to home is assigned a zero distance, and this trip is not counted in any trip statistics.

2.3.2.2.2 Routine trip arrival times

For driver agents who work, the arrival time at work for each agent was chosen at random from the distribution of arrival times for trips to work (WHYTRP01 = 11) in the 376,885 record subset of the 2001 NHTS trip data described in Section 2.3.2.2.1. Arrival times for these trips, and of trips to home

(WHYTRP01 = 1), to return to work (WHYTRP01 = 12) and for all trips were estimated by totaling the weighted number of trips of each purpose for each arrival hour (ENDHOUR). The distributions estimated are shown in Figure 2.5. Arrivals at work shown in Figure 2.5 include both trips to work and trips returning to work (WHYTRP01 = 11 or 12).

A fraction of the driver agents who work have a lunch hour in their routine schedule, that is, a time interval is left open for these agents to schedule optional trips during their lunch hour. Only agents who work a full shift and who first arrive at work earlier than 6:30 pm are allowed have such a time gap for lunch hour. This was to make agents' arrivals at work consistent with the observation that there are very few arrivals back to work (WHYTRP01 = 12) earlier than 6:00 am in the 2001 NHTS data, as can be seen in Figure 2.5. In this figure, the number of vehicle trips per day per vehicle estimated from the 2001 NHTS is shown as points, and model results are shown as lines. The 2001 NHTS distributions and model simulation distributions are in reasonable agreement.

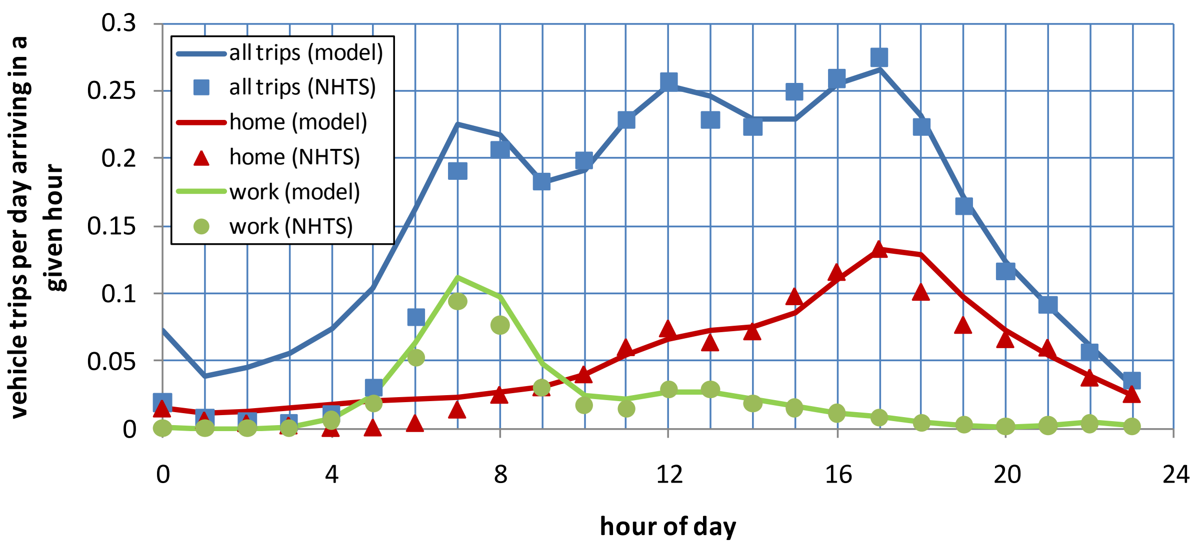

Figure 2.5. Arrival time distribution; number of vehicle trips per vehicle per day, as estimated from the 2001 NHTS (points) and as calculated by the model, (lines).

The arrival time for a driver agent's routine trip is a nominal arrival time. When a driver schedules his trips each day, a random increment from –0.5 to 0.5 hour is added to the routine arrival time in order to give some day-to-day variability in arrival times. Once this increment is added, the arrival time is further adjusted as necessary to prevent the trip from departing before the end of an earlier trip, if any, or to prevent the arrival time from occurring on the day before or day after (for trips arriving near midnight).

2.3.2.2.3 Routine trip dwell times

Driver agents who work full time are assumed to dwell at work for 7.5 to 8.5 hours plus a lunch hour, which ranges from 0.45 to 1.5 hours. A fraction of driver agents is assumed to work part time, and they dwell at work 4 hours, nominally, with up to 0.5 hour variability from day to day. This fraction was set to 0.2 to match the arrival time distribution for trips to work and trips to home, as shown in Figure 2.5. These dwell times were nominal times. When a commute trip is added to a driver agent's list of trips for a day, a random increment from –0.5 to 0.5 is added to the dwell time for that day, in order to give some day-to-day variability.

Drivers are assumed to spend some nominal dwell time at home each day. For drivers who work, on workdays this dwell time is a random number between 6 and 14 hours. The arrival time for the routine trip home is chosen at random such that the time at the end of the dwell at home is not later than the time the driver routinely departs for work the next day, or such that the driver would arrive between midnight at 4:00 am. This is the least restrictive manner for choosing an arrival time consistent with the observation that very few drivers arrive at home between midnight and 4:00 am. On days off, the arrival time at home is randomly chosen to be within 2 hours of the routine arrival time at home on work days, and the dwell time is randomly chosen to be within 80 to 110% of the dwell time at home on work days. This assumes that workers tend to stay home during approximately the same hours on days off as they do on workdays.

For non-workers (driver agents with no commute trips), a routine trip to home is defined to block out the time when each of these agents is routinely at home each day. The arrival times for non-workers are chosen from a normal distribution with a mean of 18 (6:00 pm) and a standard deviation of 2 hours, truncated to be no earlier than 0.01 hour past midnight or 0.01 hour before midnight. Dwell times at home are randomly chosen to be within 80% to 110% of 8 hours (6.3 to 8.8 hours).

2.3.2.2.4 Optional trip arrival times

When a driver agent decides to take add an optional trip to his list of trips for the day, a trip is generated. The arrival time is chosen from a bimodal distribution with peaks at noon and one half-hour later than the driver agent's departure time for his routine trip home. This assumes that many drivers take trips in the middle of the day or on their way home. The arrival time was picked for 50%

of the optional trips from a normal distribution centered on 12 (noon) with a standard deviation of 3 hours, and for the other 50% from a normal distribution centered on the departure time for the agent's routine trip home with a standard deviation of 4 hours. This distribution resulted in the arrival time distribution of trips of all purposes matching the arrival time distribution seen in the 2001 NHTS, as seen in Figure 2.5.

2.3.2.2.5 Optional trip dwell times

The dwell times of optional trips was assumed to be a truncated log-normal distribution, and was chosen as

$$dwell = e^{r} \tag{2.17}$$

where r = random number picked from a normal distribution centered on 0.1, with a standard deviation of 1.5, truncated so that $-2.5 < r < 2.0$.

This was chosen to give a distribution skewed to shorter times, but limited dwell times to between 5 minutes and about 7.5 hours.

2.3.2.2.6 Trip distances

The distribution of trip distances in the 377,115 record subset of the 2001 NHTS described in Section 2.3.1, (vehicle trips driven in cars, vans, SUVs or pickups for which trip distance > 0), was determined by counting the weighted number of trips in different distance ranges. Totaling the weight WTTRDFIN for this subset gave an estimate of 2.27638×10^{11} vehicle trips per year (for cars, vans, SUVs, and pickups), and the total of the product of the weight and distance for each trip in the subset gave an estimate of 2.201792×10^{12} vehicle-miles per year for these same vehicle types. The ratio gives an average trip distance of 9.672 miles per vehicle trip. The distribution of vehicle trips by trip distance range for this subset is shown in Figure 2.6, and the distribution of the vehicle-miles for trips in each trip distance range is shown in Figure 2.7.

From the same subset, the distribution of trip distances for trips to work (WHYTRP01=11) was estimated and the fraction of trips to work by trip distance is shown in Figure 2.8.

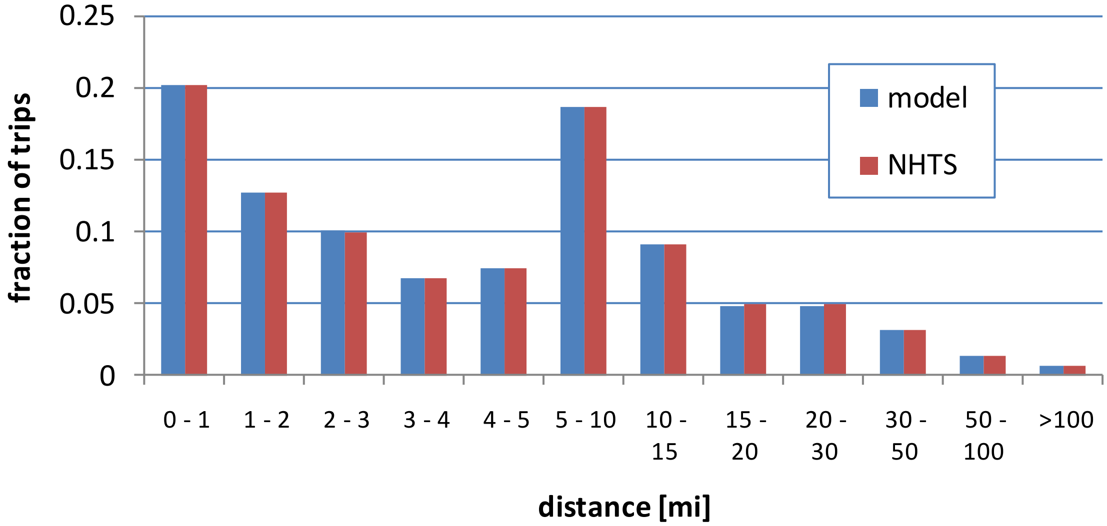

Figure 2.6. Trip distance distribution; fraction of vehicle trips per vehicle with a trip distance within the given range, as estimated from the 2001 NHTS (red) and as calculated by the model, (blue).

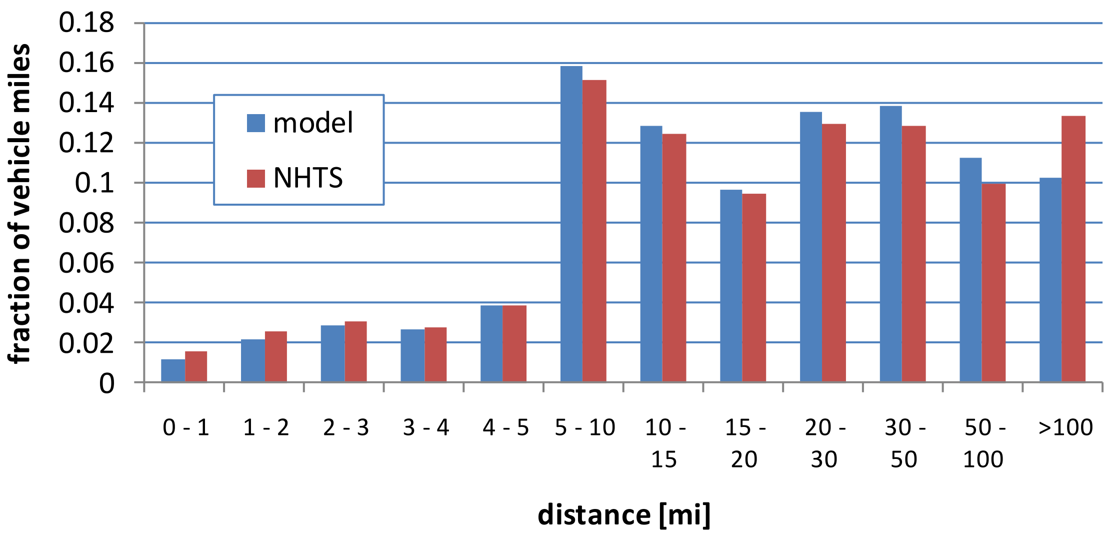

Figure 2.7. Trip vehicle-mile distribution; fraction of vehicle-miles per vehicle for trips with a trip distance within the given range, as estimated from the 2001 NHTS (red) and as calculated by the model, (blue).

In the model, driver agents who worked had a distance for their routine trip to work drawn from a truncated normal distribution. The underlying normal distribution was centered on 0.3 miles with a standard deviation of 15 miles, but was truncated with a minimum distance of 0.25 miles and a maximum of 100 miles. This assumes no workers living within 0.25 miles of their place of work drives to work, and no worker drives more than 100 miles to work. This gave a distance distribution having an average of 12.2 miles, distributed as shown in Figure 2.8. The distance to work distribution used in the model has fewer long commutes (greater than 30 miles), but gives a good approximation of the distribution of the majority of trips to work.

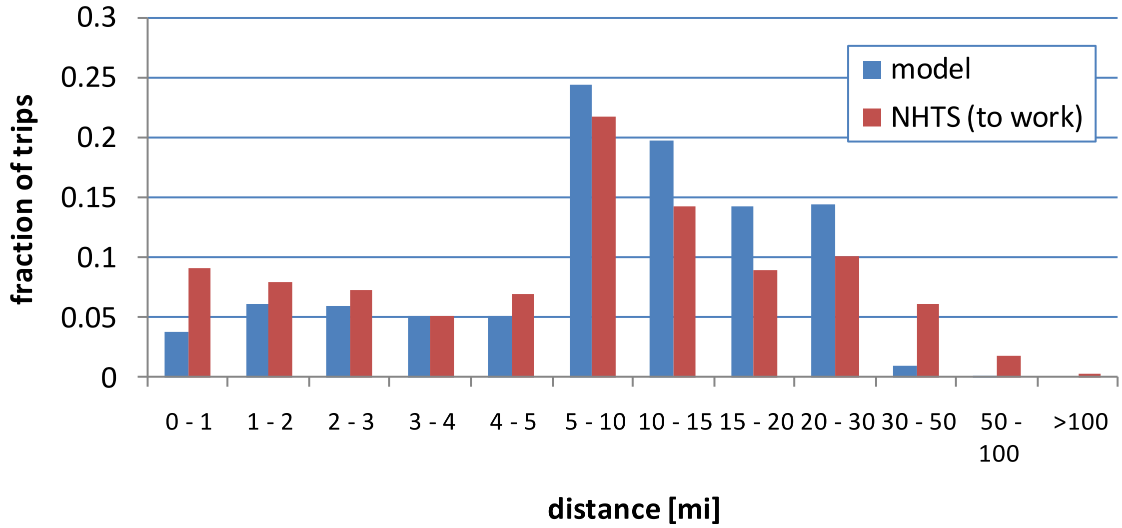

Figure 2.8. Distribution of trip distances for trips to work; fraction of vehicle trips per vehicle with a trip distance within the given range, as estimated from the 2001 NHTS (red) and as predicted by the model, (blue).

For optional trips, as each trip was generated, a distance was picked from a distribution defined at model initiation. This input distance distribution was set so that the resulting distribution of trip distances matched the distribution estimated from the 2001 NHTS data, as shown in Figure 2.6. The trip length distribution of trips driven by agents differs from the input distribution because as optional trips are generated, trip distances are adjusted as described in Section 2.2.1.2.

The same input trip distance distribution was used for routine trips to home for non-working driver agents, so that the distance for all non-commute trips were drawn from the same distribution.

2.3.2.2.7 Trip travel times

For all trips, once a trip distance was determined, the travel time in hours was calculated from the trip distance and average speed. The average speed was taken to be correlated with distance in mi/hr.

Here, for long trips, the average speed, U, was a uniformly distributed random value between 35 and 50 mi/hr, and for short trips, the average speed was proportional to the square root of the distance.

$$average\ speed = \min\left(10\sqrt{distance}, U\right) \tag{2.18}$$

These parameters were chosen to approximate the distribution of trip travel times in a subset of trips from the 2001 National Household Travel Survey (2001 NHTS, USFHWA, 2010). Trips records from the 2001 NHTS data file "DAYPUB.csv" for household vehicles (car, van, SUV or pickup truck) driven by the survey respondent, and for which the recorded start time was greater than or equal to zero, and for which the dwell time and trip distance were greater than zero. This subset contained 286,392 records.

2.3.3 Vehicle parameters

Vehicles were assigned city and highway fuel consumption rates (the reciprocals of city and highway fuel economy or mileage values). PHEVs were also assigned an electricity consumption rate (kWh/km), a charge-depleting range, and were assumed to charge at 1.2kW. All PHEVs were assumed to have a series power train configuration, and traveled under electric power until the usable battery energy was depleted, after which the vehicle travels only under gasoline power. Fuel consumption by conventional vehicles and the gasoline-powered portion of PHEV trips was estimated using the average speed for each trip and the effective fuel consumption, $F_{c,eff}$, which was taken to be a combination of the city and highway values, as given by equations (2.6) and (2.7).

The fleet of vehicles is a mix of eight different market segments, with high, medium or low performance and size small, medium or large (there were no large, low-performance vehicles). For each segment, there was a conventional vehicle model with the fuel economy values listed in Table 2.8, and a comparable PHEV having the electrical efficiencies and charge-depleting range shown. The useful battery capacity is the amount of energy available between recharges, i.e., the total battery capacity times the allowable swing in energy state of charge. The values chosen for conventional vehicles are representative of the U.S. light-duty fleet in recent years and are consistent with the mix of vehicles modeled by Sullivan et al (2009). Values for PHEV electrical efficiency, charge-depleting range and useful battery capacity are consistent with values for PHEVs assumed in earlier studies (EPRI, 2001; Stephan and Sullivan, 2008). Fuel economy values and electricity consumption rates were not adjusted for differences between fuel economy test cycle conditions and real-world driving condition; vehicles were assumed to have the fuel economy and electricity consumption rates given in Table 2.8 under actual driving conditions.

Table 2.8. Fuel economy and electric efficiency values assigned to vehicles

			conventional		PHEV				
segment	size	perform	fuel econ, city [mpg]	fuel econ, hwy [mpg]	fuel econ, city [mpg]	fuel econ, hwy [mpg]	electricity consumption [kWh/km]	charge-depleting range [mi]	useful batt cap [kWh]
1	small	low	27	34	48	48	0.162	10	2.61
2	small	med	24	32	48	48	0.162	10	2.61
3	small	high	22	29	48	48	0.186	20	5.99
4	med	low	23	30	40	40	0.186	10	2.99
5	med	med	20	28	40	40	0.186	20	4.18
6	med	high	18	24	40	40	0.149	40	9.59
8	large	med	18	24	36	36	0.286	10	4.60
9	large	high	17	22	36	36	0.286	20	9.20

Vehicles were assigned to drivers with a probability depending on the driver's income, with higher income drivers having a higher probability of owning a large, high-performance vehicle, and lower income drivers having a higher probability of owning a small, low-performance vehicle. These probabilities were chosen on the basis of the model by Sullivan et al (2009). Here, brackets for annual, pre-tax, household incomes were defined as low: 0 to $26,000, middle: $26,000 to $121,000, and high: $121,000 and higher. These represented the lowest 30%, the middle 60% and the top 10% of the driver agents by income. The probabilities used for each income bracket are listed in Table 2.9.

The fraction of vehicles that are PHEVs was a user-settable input parameter. It was assumed that PHEVs would not be owned by drivers in the lowest 30% income bracket (less than $26,000/yr) unless PHEVs made up more than 70% of the fleet. That is, at PHEV fractions less than 0.7, all drivers with incomes less than $26,000/yr were assigned a conventional vehicle, and drivers with higher incomes were assigned a PHEV with a probability proportional to the PHEV fraction of the fleet.

Table 2.9. Probability of vehicle ownership for three driver agent income brackets

segment	size	perform	income ≤ \$26,000/yr	\$26,000/yr < income ≤ \$121,000/yr	\$121,000/yr < income
1	small	low	0.4066	0.1302	0.0760
2	small	med	0.2130	0.1500	0.0429
3	small	high	0.1488	0.1272	0.0721
4	med	low	0.0642	0.0466	0.0351
5	med	med	0.0895	0.1612	0.0975
6	med	high	0.0321	0.0988	0.1637
8	large	med	0.0379	0.1592	0.1404
9	large	high	0.0078	0.1269	0.3723

All vehicles were assumed to burn gasoline, and emissions from use of fuel in vehicles were estimated using emissions factors for combustion of fuel and upstream fuel supply. Total fuel cycle greenhouse gas emissions were taken to be 11.185 kg CO_2 eq/gal for gasoline, based on the GREET model (ANL, 2009).

2.3.4 Electricity supplier parameters

2.3.4.1 Electricity generation emissions factors

For 181 electric power plants in Michigan operated by the four utilities, DTE Energy, Consumers Energy, Upper Peninsula Power Company, and Wolverine Power Cooperative, capacity factor data, type of fuel used, and combustion emissions were obtained from the U.S. Environmental Protection Agency's (EPA) Emissions & Generation Resource Integrated Database (EPA, 2007) for year 2005. Upstream emission factors of fuels for nuclear, natural gas, biomass, residual fuel oil, bituminous coal and sub-bituminous coal or lignite power plants were obtained from the U.S. Life Cycle Inventory database (USLCI, 2010).

For these 181 plants, Figure 2.9 shows the greenhouse gas (GHG) emissions as a function of power generated, with no PHEV charging (the factor η of eq (2.8) is unity). Because of the mix of different types of plants and the assumed order of dispatch, the marginal GHG emissions rate, while variable, averages about 900 g CO_2 eq/kWh (combustion + upstream).

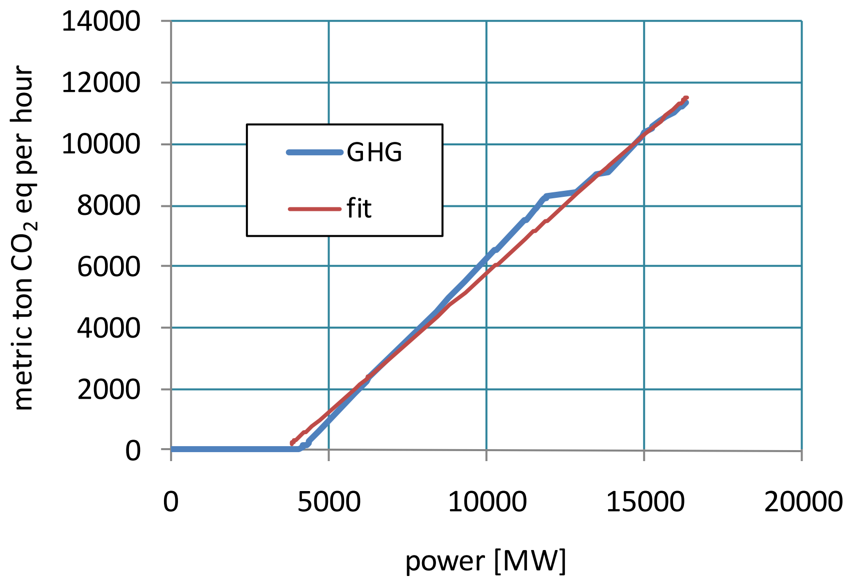

Figure 2.9. Greenhouse gas emissions as a function of power generated for 181 power plants in Michigan. The line shown is a straight line fit to the portion of the curve above a power of 4000 MW.

2.3.4.2 Electricity demand

Hourly electricity demand in Michigan for year 2008 was obtained from the Federal Energy Regulatory Commission Forms 714 (FERC, 2009) for the four electrical utilities in Michigan mentioned in Section 2.3.4.1. This demand was assumed to be independent of the additional demand from PHEV charging and not responsive to electric rate changes. Selected weeks were chosen from the 2008 data to represent the non-PHEV charging demand in various scenarios modeled. This is described in Section 3.1, below.

CHAPTER 3

Projections of PHEV use, energy demand and greenhouse gas emissions

3.1 Scenarios modeled

The DVUD model was used to project changes in vehicle use, fuel and electricity demand, and resulting greenhouse gas emissions under several scenarios in which factors such as PHEV market penetration, charging locations (home or work), electricity price and fuel price were changed. Table 3.1 describes the scenarios modeled and gives the values of different factors used in each scenario.

Table 3.1. Scenarios modeled and factors controlled for each.

	Factor	Gasoline price $/gal	Electricity rate $/kWh	Charging locations	Section
Scenario 1	Fraction of fleet PHEVs 0 – 0.5	2.50	0.10	home	3.2
Scenario 2	Gasoline price	1.83 – 6.00	0.10	home	3.3
Scenario 3	Electricity rate	2.50	flat rate, 0.1 – 0.3	home	3.4.1
Scenario 4	TOU electricity rates	2.50	peak: 0.20, off-peak: 0.05 peak: 0.15, off-peak: 0.07	home	3.4.2
Scenario 5	Charging locations	2.50	0.10	home, work	3.5.1
Scenario 6	Interruptible electricity	2.50	0.10, charging allowed only during off-peak hours	home	3.5.2
Scenario 7	Average arrival times 1 hr earlier or later	2.50	0.10	home	3.6.1
Scenario 8	Average trip distance shorter or longer	2.50	0.10	home	3.6.2

For most scenarios, five runs were made with 1000 agents. The results for quantities such as vehicle miles traveled, fuel consumption, electricity use, and emissions were averaged over two week periods of the five runs to give an ensemble average, taken to be a representative response to the conditions modeled. This was sufficient to average out run-to-run and day-to-day variability. In some cases, a larger number of runs were made, or quantities were averaged over longer periods so that observed differences were large in comparison with the variability or standard deviations of mean quantities.

Driver income distribution, arrival time and trip distance distributions were kept the same, using the distributions representative of U.S. drivers, as described in Section 2.3.2.1. Vehicle characteristics were held constant, as described in Section 2.3.3, but in some scenarios, the PHEV fraction of the fleet was varied.

Electricity demand in Michigan for year 2008 was obtained from the Federal Energy Regulatory Commission Forms 714 (FERC, 2009) for electrical utilities in Michigan. These included DTE Energy, Consumers Energy, Upper Peninsula Power Company, and Wolverine Power Cooperative. Figure 3.1 shows state-wide demand as a function of time of day for the second week of January 2008, which is typical of moderate-demand weeks during the winter. Demand on Saturday and Sunday is lower than on weekdays.

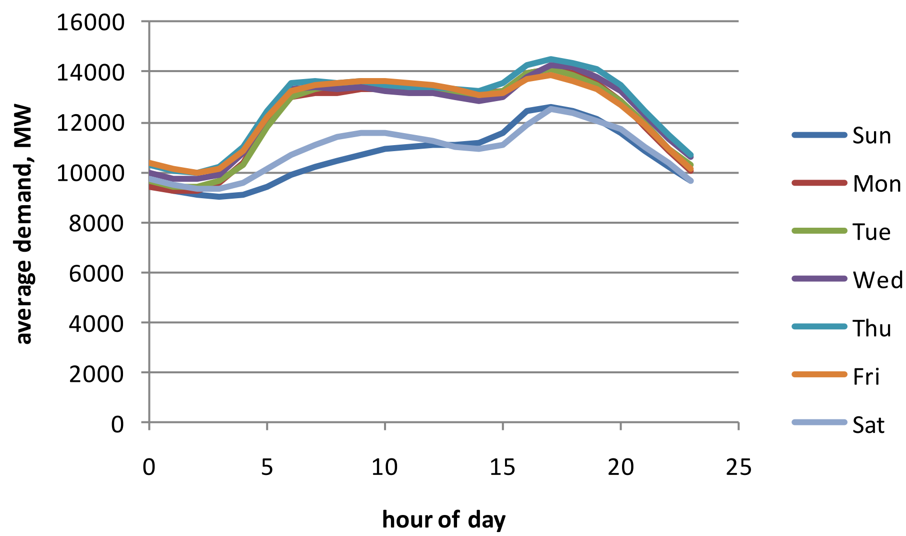

Figure 3.1. Electricity demand as a function of the hour of day in Michigan in the second week of 2008.

For the second week of January, average demand was close to the annual average, and the hourly and daily patterns are essentially the same for both averages. This can be seen by comparing Figure 3.1 with the electricity demand averaged over the year for each day of 2008, as shown in Figure 3.2.

For each of the scenarios modeled, the electricity demand in the absence of PHEV charging was assumed to be the same each week. Demand for Saturdays and Sundays were taken to be the demand reported for Michigan for the Sunday of the second week of January 2008, and the demand for weekdays was taken to be the Michigan demand for the Monday of the second week of January 2008. This is plotted over one week in Figure 3.3. This was used to represent the demand in the absence of PHEVs in several scenarios modeled.

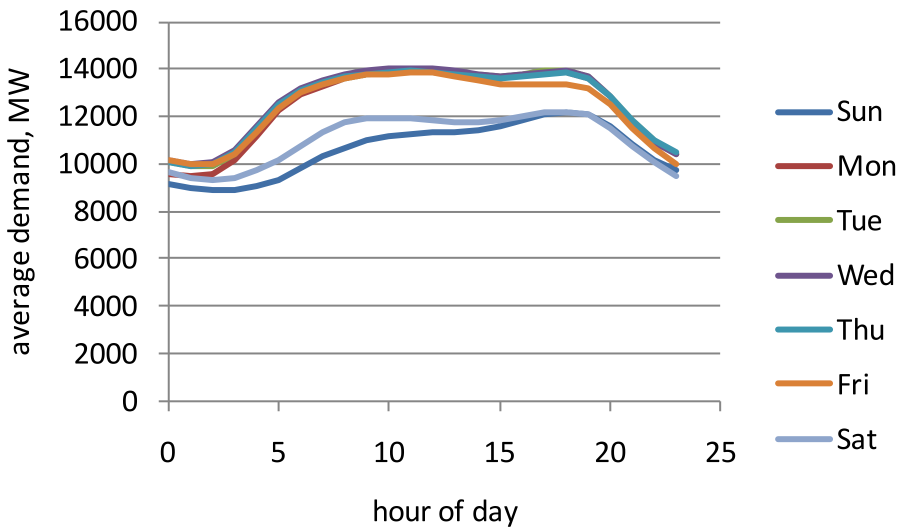

Figure 3.2. Electricity demand as a function of the hour of day in Michigan in year 2008, averaged over each day of the week.

Electricity demand is higher in summer, when air-conditioning and other loads are higher. Figure 3.4 shows the electricity demand in Michigan for the first week of August, 2008, which was one of the highest demand weeks of the year. In several scenarios modeled, demand on Saturday and Sunday were taken to be the demand reported for Michigan for the Saturday of the first week of August, 2008, and the demand for weekdays was taken to be the Michigan demand for Wednesday of the same week. This is shown in Figure 3.3.

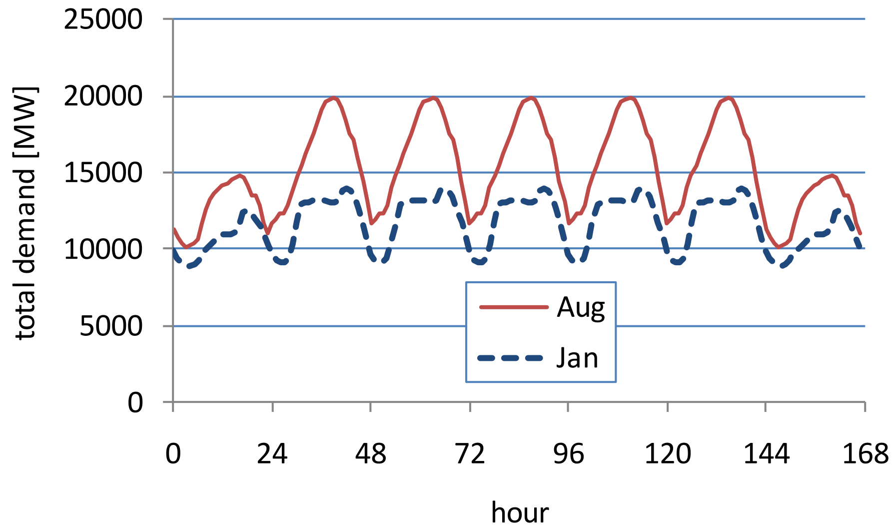

Figure 3.3. Electricity demand in Michigan as represented in the model for a moderate demand week in January and for a high demand week in August. This is the demand with no PHEVs.

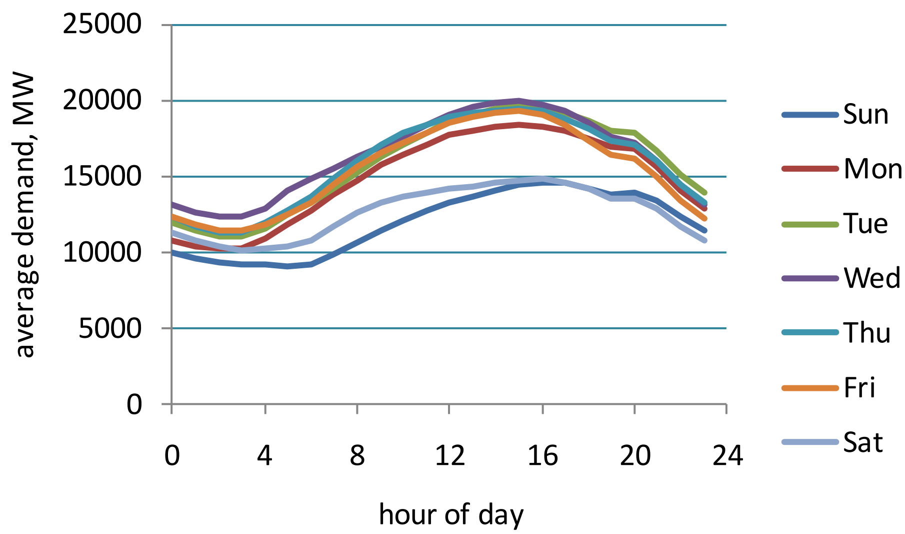

Figure 3.4. Electricity demand as a function of the hour of day in Michigan in the first week of August, 2008.

Electricity demand shown here is site demand, i.e., the electricity consumed by the end user. Electricity generation is larger than demand due to losses during transmission and distribution. A 9% loss was assumed for transmission and distribution (EIA, 2008, p 221).

To represent Michigan, results from the model were scaled to the state's projected energy demand, vehicle-miles traveled, and emissions. As of 2008, there were about 7.3 million passenger vehicles registered in Michigan (Insurance Institute of Michigan, 2009). Results from runs were scaled up by a factor 7,300,000/N_{agents}, where N_{agents} is the number of driver agents.

3.2 Scenario 1: PHEV penetration levels

The vehicle-miles driven, fuel and electricity consumed, and resulting GHG emissions were estimated for the population of Michigan driving a fleet of 7.3 million vehicles with the characteristics as described in Section 2.3.3, but with PHEVs making up a fraction of the fleet ranging from 0 to 0.5. Gasoline price was held constant at $2.50/gal, and the electricity rate was constant at $0.10/kWh.

Average hourly electricity demand projected for PHEV charging at PHEVs fractions from 0 to 0.5 is shown as a function of time of day in Figure 3.5. Demand for each hour was averaged over two weeks for five runs of 1000 driver agents. The demand shown is not for a single day, but for the demand at each hour averaged over two weeks.

In this scenario, driver agents with PHEVs charged their batteries when they arrived home if they intended to stay at home for at least 2 hours. Under these electricity rates and fuel price, PHEVs are less expensive to operate per mile under electric power than under gasoline power, so drivers would always choose to charge their vehicle batteries. Demand for charging is high when most drivers arrive home after approximately 6:00 pm. Demand tapers off after midnight as arrivals decrease and the batteries of plugged-in vehicles reach full charge. Each PHEV model has a given battery capacity, and the state of charge of the batteries of each individual PHEV will vary according to the distance driven since the previous charge, so the time required for each PHEV to complete charging will be different.

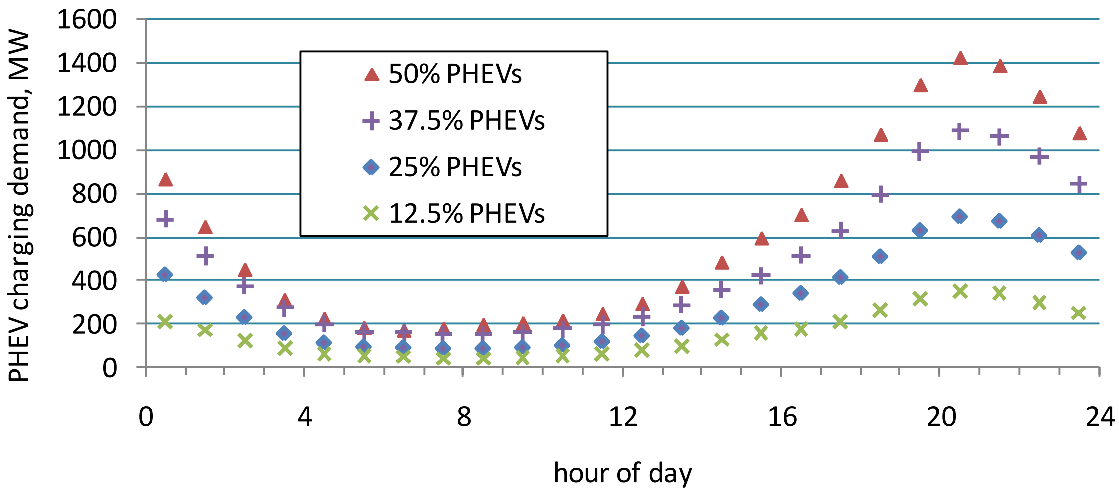

Figure 3.5. Electricity demand for PHEV charging in Michigan with PHEVs making up different fractions of the personal vehicle fleet of 7.3 million vehicles.

The total electricity demand, including PHEV charging was estimated using the non-transportation demand for a moderate-demand week in January and for a high-demand week in August, as described in Section 3.1, In the DVUD model, driving patterns and PHEV charging demand are assumed to be independent of non-transportation electricity demand, so demand for PHEV charging is projected to be the same in January as in August, but total demand and emissions will differ. The total electricity demand for a moderate-demand week in January is shown with and without PHEV charging at 50% PHEV fleet penetration in Figure 3.6. The peak in PHEV charging demand occurs at nearly the same time of day as the peak in non-transportation demand, so at a fleet penetration of 50%, PHEV charging increases the peak demand by about 8.2%. Total electricity demand for a high-demand week in August is shown with and without PHEV charging in Figure 3.7. In this case, the peak occurs in the early afternoon when PHEV charging is not high, so PHEV charging increases the peak demand by only 3.2%, but this is significant, since it represents an increase in the total power requirement and would require an increase in generation capacity or an increase in electricity importation.

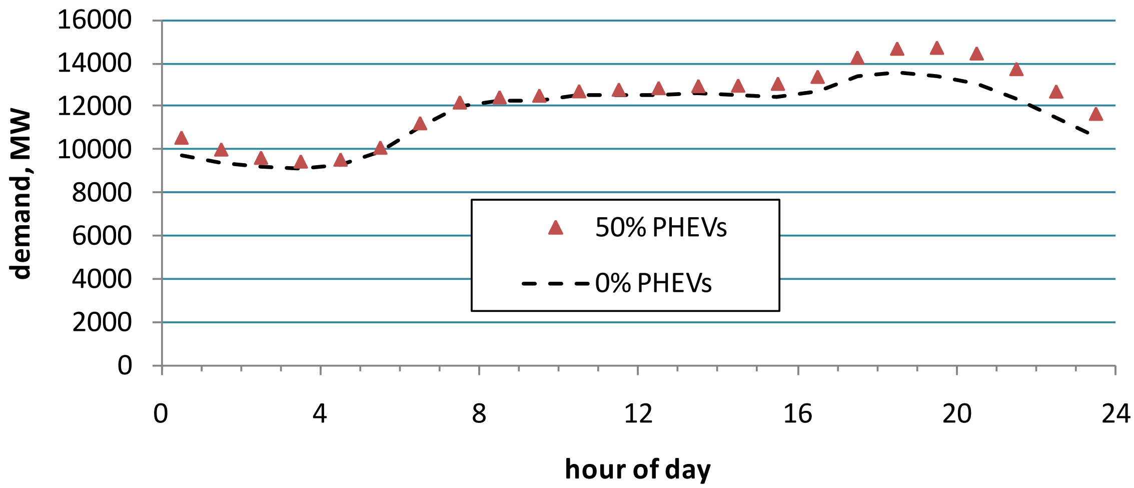

Figure 3.6. Electricity demand in Michigan with and without PHEVs making up 50% of the fleet. Demand with no PHEVs is from a moderate-demand week in January.

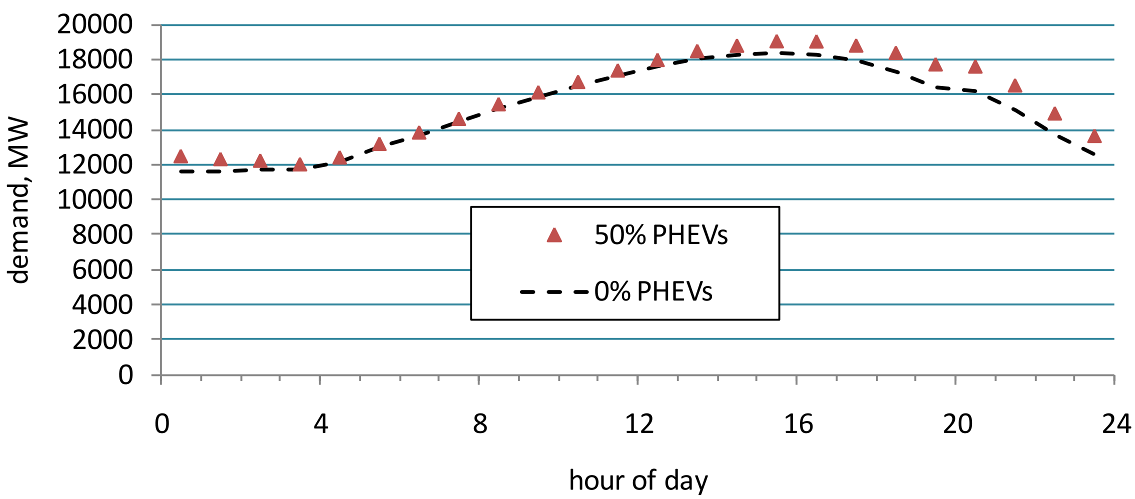

Figure 3.7. Electricity demand in Michigan with and without PHEVs making up 50% of the fleet. Demand with no PHEVs is from a high-demand week in August.

For this fleet of 7.3 million vehicles, gasoline consumption, total fuel cycle GHG emissions from gasoline and total GHG emissions (including tailpipe, electricity generation and fuel supply emissions) in metric tons per day are shown in Table 3.2 for the two cases of January non-transportation electricity demand and August non-transportation electricity demand. Gasoline demand is the same for the two cases, since driving patterns are the same. GHG emissions from electricity generation are nearly the same for the two cases, since the marginal GHG emission rate for MI power plants is not strongly dependent on total power level, at least in the range of electricity demand in these cases. This can be seen in Figure 2.9.

For the August demand case, Figure 3.8 shows GHG emissions for the total fuel cycle, i.e., including both fuel combustion and fuel supply GHG emissions. Also shown are GHG emissions from electricity generation (total fuel cycle) for PHEV charging and gasoline consumption by vehicles in millions of gallons per day. Emissions and gasoline consumption are linear in the fraction of PHEVs in the fleet, as expected. As noted in Table 3.2, GHG emissions for the January case are approximately the same and are not plotted.

Table 3.2. Model predictions of GHG emissions (total fuel cycle) in metric tons per day and gasoline consumption by a fleet of 7.3 million vehicles at different PHEV fractions. GHG from electricity generation are shown for both January and August.

Fraction of fleet PHEV	0	0.125	0.25	0.375	0.50
Gasoline use, total fleet [10^6 gal/day]	11.4	10.4	9.4	8.3	7.3
GHG emissions, gasoline, total fuel cycle [mt/day]	127,900	116,600	104,800	91,800	81,100
August					
GHG emissions, PHEV charging [mt/day]	0	3,400	6,800	10,600	13,581
GHG emissions, total fleet [mt/day]	127,900	120,100	111,600	102,400	94,700
January					
GHG emissions, PHEV charging [mt/day]	0	3,600	6,700	10,200	13,803
GHG emissions, total fleet [mt/day]	127,900	120,200	111,500	102,000	94,900

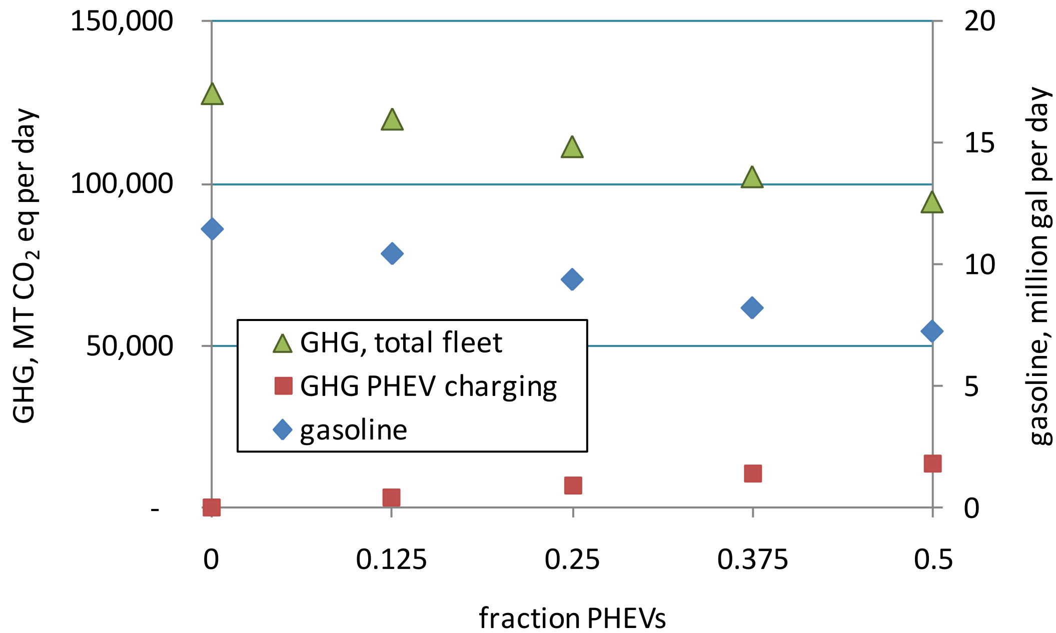

Figure 3.8. Greenhouse gas emissions (total fuel cycle) from vehicles and from electricity generation (GHG, total fleet), GHG emissions from electricity generation (total fuel cycle) for PHEV charging (GHG, PHEV charging), and gasoline consumption per day (gasoline), for a fleet of 7.3 million vehicles with various fractions of PHEVs. Non-transportation electricity demand was assumed to be that of the first week of August.

In these scenarios, driver agents with conventional vehicles averaged 33.1 vehicle-miles per day, while PHEV driver agents averaged 34.6 mi/day. PHEV drivers drove slightly more trips (and more miles) since operating costs were lower than for conventional vehicles. This difference is small (5%), since the elasticity of demand for transportation energy is small, as discussed in Section 2.3.2.1.

For PHEVs of each charge-depleting range the fraction of vehicle miles driven electrically was calculated, and these are shown in Table 3.3.

Table 3.3. Fraction of vehicle-miles driven electrically by PHEVs of different charge-depleting ranges.

Charge-depleting range [mi]	fraction of miles driven electrically
10	0.321
20	0.450
40	0.764

The fraction of vehicle-miles drivers travel electrically is compared with estimates of this fraction by Samaras and Meisterling (2008), Kromer and Heywood (2008) and Vyas et al. (2009) as a function of PHEV charge-depleting range in Figure 3.9. While the fraction calculated from the DVUD model is at the upper end of the range of estimates by others, it has a similar dependence on charge-depleting range and as such is considered to be in reasonable accord with those results.

The fraction of miles driven electrically, f_{elec}, varied widely among PHEV drivers with the same charge-depleting distance. The distribution of this fraction for drivers of PHEVs with 10, 20 and 40 mile charge-depleting range are plotted in Figure 3.10. Much of this variability is presumably due to the agent-to-agent and day-to-day variability of trips driven. Some is likely due to the manner in which vehicles were chosen, which was correlated with income, but not with driving patterns. Additionally, some variation may be due to the fact that in the DVUD model, driver agents always use the same vehicle, whereas many actual households own more than one vehicle, and drivers can often choose their most economical vehicle for a given trip. If driver agents were able to choose vehicles that are more efficient, given their average driving patterns, the utilization of vehicles, as measured by f_{elec}, might be slightly higher on average, and might also be slightly more uniform, i.e., more tightly clustered about the mean, than the results obtained from the model. The fact that the values for f_{elec}, calculated from the model are consistent with estimates from other work indicates that the simplifying assumptions made about driver vehicle choice do not strongly bias the estimates of f_{elec} from the model.

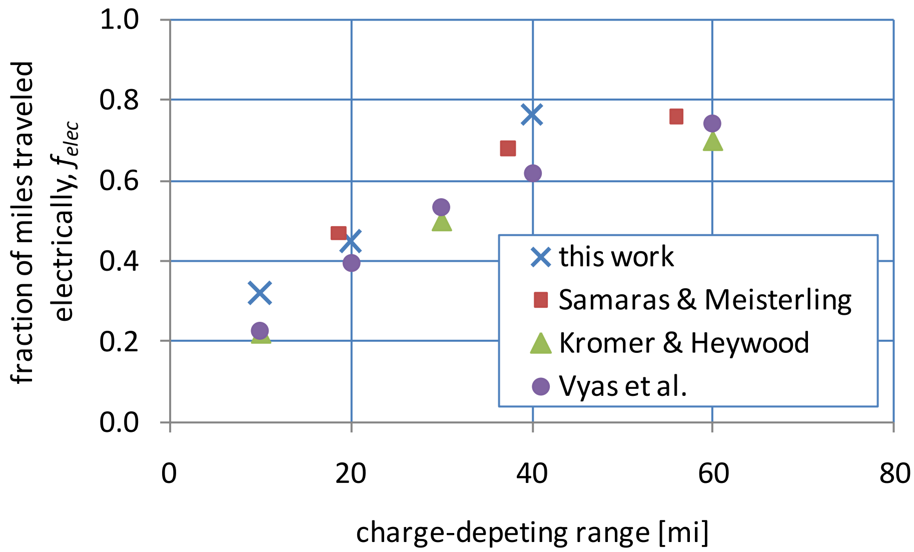

Figure 3.9. Fraction of miles traveled electrically, f_{elec}, by PHEVs having different charge-depleting distances, as calculated from the model (this work) and as estimated by others.

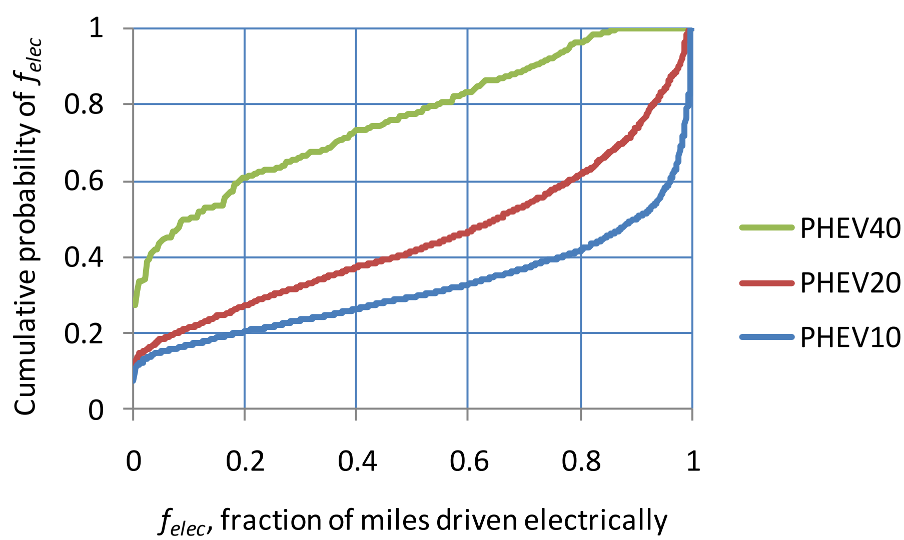

Figure 3.10. The cumulative distribution of the fraction of PHEVs traveling a given fraction of miles electrically f_{elec}, for PHEVs having charge-depleting ranges of 10, 20, and 40 miles.

The average on-road fuel economy (total PHEV-miles per gallon) and GHG emissions calculated by the DVUD model for the conventional vehicle and PHEV fractions of the fleet are listed in Table 3.4. GHG emissions are shown for both January and August. They are nearly the same (within 1.5%), since the marginal emission rate from electricity generation is nearly constant. No degradation of PHEV efficiency with ambient temperature was accounted for. In reality, the efficiency of PHEVs may depend on ambient temperature, since the use of air-conditioning and other accessories and the efficiency of the battery and associated electronics will likely be temperature dependent.

Table 3.4. Model results for on-road average fuel economy and GHG emissions (total fuel cycle) per mile for conventional vehicles and PHEVs in scenarios with different fractions PHEVs. GHG emissions for both January and August are shown.

Fraction of fleet PHEV	average conventional vehicle fuel economy [mi/gal]	average PHEV fuel economy [mi/gal]	GHG per conventional vehicle-mile [g/mi]	GHG per PHEV-mile, August [g/mi]	GHG per PHEV-mile, January [g/mi]
0	21.3	-	530	-	
0.125	21.4	65.5	522	282.0	286.2
0.25	21.7	64.3	516	281.3	279.9
0.375	22.0	65.1	509	284.9	281.1
0.50	22.4	64.4	500	280.8	282.5

The average fuel economy shown in Table 3.4 is the total fuel consumed per total vehicle miles driven in the simulation, by either the conventional vehicles or by the PHEVs in the fleet. In these scenarios, as the PHEV fraction of the fleet increased, the remaining conventional vehicle fleet was very slightly more fuel-efficient (about 5% as the PHEV fraction increased from zero to 50%). As described in Section 2.3.3, PHEVs were assumed to initially penetrate vehicle market segments preferred by high and middle income drivers. It was also assumed that high and middle income drivers tend to drive larger, higher-performance vehicles, with fuel economies lower than the vehicles preferred by low income drivers. Therefore, as PHEVs initially penetrate the market, they tend to displace low fuel economy conventional vehicles on average, while at high market penetration, they displace more conventional vehicles with average fuel economy. The effect is very small, since vehicle preferences are not hard-and-fast rules, they are merely tendencies, and not all high income drivers drive vehicles with low fuel economy. PHEV drivers, at least early adopters, may tend to be more conscious of fuel economy than most drivers. However, if PHEVs achieve high levels of market penetration, then the population of PHEV owners will comprise a significant fraction of the entire vehicle owner population, and their preferences will more closely resemble the preferences of the vehicle owner population at large, rather than those of early adopters.

As the fraction of PHEVs in the fleet is increased, the average number of trips per day increased very slightly, since with lower operating costs, PHEV drivers tend to drive slightly more than drivers of conventional vehicles. Neither the arrival time distribution nor the trip distance distribution changed, as expected. No change in these distributions should be expected with very small changes in the average number of trips.

In Scenario 1, it is seen that replacing conventional vehicle with PHEVs can reduce fuel consumption, and, even with a mix of power plant as coal-intensive as the plants in Michigan, PHEVs can reduce GHG emissions. Fuel savings depend on the fraction of vehicle miles driven electrically, which depends on the charge-depleting range of the PHEV, but is also highly variable due to the diversity of distances driven by different agents. This variability makes it difficult to estimate fleet-wide energy and emissions reductions without trip-level details of driving patterns. This is because the energy consumption and emissions from PHEVs depend on the fraction of miles driven electrically, which must be estimated using approximate methods when trip-level details are not available. However, estimates of the average fraction of miles driven electrically, f_{elec}, estimated using the DVUD model that does use trip-level details are fairly consistent with estimates of previous work based on trip distance distributions from travel surveys.

3.3. Scenario 2: Gasoline price

The response of a population of drivers with 50% of the vehicles PHEVs to changes in gasoline prices was examined. The gasoline price was set initially to $1.83/gal and was increased by $0.50 increments every 30 days up to $3.33/gal. All drivers were assumed to pay a flat electricity rate (independent of demand and time of day) of $0.10/kWh. At this electricity rate, if fuel prices are set much lower than $1.83/gal price, the drivers of the least electrically-efficient PHEVs will find it cheaper to travel under gasoline power and will not travel electrically, i.e., they will not charge their vehicle batteries. This is discussed in Section 3.4.1, below (Scenario 3), in which driver responses to high electricity rates and low gas prices are investigated, including cases in which drivers find it more economical to not charge their batteries. In Scenario 2, gasoline prices are high enough that PHEV drivers choose to travel electrically when possible, and their response is to change the average number of trips they drive per day.

With 50% of the fleet PHEVs, as gasoline price increased, the average number of trips decreased, as expected. The change in number of trips per day was small, and similar in magnitude to the response of the fleet consisting of all conventional vehicles, discussed in Section 2.3.2.1, above. Figure 3.11 shows the average number of trips per day for the PHEV drivers and the conventional vehicle drivers as a function of the price of gasoline. Figure 3.12 shows the vehicle-miles traveled per day for the same two populations of drivers. Conventional vehicle drivers showed a higher response, which is expected, since the cost per mile of travel in a conventional vehicle is higher than that in a PHEV, and conventional vehicle drivers spend more per mile on gasoline than do PHEV drivers. Even though conventional vehicle drivers have the same sensitivity to transportation energy spending per mile as PHEV drivers, all of their transportation energy costs are proportional to the price of gasoline, whereas only a portion of PHEV drivers' transportation energy costs are for gasoline.

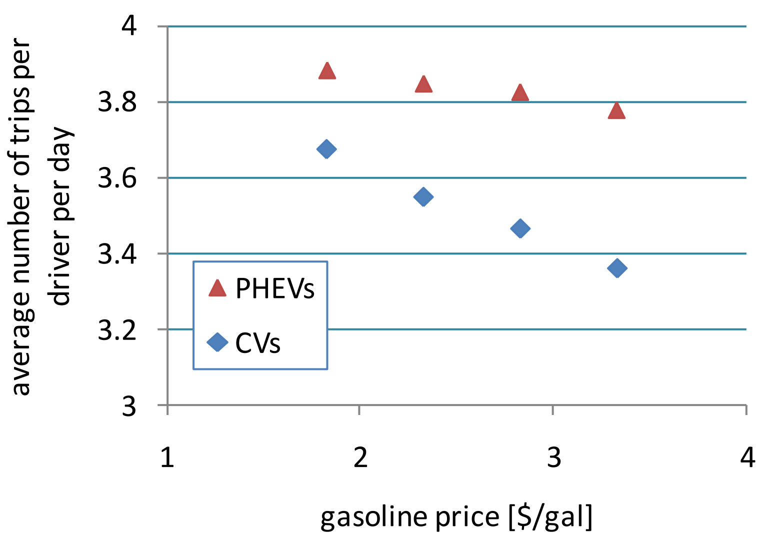

Figure 3.11. The average number of trips per day per vehicle for PHEV drivers (triangles) and conventional vehicle (CV, diamonds) drivers as a function of the price of gasoline.

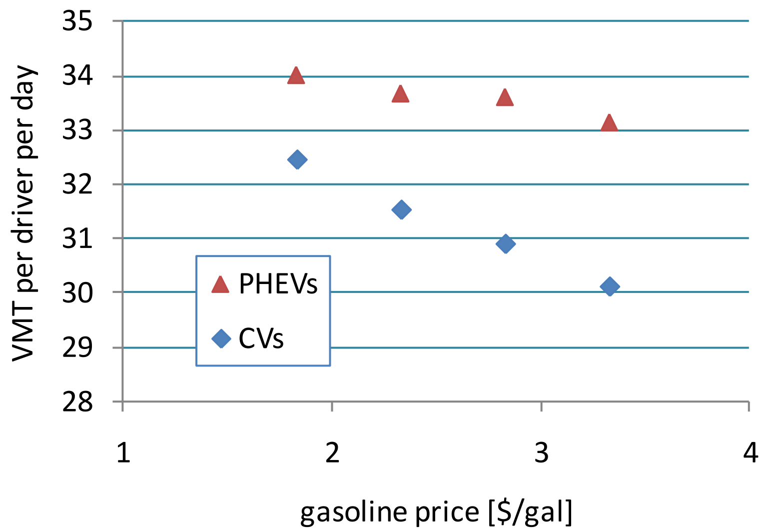

Figure 3.12. The average number of vehicle-miles per day per vehicle for PHEV drivers (triangles) and conventional vehicle (diamonds) drivers as a function of the price of gasoline.

The model projects that PHEV drivers, with a lower cost per mile, will drive slightly more vehicle-miles than conventional vehicle drivers. At gas prices between $1.83/gal and $3.33/gal the additional driving is small, approximately 5 to 10%, due to the low sensitivity of drivers to operating costs.

For each set of drivers, the sensitivity to the price of gasoline, in terms of average number of trips per day and volume of gasoline consumed were calculated. Figure 3.13 shows the gasoline price sensitivity of the average number of trips per day driven by the PHEV drivers and by the conventional drivers in the fleet as a function of driver income. Figure 3.14 shows the price sensitivity of the volume of fuel consumed per time for drivers of conventional vehicles and PHEVs. These plots show the expected dependence on driver income, as discussed in Section 2.3.2.1. Since at 50% fleet penetration, PHEVs are assumed to be purchased only by middle- or upper-income drivers, no drivers with incomes less than $26,000/yr drive PHEVs.

The sensitivity of PHEV drivers to fuel price increase is generally lower than that of conventional vehicle drivers. This is expected, since PHEVs are more fuel efficient, and PHEV drivers’ operating cost per mile are less affected by changes in gasoline prices than the costs of CV drivers.

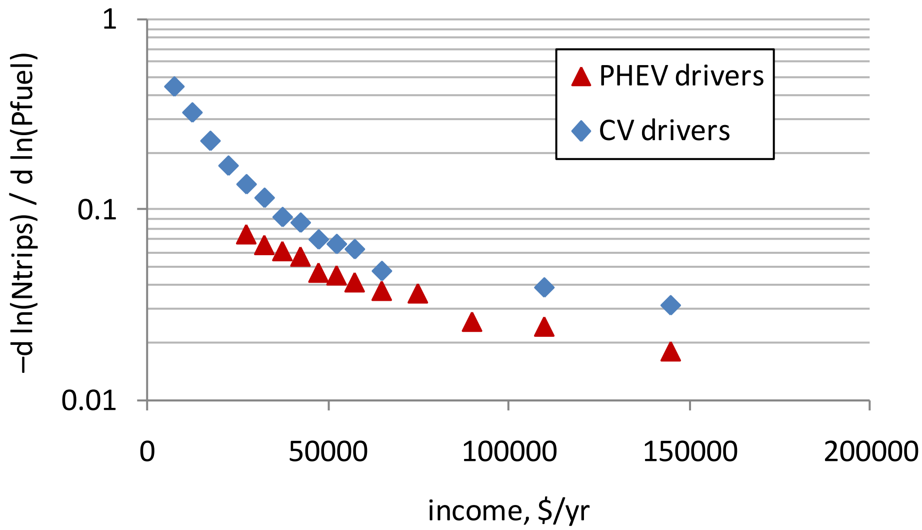

Figure 3.13. Sensitivity of the average number of trips per day to changes in the price of gasoline by PHEV (triangles) and by conventional vehicle drivers (diamonds), as a function of driver annual income.

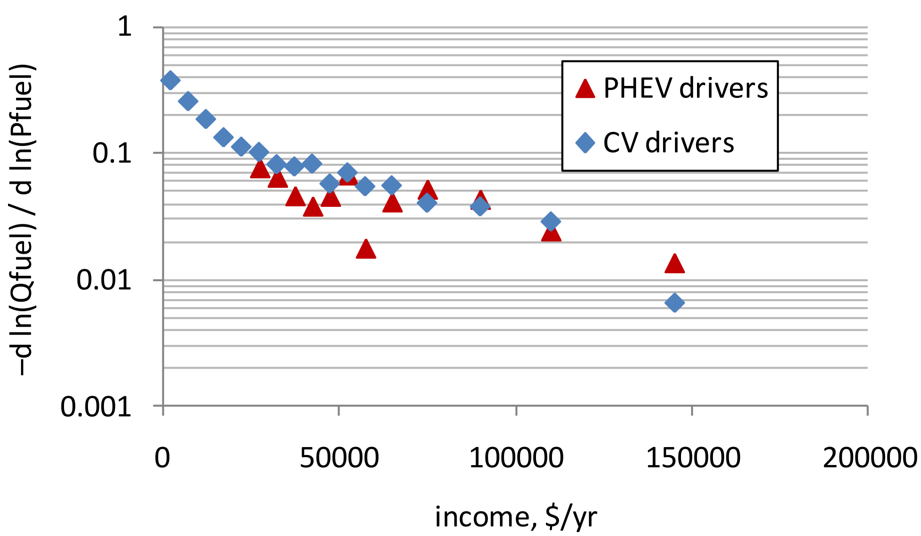

Figure 3.14. Sensitivity of the rate of gasoline consumption to changes in the price of gasoline by PHEV (triangles) and by conventional vehicle drivers (diamonds), as a function of driver annual income.

Figure 3.14, showing the response in terms of change in fuel consumption is more scattered than the response in terms of the number of trips (Figure 3.13) since the drivers respond to operating cost by changing the number of trips, not by choosing to consume less fuel. The fuel consumed depends on distance driven, average speed, and vehicle fuel economy, and the diversity of these factors among the driver population increases the variability of the change seen in fuel consumed. The trend is clear, however, that PHEV drivers are less exposed to changes in gasoline prices and will tend to alter their driving less in response to a change in gasoline price than conventional drivers.

At typical fuel and electricity prices, PHEVs are less expensive to operate per mile than conventional vehicles. The cost savings of operating a PHEV vs. a conventional vehicle was estimated for each PHEV driver, based on the vehicle parameters listed in Table 2.8, in Section 2.3.3, and based on the trips driven. The operating cost savings, *S/wk*, in dollars per week, were estimated by PHEV drivers as

$$S/wk = CV_{op} - PHEV_{op} \tag{3.1}$$

where

CV_{op} is the weekly operating cost (fuel) for a conventional vehicle

$PHEV_{op}$ is the weekly operating cost (fuel) for a comparable PHEV

and

$$CV_{op} = \frac{(VMT/wk)(P_{fuel})}{E_{fuel}^{CV}} \tag{3.2}$$

where

VMT/w_p is the weekly vehicle-miles traveled,

P_{fuel} is the fuel price,

E_{fuel}^{CV} is the conventional vehicle combined fuel economy, $= \frac{2}{\frac{1}{E_{city}}+\frac{1}{E_{hwy}}}$ (3.3)

and

$$PHEV_{op} = Q_{fuel}P_{fuel} + Q_{elec}P_{elec} \tag{3.4}$$

where

Q_{fuel} is the quantity of fuel consumed weekly,

Q_{elec} is the quantity of electricity consumed weekly, and

P_{elec} is the electricity rate.

For the PHEV driver, the quantities of fuel and electricity depend on the vehicle miles driven and the fraction of those miles driven electrically, f_{elec},

$$Q_{fuel} = \frac{(VMT/wk)(1-f_{elec})}{E_{fuel}^{PHEV}} \quad (3.5)$$

$$Q_{elec} = (VMT/wk) f_{elec} C_{elec} \quad (3.6)$$

where

E_{fuel}^{PHEV} is the fuel consumed by the PHEV per mile in charge-sustaining mode,

C_{elec} is the electricity consumed by the PHEV per mile in charge-depleting mode,

So the weekly operating cost savings, from eq (3.1) may be written

$$S/wk = (VMT/wk)\left[\frac{P_{fuel}}{E_{fuel}^{CV}} - \frac{(1-f_{elec})P_{fuel}}{E_{fuel}^{PHEV}} - f_{elec}C_{elec}P_{elec}\right] \quad (3.7)$$

Per mile operating cost savings are given by

$$\frac{S}{VMT} = \frac{P_{fuel}}{E_{fuel}^{CV}} - \frac{(1-f_{elec})P_{fuel}}{E_{fuel}^{PHEV}} - f_{elec}C_{elec}P_{elec} \quad (3.8)$$

As can be seen from eq (3.7), the weekly cost savings are determined in part by the vehicle fuel economy and electrical efficiency, but are proportional to the vehicle miles traveled per week and are sensitive to the fraction of vehicle-miles driven electrically, f_{elec}.

The fraction of vehicle-miles driven electrically depends on each driver’s trips and frequency of charging, as well as the charge-depleting range of the PHEV. Statistics were collected from 5 runs with 1000 agents each, with 50% PHEVs to examine correlations between some of these variables. The correlation coefficients between weekly cost savings, operating cost, vehicle-miles electrically per week, and fraction of vehicle miles electric and other variables are shown in Table 3.5.

It should be noted that the operating cost savings estimated here are highly uncertain since the efficiencies of the comparable conventional vehicles assumed (Table 2.8) may not be representative of fuel efficiencies of future conventional vehicles. Conventional vehicle efficiencies will increase in the future due to increased CAFE standards, but how much they will increase will depend on consumer demand for fuel efficient vehicles and the replacement rate for vehicles. Consumer demand, as well as the operating cost savings, will depend on the future price of gasoline. Future fuel prices are highly uncertain.

Table 3.5. Correlation coefficients estimated from statistics on driver agents with PHEVs

	weekly operating cost savings [$/wk]	weekly operating cost [$/wk]	weekly average electric vehicle-miles [mi/wk]	fraction miles electric, f_{elec}
weekly operating cost savings [$/wk]	1.0	0.7584	0.6134	-0.2016
weekly operating cost [$/wk]	0.7584	1.0	0.0286	-0.7115
weekly average electric vehicle-miles [mi/wk]	0.6134	0.0286	1.0	0.5004
weekly average vehicle-miles [mi/wk]	0.8284	0.9147	0.3109	-0.5658
charge-depleting range [mi]	0.4412	-0.1705	0.7316	0.6369
average distance between charging [mi]	0.7654	0.8467	.2828	-0.5320
average number of trips per day	0.4236	0.3998	0.2941	-0.1649
average trip distance [mi]	0.5614	0.6640	0.1232	-0.4968
commute distance [mi]	0.3893	0.4081	0.1911	-0.1920
number of workdays	-0.0162	-0.0848	0.1187	0.1871

Some correlations are expected, e.g., operating costs and operating cost savings are highly correlated with vehicle-miles traveled per week. The negative correlation between the fraction of miles driven electrically, f_{elec}, and vehicle-miles traveled per week is mostly due to drivers traveling farther than the charge-depleting range between charging, consistent with the negative correlation between f_{elec} and average distance between charging and between f_{elec} and average trip distance. This explains, in part, why f_{elec} is more strongly (and negatively) correlated with weekly operating costs than with weekly cost savings. Driving a greater fraction of miles electrically saves the driver more per mile, but drivers traveling fewer miles per week will save less per week.

As noted in Section 3.2, the range of the fraction of miles driven electrically is quite wide, even for drivers of PHEVs with the same charge-depleting range. Figure 3.10, above, shows that for many PHEV drivers with a PHEV of a given charge-depleting range, the fraction of miles driven electrically, f_{elec}, is distributed widely around the average. Although f_{elec} is positively correlated with charge-depleting range, the correlation coefficient is only 0.6369, as shown in Table 3.5. Diversity in driving patterns from day-to-day and from driver-to-driver gives rise to a wide range of miles driven electrically and thus to a wide range of operating cost savings.

The wide range is related to the distance PHEV drivers travel between recharging their batteries. This distance was recorded for each PHEV driver, and the distribution of distance driven between recharging is plotted in Figure 3.15. This shows the probability of driving a given distance between recharging as a function of the distance. This is the fraction of times a PHEV was plugged in after driving a given distance since the PHEV was unplugged. The distribution is quite broad, with a sharp peak for distances less than one mile and a broad tail with a semi-logarithmic dependence on distance. The fitted line shown in Figure 3.15 is

$$P\left(D_{charge}\right) = 0.02246(0.9771)^{D_{charge}} \tag{3.9}$$

or,

$$\log\left[P\left(D_{charge}\right)\right] = -1.649 - 0.0101 D_{charge} \tag{3.10}$$

where

$P\left(D_{charge}\right)$ is the probability of driving distance D_{charge} between recharging.

In five runs with approximately 500 PHEVs each, in which the distance driven between recharging was recorded each time a driver plugged in a PHEV, drivers plugged in on average 1.11 times per day, and drove from less than 1 mile to 450 miles between recharging. The wide range is due to driver-to-driver and day-to-day variability in distances driven.

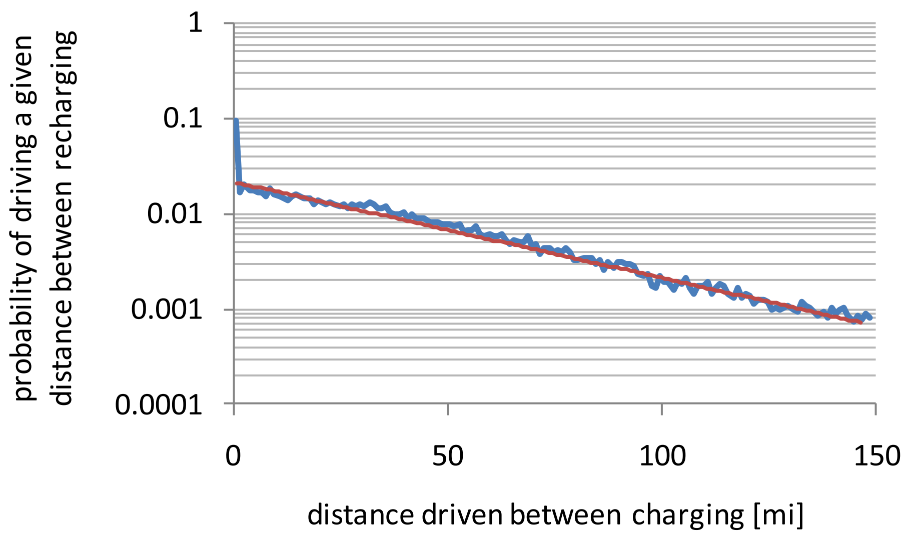

Figure 3.15. The probability of PHEV drivers traveling a given distance between recharging their vehicle batteries. The red line is a semi-logarithmic fit.

To examine correlations between the weekly average distance traveled between recharging and other driving statistics, correlation coefficients were calculated for the same five runs for which statistics are tabulated in Table 3.5. These coefficients are listed in Table 3.6.

The distance driven between recharging is correlated with vehicle miles driven per week and average trip distance, but not highly correlated with the number of trips per day. Drivers taking longer trips tend to drive farther between recharging, while drivers who take many trips are able to recharge when any of their trips are to home and they dwell at home for at least two hours.

Table 3.6. Correlation coefficients between the weekly average distance traveled between recharging and other statistics on driver agents with PHEVs.

	weekly average distance traveled between recharging [mi]
weekly operating cost savings [$/wk]	0.7654
weekly operating cost [$/wk]	0.8467
weekly average electric vehicle-miles [mi/wk]	0.2828
weekly average vehicle-miles [mi/wk]	0.9284
charge-depleting range [mi]	-0.0145
average number of trips per day	0.2785
average trip distance [mi]	0.7876
commute distance [mi]	0.6267
number of workdays	0.0937

The correlation between the distance driven between recharging and operating cost savings per week is due to the correlation between both of these variables and the vehicle-miles driven per week. PHEV drivers save more on operating costs they farther they drive, even when driving on gasoline. However, the farther they drive per day, the farther they drive between recharging, so both the distance driven between charging and the operating cost savings per week are positively correlated with vehicle-miles driven per week, and therefore are positively correlated with each other.

How the distance between charging changes when drivers are able to charge at work as well as at home is examined in Scenario 5, which is described in Section 3.5.1.

Since PHEVs will cost more to buy than comparable conventional vehicles, a question for those considering purchasing a PHEV is whether the cost savings will offset the increased purchase price. The price premium is the difference in the purchase price of a PHEV and a comparable conventional vehicle. Rough estimates of the price premium for each PHEV represented in the model were made based on long-term estimates of Simpson (2006), as listed in Table 1.7, above. The price premium was assumed to be a function of the battery size: $6,000 for PHEVs having a battery capacity from 4 – 5 kWh, $8,500 for PHEVs with a battery capacity of 7 – 10 kWh, and $12,000 for PHEVs with a battery capacity of 15 – 16 kWh. Also estimated from the battery size was the approximate value of the tax credit available for PHEVs under the federal Energy Improvement and Extension Act of 2008 (EIEA, 2008), which provides a federal tax credit for PHEVs for the first 250,000 vehicles sold. The credit is $2,500 plus $417 for each kWh of battery pack capacity in excess of 4 kWh to $7,500 for 12 kWh or more. Here, it was simply assumed that the useful battery capacity was 60% of the total battery capacity, and the tax credit was estimated based on the total battery capacity. The tax credit estimate was rounded to the nearest $500. The price premium was calculated with the credit and without the credit.

From the price premium, the difference in the monthly payment for each PHEV and the comparable conventional vehicle was estimated, assuming a five year loan at an annual interest rate of 0%. The difference in monthly payments was estimated with and without the tax credit. At an interest rate of 10%, the difference in monthly payments would be about 20% higher, which is not significant at this level of approximation. The estimated difference in purchase price and in monthly payment between PHEVs and comparable conventional vehicles modeled (listed in Table 2.8) are shown in Table 3.7.

Table 3.7. Estimated difference in purchase price and in monthly payment between PHEVs of different models and comparable conventional vehicles, with and without the EIEA tax credit, for a five-year loan at 0% interest.

PHEV model	useful battery capacity [kWh]	total battery capacity [kWh]	purchase price premium	EIEA tax credit	price premium with credit	difference in mo. payment without tax credit	difference in mo. payment with tax credit
1	2.61	4.34	$6,000	$2,500	$3,500	$100	$60
2	2.61	4.34	$6,000	$2,500	$3,500	$100	$60
3	5.99	9.98	$8,500	$5,000	$3,500	$140	$60
4	2.99	4.99	$6,000	$3,000	$3,000	$100	$50
5	5.99	9.98	$8,500	$5,000	$3,500	$140	$60
6	9.59	15.98	$12,000	$7,500	$4,500	$200	$75
8	4.60	7.67	$8,500	$4,000	$4,500	$140	$75
9	9.20	15.34	$12,000	$7,500	$4,500	$200	$75

The difference in monthly payments is estimated to be in the range of \$100 to \$200 per month with no tax credit, and \$60 to \$75 per month with the tax credit. These numbers are highly uncertain, since they represent the difference between two uncertain numbers (the purchase price of PHEV and that of a comparable conventional vehicle), but they provide a context for evaluating the magnitude of operating cost savings estimated by PHEV drivers in the model.

The savings in operating costs per week for each PHEV driver were tracked and averaged over four weeks in five runs of the model with approximately 500 PHEVs each at a gasoline price of \$2.50/gal and an electricity rate of \$0.10/kWh. The payback time, $T_{payback}$, was calculated assuming a zero interest rate.

$$T_{payback} = \frac{\Delta P}{52 S_{wk}} \tag{3.11}$$

where $T_{payback}$ is the payback time in years,
ΔP is the purchase price premium, and
S_{wk} is the operating cost savings per week.

Payback times were calculated using values of the price premium with and without the EIEA tax credit, and these are listed in Table 3.8, by PHEV model.

Table 3.8. Estimated mean and standard deviation of payback time for different models of PHEVs with and without the EIEA tax credit, at a gasoline price of \$2.50/gal and an electricity rate of \$0.10/kWh, assuming a 0% interest rate.

PHEV model	mean payback time with no tax credit [yr]	payback time with no tax credit standard deviation [yr]	mean payback time with tax credit [yr]	payback time with tax credit standard deviation [yr]
1	14.7	6.2	8.5	3.6
2	12.6	6.3	7.4	3.7
3	14.4	9.4	5.9	3.9
4	13.6	6.9	6.8	3.4
5	13.5	6.8	5.6	2.8
6	13.6	6.2	5.1	2.3
8	14.3	8.1	7.5	4.3
9	16.4	8.0	6.1	3.0

For each PHEV model, there was a range of payback times, since operating cost savings varied from agent to agent. The standard deviations of payback times are listed in Table 3.8. The payback time is seen to be widely variable, due to variability in driving patterns.

To compare the approximate difference in monthly payments to the saving in operating costs estimated by PHEV drivers in the model, the fraction of PHEV owners whose cost savings met or exceeded the increase in monthly payments was calculated. This is the fraction of drivers who realize a net economic benefit from the model of PHEV they drive within five years of ownership. This was calculated from averages of five runs made at each gasoline price, with gasoline prices ranging from $2.00/gal to $6.00/gal. The fraction of PHEV owners who realize an economic benefit is plotted in Figure 3.16 for the case of no EIEA tax credit. At gasoline prices lower than $5.00/gal, the majority of PHEV owners do not save more per month than the increase in their monthly payment, i.e., purchasing the PHEV they drive is not economical. For the case with the EIEA tax credit, shown in Figure 3.17, many more PHEV drivers do realize an economic benefit; however, the benefit is more sensitive to which model of PHEV they drive.

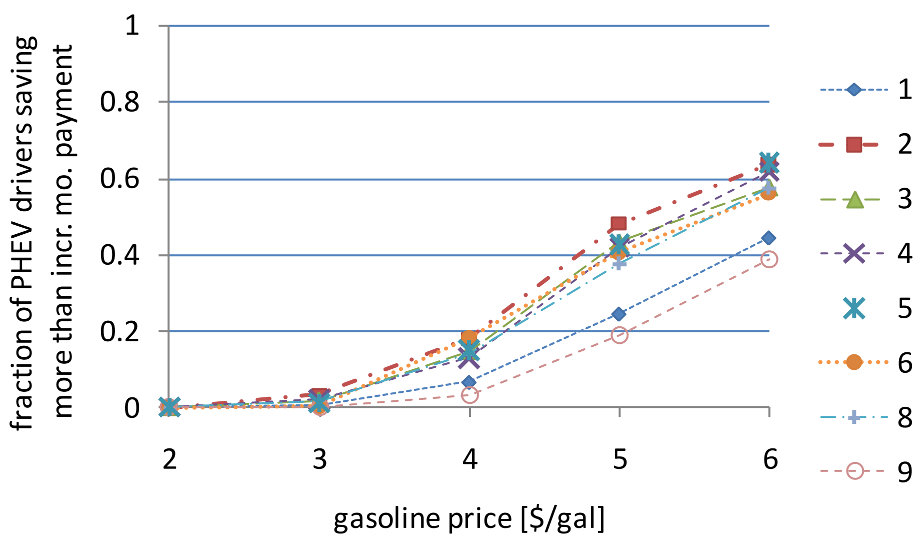

Figure 3.16. Fraction of PHEV owners of each PHEV model whose savings in operating cost meet or exceed the additional monthly payment of their PHEV over that of a comparable conventional vehicle, with no tax credit. Numbers refer to the PHEV model.

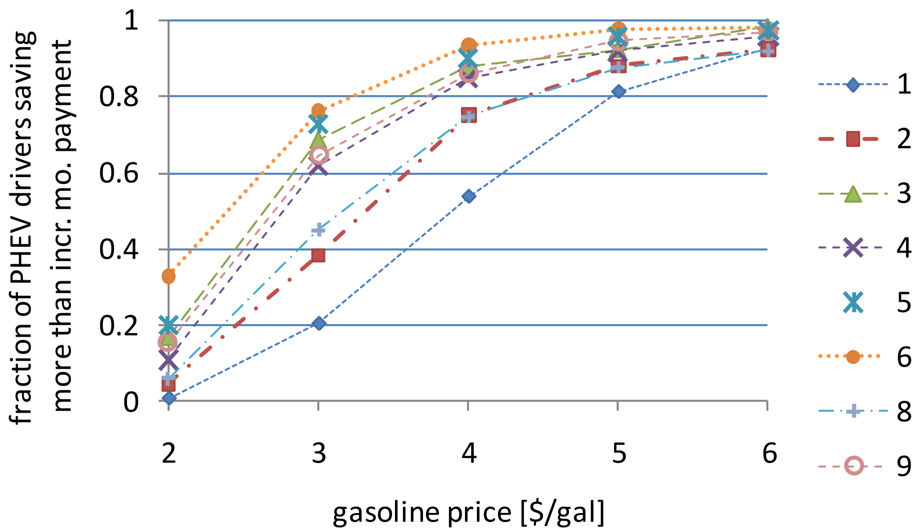

Figure 3.17. Fraction of PHEV owners of each PHEV model whose savings in operating cost meet or exceed the additional monthly payment of their PHEV over that of a comparable conventional vehicle, with the EIEA tax credit. Numbers refer to the PHEV model.

The effect of the EIEA tax credit is to make PHEVs more economical, since it decreases the difference in purchase price, enabling more owners to offset the difference by the savings in operating cost. However the effect is not the same across PHEV models. Without the tax credit, the most economical PHEVs are those that are the most energy-efficient relative to the comparable conventional vehicle. However, with the tax credit, the most economical PHEVs tend to be those with the largest battery capacity, since the tax credit favors PHEVs with larger battery capacity. The tax credit incentivizes more consumers to purchase PHEVs, but the incentive is greatest for PHEVs with large battery capacities, not necessarily those that are most efficient.

The estimated cost savings are sensitive to the assumed operating cost of the conventional vehicle that each PHEV model is compared with. This can be seen from Figure 3.16, in which PHEV models 1 and 2 show significantly different fractions of owners who benefit economically. The difference is not due to the any difference in the operating costs of the two PHEV models. PHEV models 1 and 2 have the same fuel economy and electric efficiency, therefore the same operating cost per mile. The comparable conventional vehicles are different; conventional model 1 vehicle is more efficient than conventional vehicle model 2, therefore the costs savings estimated for owners of PHEV model 1 are lower than those of PHEV model 2. This illustrates the sensitivity of these results to assumptions about the fuel economy and operating costs of conventional vehicles. The results presented here are not to be taken as predictions of actual cost savings of PHEV owners, but to examine trends and dependencies.

From model projections of driving by PHEV owners at different gasoline prices, it is seen that PHEV owners tend to be slightly less responsive to gasoline price changes than drivers of conventional vehicles, since they are less exposed to the price of gasoline. PHEVs are less expensive to operate, but with low sensitivity to operating costs, PHEV drivers increase their driving only slightly (5 to 10%). Projections of energy savings and economic benefit of PHEVs relative to conventional vehicles are highly sensitive to assumptions about fuel price, vehicle purchase prices, and the fuel efficiency of the conventional vehicles that PHEVs are compared with. Estimates made here may be optimistic, since the range of fuel economy assumed for conventional vehicles, while close to that of the current U.S. fleet, is probably lower than that of the future U.S. fleet. The future fleet will be more fuel efficient once newer, more efficient vehicles, complying with increasing CAFE standards, begin to replace older, less efficient vehicles. This makes it difficult to predict the economic benefit achievable from PHEVs. It also make it difficult to predict which models of PHEVs will be made more attractive to consumers by incentives such as tax credits or subsidies, or to estimate the cost effectiveness of such incentives. Incentives should be designed with some flexibility, so that as the vehicle market develops and fuel prices fluctuate, incentives can be adjusted as needed to achieve the desired outcome.

An important observation from model results is the wide range of the fraction of distance driven electrically by PHEV drivers, and the resulting wide range of operating cost savings. This range is due to diversity in driving and is sensitive to the average distance per trip. The dependence on distance per trip is examined further in Scenario 8.

3.4 <u>Electricity rate</u>

3.4.1 Scenario 3: Constant electricity rate

The response of a driver population to an increase in the electricity rate was examined. All drivers were assumed to pay a flat electricity rate (independent of demand and time of day). The electricity rate was initially set to \$0.10/kWh and was increased in increments of \$0.02/kWh. Rate increases were made every 30 days. Thirty day intervals were used to allow driver agents' charging and driving patterns to equilibrate. This equilibration took just over one week of simulation time, and driving and energy consumption statistics were calculated from the last two weeks of each 30-day interval. One-half of the vehicles were PHEVs, and the fuel price was constant at $2.50/gal.

In this scenario, PHEV drivers would choose to charge their batteries when they were at home for more than two hours, and if their estimated cost per mile under electric power was less than their estimated cost per mile under gasoline power. Drivers responded the following day when they updated their weekly average spending rates, and their number of trips equilibrated in just over 7 days. Vehicle-miles, energy use, and emissions were averaged over two weeks just prior to the next rate change, that is, once values had equilibrated, data were collected for two weeks and averaged to give representative values for each rate condition. This was not intended to mimic realistic dynamics or time-dependence of driver response to a change in electricity rate, but simply to calculate equilibrium values of vehicle-miles, energy use, and emissions.

At the initial electricity rate all PHEV drivers charged their batteries when at home for more than two hours. As the electricity rate was increased, little or no change in driving was seen for the first few increments in rate. For the PHEVs modeled, the operating cost per mile under electric power (charge-depleting mode) at an electricity rate of $0.10/kWh was less (about 50% less for most PHEV models at a gasoline price of $2.50/gal) than the cost per mile under gasoline power (charge sustaining mode). At higher electricity rates, some PHEVs cost more to operate per mile under electric power, and drivers of these vehicles refrained from charging their batteries at such rates and would drive under gasoline power. This can be seen by examining the vehicle-miles traveled by the fleet under electric power, as shown in Figure 3.18.

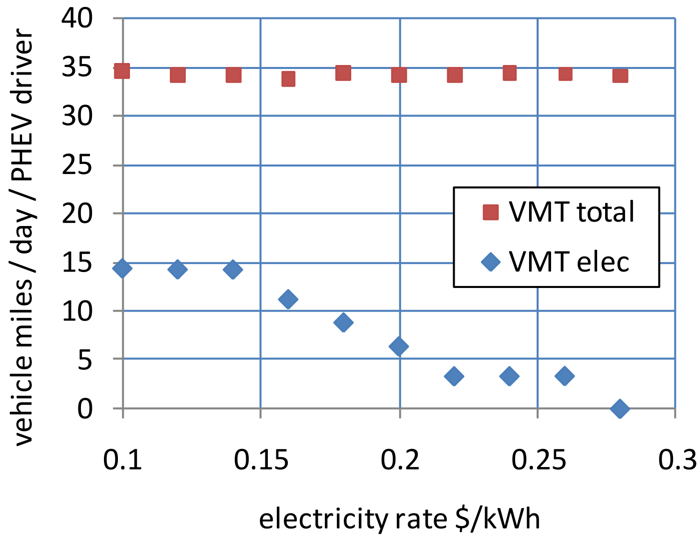

Figure 3.18. Vehicle-miles traveled by PHEV drivers (VMT total) and vehicle miles traveled under electric power (VMT elec) by PHEV drivers at different electricity rates. The gasoline price was $2.50/gal.

In Figure 3.18, the number of vehicle-miles traveled under electric power per day per PHEV driver decreases at rates above $0.15/kWh, at which rate some PHEVs are more economical to operate in charge-depleting mode (on gasoline). At a fuel price, P_f, the breakeven rate, R_e, ($ per kWh) or rate at which electricity becomes equally expensive per mile is related to the fuel economy, E_f, (miles per gallon) and electricity consumption, C_e, (kWh per km) of the PHEV, as

$$R_e = \frac{P_f}{(C_e)(E_f)\left(1.609\frac{\text{km}}{\text{mi}}\right)} \tag{3.12}$$

For the PHEVs in the model, with electrical efficiencies listed in Table 2.8, the breakeven electricity rates range from $0.151/kWh to $0.209/kWh when the fuel price is $2.50/gal. Breakeven electricity rates are listed for each PHEV model in Table 3.9. While these rates are significantly higher than the U.S. average residential electricity rate of $0.1099/kWh as of January, 2009, they are not higher than peak rates under some time-of-use (TOU) rate schemes (Lemoine et al., 2008; Borenstein et al., 2002). Dynamic electricity rates, such as TOU rates, may be useful in providing PHEV owners an incentive to charge their batteries during off-peak hours. This is examined in scenarios below.

Table 3.9. Break-even electricity rates and energy cost per mile for the PHEVs listed in Table 2.8, at a gasoline price of $2.50/gal

segment	break-even electricity rate [$/kWh]	energy cost per mi [$/mi]
1	0.200	0.0521
2	0.200	0.0521
3	0.174	0.0521
4	0.209	0.0625
5	0.209	0.0625
6	0.261	0.0625
8	0.151	0.0694
9	0.151	0.0694

The break-even electricity rate depends on the gasoline price, as well as the efficiency of the vehicle. The breakeven rate is plotted in Figure 3.19 for the PHEVs modeled as a function of gasoline price. PHEVs that have high electric efficiency are more economical to operate under electric power even at high electricity rates and low gasoline prices. With a fleet of vehicles including PHEVs having different electric efficiencies, not all drivers can be expected to respond to electricity rates similarly.

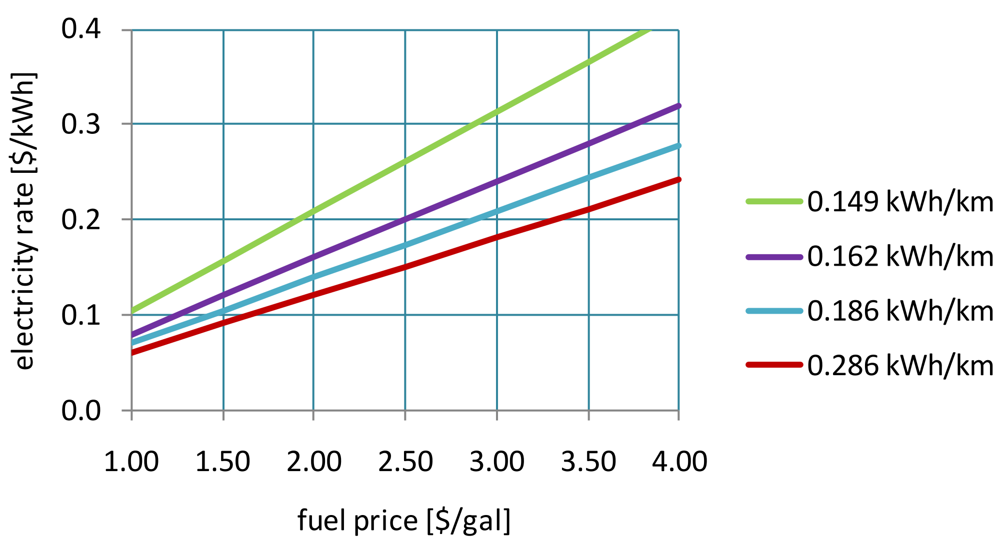

Figure 3.19. The electricity rate at which the cost of electricity per mile in charge-depleting mode equals the cost of gasoline per mile in charge-sustaining mode as a function of the price of gasoline. The lines are for the PHEVs modeled, having electric efficiencies as shown.

At sufficiently high electricity rates where no PHEV drivers charged their vehicles, most PHEV drivers decreased the number of trips only slightly. This is due to two factors, one being that since PHEVs have higher fuel economy than comparable conventional vehicles, the transportation spending rate (operating cost per time) of PHEV drivers is less sensitive to the number of trips or vehicle-miles driven than that of a conventional vehicle. The other factor is that in this scenario, with 50% of drivers owning a PHEV, PHEV drivers have incomes in the middle or upper income brackets and have low elasticities of demand for electricity or gasoline.

In this scenario, it is observed that PHEV drivers do not significantly change their driving with increasing electricity rates. Their operating costs increase slightly, but under reasonable gasoline prices and electricity rates traveling under electric power is less expensive per mile than traveling under gasoline power. Therefore PHEV drivers continue charging their vehicles when electricity is available in order to maximize the fraction of distance traveled, independent of the electricity rate, at least at modest rates. When electricity rates are increased to levels at which it is less expensive per mile to travel under gasoline power, PHEV owners refrain from charging their batteries. The rate at which this happens depends on the price of gasoline and the electrical efficiency of the PHEV. When PHEV drivers pay a flat electricity rate, adjusting the rate is not a good way to manage electricity demand for PHEV charging. Time-dependent rates are examined in the following scenario.

3.4.2 Scenario 4: Time-of-use electricity rates

To examine the response of PHEV drivers to time-of-use (TOU) electricity rates, two scenarios were modeled in which PHEV drivers pay a higher electricity rate during peak hours and a lower electricity rate during off-peak hours. In these scenarios, the peak hours were between 12:00 pm and 8:00 pm, every day, and in one scenario, the peak rate was $0.20/kWh, and the off-peak rate was $0.05/kWh; in the other scenario, the peak rate was $0.15/kWh, and the off-peak rate was $0.07/kWh. Non-transportation electricity demand was assumed to be that of the first week of August, a high-demand week. It is assumed that the non-transportation demand does not respond to electricity rates paid by PHEV drivers, and was therefore the same in the two TOU scenarios as in the flat-rate scenario. Gasoline remained priced at $2.50/gal. PHEV drivers could charge their batteries only at home and would choose to do so if their dwell time at home were two hours or more, and if the cost per mile of electric-powered travel were less than the cost per mile of gasoline-powered travel. The fleet was assumed to consist of 7.3 million vehicles, half of which were PHEVs.

Electricity demand for the two scenarios is shown in Figure 3.20, along with the scenario with PHEV drivers paying a flat electricity rate of \$0.10/kWh. In the scenario with the peak rate of \$0.20/kWh, most PHEV drivers chose not to charge their batteries during the peak period. They deferred charging to the hours immediately following the end of the peak period (9:00pm). In this scenario, the maximum total demand is lower than in the case with all drivers paying a flat rate. This shows a potential benefit of TOU rates in incentivizing PHEV drivers not to charge during high demand hours. However the demand for PHEV charging increased suddenly at the end of the peak period. For utilities using TOU rates to control peak demand, it may be desirable to establish different peak hours for different consumers, in order to desynchronize the time at which rate payers see a decrease in the electricity rate, and thus avoid a large surge in demand at the end of the peak period.

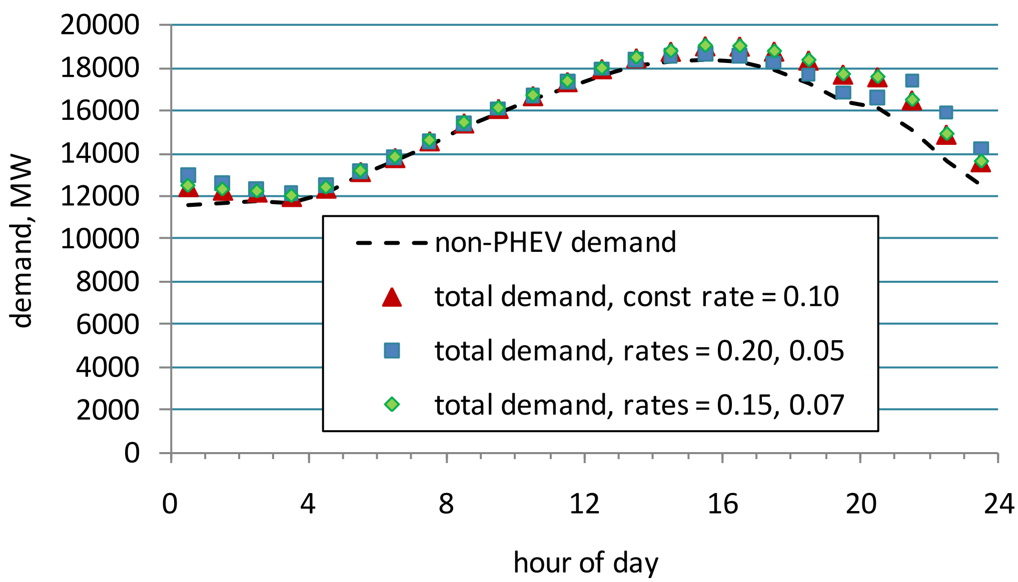

Figure 3.20. Electricity demand in Michigan with PHEVs drivers paying TOU rates as shown, compared with PHEV drivers paying a constant rate of \$0.10/kWh. The demand with no PHEVs is also shown; this is the non-transportation demand from a high-demand week in August.

For the scenario with a more modest rate change, with the peak rate of \$0.15/kWh and the off-peak rate of \$0.07/kWh, no PHEV drivers defer charging, as it is less expensive per mile to travel electrically than on gasoline, even for the least electrically efficient PHEVs in the fleet. The demand is the same as in the scenario with PHEV drivers paying a flat electricity rate, as shown in Figure 3.21, which shows the PHEV charging demand for the three cases.

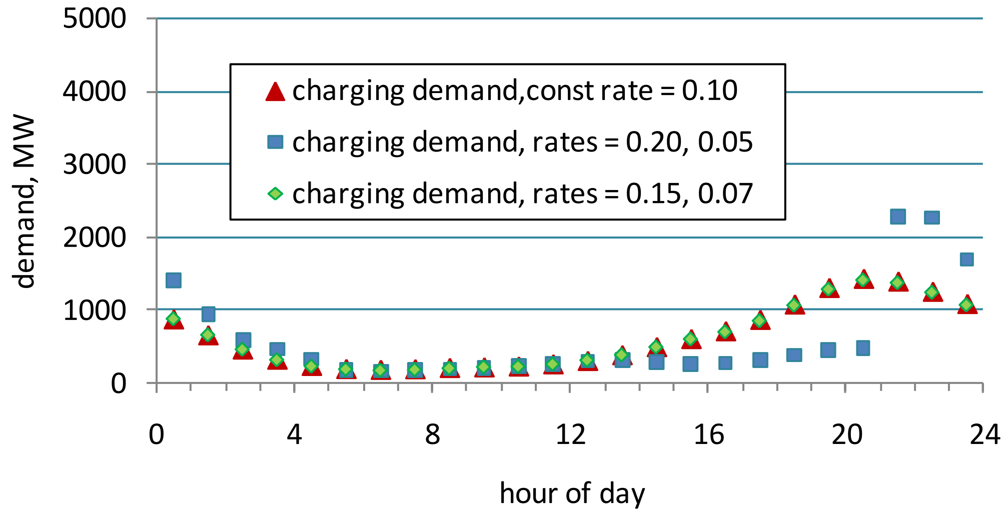

Figure 3.21. Electricity demand for PHEV charging, with PHEVs making up 50% of the fleet, with flat electricity rates, and with peak and off-peak rates as indicated.

This lack of response at a peak rate of \$0.15/kWh may not be representative of PHEV drivers whose schedule permits delaying battery charging without forgoing electric-powered travel. These drivers may compare the cost of peak electricity to off-peak electricity rather than peak electric cost per mile to gasoline cost per mile. In such a case a fraction of PHEV owners may choose to delay charging until the off-peak period, even with a modest difference between peak and off-peak rates. The resulting demand in such a case would be closer to that that seen with a peak rate of \$0.20/kWh, depending on how many drivers could complete charging in the off-peak hours. This would include most PHEV drivers for the peak/off-peak hours studied here, since most PHEV drivers are at home during off-peak hours, and most do not leave home before 5:00 am, which would permit even PHEVs with large battery capacities to fully charge before the first trip of the next morning.

In the higher peak rate case, most PHEV drivers defer charging until the off-peak hours, but nearly all are able to fully charge their vehicles prior to their next trip. This is indicated by the fact that the fraction of distance traveled electrically and the gasoline consumed by PHEVs change only slightly when most PHEV drivers defer charging to off-peak hours. The average distance driven electrically under the TOU rates with a peak rate of $0.20/kWh is only about 1.5% less than that under a flat rate, as seen in Table 3.10.

Table 3.10. Model results for average daily PHEV charging demand, average distance traveled electrically, average fraction of distance traveled electrically, and maximum total electricity demand under flat and TOU rates.

Electricity rates	daily charging demand per PHEV [kWh]	average daily elec-powered vehicle-miles per PHEV [mi/day]	average fraction PHEV-miles traveled electrically	maximum hourly electricity demand [MW]
$0.1/kWh, flat	4.04	12.60	0.363	19,000
$0.15/kWh peak, $0.07/kWh off-peak	4.00	12.50	0.360	19,000
$0.20/kWh peak, $0.05/kWh off-peak	3.96	12.40	0.357	18,700

The peak in electricity demand for PHEV charging under the higher peak rate case occurs at the same hour than in the flat rate case, as seen in Figure 3.20, but the peak in total demand is slightly lower (by about 1.8%), as seen in Table 3.10. In this scenario, at the peak demand hour the demand for PHEV charging is a small fraction of the total demand (about 3.7%), but this could be significant if additional generating capacity is required or purchase of power from outside the region is required during the peak hours when wholesale electricity is expensive. Additionally, management of PHEV charging could be combined with management of the non-transportation demand to achieve further decrease in peak demand.

Under this scenario, where PHEV drivers compare the cost per mile traveled electrically to the cost per mile under gasoline, the response of PHEV drivers depends on gasoline prices as well as electricity rates. If PHEV drivers were to compare only the peak to off-peak electricity rates, their response would be independent of gasoline prices, but would depend on whether their driving schedule and time at home permitted charging during off-peak hours. In either case, the response of PHEV drivers to TOU rates would depend on factors beyond the control of electrical utilities. Electrical utilities using TOU rates to manage PHEV charging demand will need to take an adaptive or even trial-and-error approach to establishing rates that achieve the desired response from PHEV owners. A more direct demand management scheme, interruptible service, is examined in Scenario 6.

3.5 Electricity availability

3.5.1 Scenario 5: Charging at home and at work

To assess the possible effects of increasing the availability of electricity for charging, a scenario was modeled in which all PHEV drivers who worked could charge their vehicle batteries at work. All PHEV drivers could charge at home. As in the other scenarios modeled, it was assumed that 70% of drivers worked, approximately 90% of these full time. In this scenario, drivers would charge their vehicles when arriving either at home or at work if they planned to stay there at least two hours. As shown in Figure 2.5, most drivers arrived at work between 6:00 and 9:00 am. A few drivers arrived later or arrived back to work after driving a trip during their lunch hour. Dwell times at work were variable, but not less than two hours, so that PHEV drivers arriving at work would always choose to charge their batteries. Non-transportation electricity demand was taken to be that of the first week of August, as described in section 3.1. The resulting electricity demand is shown in Figure 3.22.

Electricity demand for PHEV charging increased with charging at work, primarily in the hours immediately after most drivers arrived at work. Charging demand later in the day when most drivers arrived home was very close to that projected for home-only charging. That is, for most drivers who charged their vehicles at work, the additional electricity used was used in driving home or on trips driven between work and home.

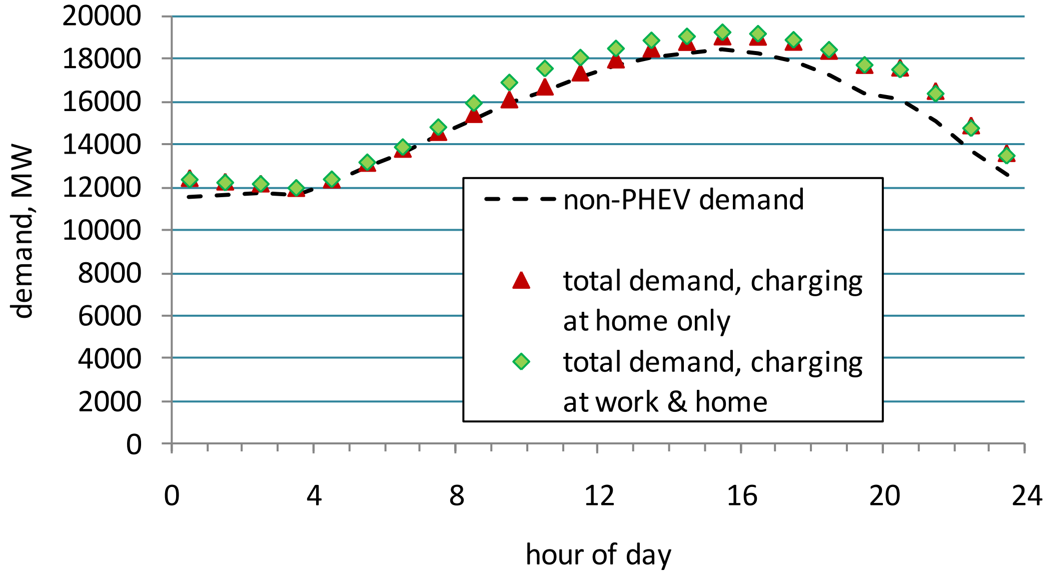

Figure 3.22. Electricity demand in Michigan with PHEVs drivers charging at work and at home. Here, 70% of drivers work. The demand with no PHEV is also shown.

Figure 3.23 shows the PHEV charging demand for the two scenarios. A peak in charging demand is seen between 8:00 am and noon. The evening demand peak is similar although it tapers off slightly sooner, indicating that some PHEVs that were charged at work arrived home in the evening with a slightly higher state of charge than if charging were only possible at home. The difference is small, and the height of the evening demand peak is very similar for the two scenarios, showing that additional charging at work is not projected to decrease charging demand in the evening or overnight.

In this scenario, the average commute distance was 12.1 miles, and many drivers made trips between leaving work and arriving at home. Under different driving patterns, more PHEV drivers leaving work with fully charged batteries might be able to arrive home with significant charge still remaining. In such a case, the charging demand at night might be decreased more than what was estimated here.

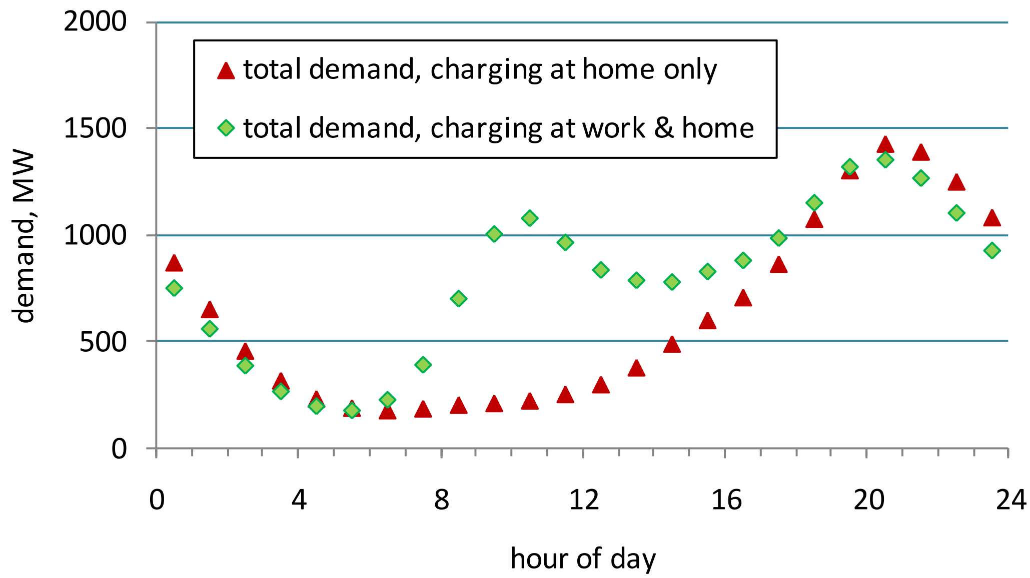

Figure 3.23. Electricity demand for PHEV charging, with PHEVs making up 50% of the fleet, with PHEVs drivers charging at work and at home.

The additional charging does allow PHEV drivers to travel more vehicle-miles under electric power and therefore decreases total GHG emissions per vehicle-mile. In Table 3.11, the vehicle-miles traveled (VMT), vehicle-miles under electric power, fuel and electricity use per day and GHG emissions per mile for PHEVs under charging only at home and for PHEVs charging at both home and work are compared.

Table 3.11. Vehicle-miles traveled (VMT), fuel and electricity use, and GHG emissions from PHEV charging only at home and PHEVs charging at home and at work.

	charging at home	charging at home and at work
VMT per day per PHEV, mi	34.7	35.1
Electric-powered VMT per day per PHEV, mi	12.6	16.0
Daily charging demand per PHEV, kWh	4.04	5.20
Daily charging GHG per PHEV, kg CO_2 eq	3.72	4.94
Daily gasoline consumption per PHEV, gal	0.54	0.47
Daily gasoline GHG per PHEV, kg CO_2 eq	6.03	5.22
total GHG emissions per PHEV, kg CO_2 eq	9.75	10.16
total GHG emissions per PHEV-mi, g CO_2 eq/mi	283.	289.

The slight difference between vehicle-miles traveled per day (35.1 vs. 34.7 mi) is within one standard deviation of five runs of the model (about 0.8 mi) and is not significant. The differences in charging demand, fuel use and GHG emissions are significant. The additional charging permits PHEV drivers to drive more miles electrically. Surprisingly, the additional miles traveled electrically result in nearly the same GHG emissions per mile and per PHEV, since the GHG emissions from the additional electricity demand are very nearly equal to the decrease in GHG emissions from lower gasoline consumption. This is due to the carbon-intensity of the electrical generation mix supplying the electricity for the increased demand. Emissions by PHEVs per mile are still lower than emissions from conventional vehicles.

The fraction of vehicle-miles traveled under electric power depends on the charge-depleting range of the PHEV, as noted previously. The opportunity for a second charge during the day increases this fraction for each type of PHEV, as shown in Table 3.12, which compares the two cases.

Table3.12. Fraction of vehicle-miles driven electrically by PHEVs of different charge-depleting ranges. Drivers can charge at home only or at both work and home.

Charge-depleting range [mi]	fraction of miles driven electrically, charging at home only	fraction of miles driven electrically, charging at work and at home
10	0.321	0.432
20	0.450	0.554
40	0.764	0.799

The fraction of vehicle-miles that drivers travel electrically increased with the additional charging opportunity (available to the 70% of PHEV drivers who worked). The increase was larger for PHEVs with a shorter charge-depleting range.

The additional charging decreases operating costs of PHEVs, so PHEV drivers save additional money when they charge more frequently. Each PHEV driver’s operating cost savings per week is the difference between the energy costs (electricity and gasoline costs) of a PHEV and costs of a comparable conventional vehicle driving the same trips. These savings are proportional to operating cost savings per mile, but since operating cost savings per week is also correlated with the number of miles driven per week, and different drivers travel different distances per week, drivers traveling the greatest fraction of miles electrically do not necessarily save the most money per unit time. Many PHEV drivers who travel fewer miles per week travel a greater fraction of miles electrically. They save more per mile, but less per week that PHEV drivers who travel more. This is relevant to a PHEV owner's economic return on the additional investment made when purchasing a PHEV vs. a conventional vehicle. A PHEV owner will be concerned with cost savings per unit time, since this determines how quickly (or whether) he recoups this incremental investment. Average operating cost savings per week were calculated for two runs with 503 agents driving PHEVs, one in which PHEV drivers charged at home, and the other in which they charged both at home and at work. Average operating cost savings per week are listed in Table 3.13. Cost savings are correlated with the efficiency of the vehicle, but not strongly dependent on whether the PHEV is charged only at home or at both home and work.

Table 3.13. Average operating cost savings per week and per vehicle-mile for PHEV owners (difference in energy costs from a comparable conventional vehicle) for different PHEV models (vehicle segments) for drivers charging only at home and for drivers charging at home and at work.

vehicle segment	fuel economy [mi/gal]	electricity consumption [kWh/km]	operating cost savings per week, charging at home [$/wk]	operating cost savings per week, charging at home and work [$/wk]	operating cost savings per vehicle-mile, charging at home [$/mi]	operating cost savings per vehicle-mile, charging at home and work [$/mi]
1	48	0.162	8.97	9.52	0.040	0.043
2	48	0.162	10.77	11.71	0.048	0.051
3	48	0.186	14.67	14.83	0.060	0.061
4	40	0.186	11.18	10.80	0.044	0.045
5	40	0.186	14.57	16.16	0.062	0.065
6	40	0.149	21.71	22.09	0.088	0.089
8	36	0.286	13.57	14.26	0.060	0.063
9	36	0.286	17.17	18.13	0.068	0.071

The estimated cost savings are highly uncertain, as noted in Section 3.3, since they are sensitive to assumed differences in vehicle purchase prices and fuel economies of future vehicles as well as future fuel prices, none of which are well known. However, in comparing the two cases of charging PHEVs at home and at both work and at home, the increase in estimated operating costs savings due to additional charging is modest, less than 10%.

In this scenario, in which PHEV drivers can charge their vehicle batteries at work in addition to at home, the additional charging results in an increased fraction of miles traveled electrically, as expected. This results in decreased gasoline use and increased electricity demand. For the mix of electrical power plants used in this scenario, the GHG emissions reduction due to reduced gasoline consumption is offset by a nearly equal increase in GHG emissions from the increase electricity generation supplying electricity for PHEV charging.

PHEV drivers realize greater operating cost savings when they can charge their vehicle batteries more than once per day. By charging more than once per day, PHEV drivers can increase the fraction of miles they travel electrically, which reduces the average operating cost per mile. The increase in operating cost savings per week is rather modest, less than 10%, but this is uncertain due to uncertainties in future vehicle costs and fuel prices.

3.5.2 Scenario 6: Interruptible electricity service

Interruptible electricity service is a means of managing electricity demand in which the electric utility can curtail or shut off power to loads, which are supplied by separate meters with some communication or remote control capability. In some cases under dynamic electricity rates, interruptible service can be implemented with rate criteria such that power is shut off when the rate exceeds established threshold rates (Smith, 1989). In the scenarios considered here, a fraction of PHEV owners had their vehicle chargers on separate meters to which the electricity utility could limit or shut off power in order to decrease total demand during peak hours. Drivers paid a flat electricity rate of \$0.10/kWh (no dynamic pricing). Two scenarios were modeled, one in which half of PHEV drivers had interruptible service and one in which all PHEV drivers did.

The fleet modeled was comprised of 50% PHEVs, and all PHEV drivers could charge vehicle batteries only at home. They would do so if they were at home for at least two hours. For both scenarios with interruptible service, the power to chargers was shut off from noon until 8:00 pm every day. Non-transportation electricity demand was taken to be that of the first week of August, a high-demand week. The resulting total demand is shown in Figure 3.24. Total demand for each hour was averaged over the week. As expected, demand during the period between noon and 8:00 pm is lower than without interruptible service. Charging demand is higher after 8:00 pm when power is restored to PHEV chargers. The peak average demand for each case is listed in Table 3.14, along with the hour the peak occurred.

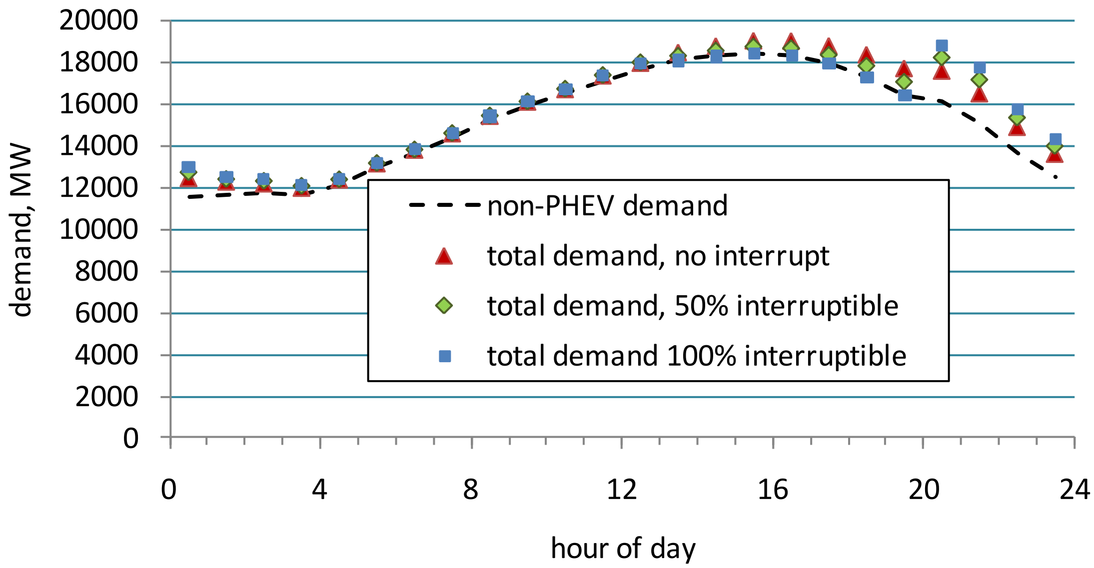

Figure 3.24. Electricity demand in Michigan with PHEVs comprising 50% of the fleet, for three scenarios, no interruptible service (triangles), half of PHEV chargers on interruptible service (diamonds), and all PHEV chargers on interruptible service (squares).

Table 3.14. The peak average total demand for 0, 50 and 100% of PHEV drivers on interruptible electricity service. The peak demand for non-PHEV charging is also listed.

	Peak average total demand [MW]	Time of peak demand
no PHEV chargers on interruptible service	19,000	15:00 - 16:00
50 % of PHEV chargers on interruptible service	18,700	15:00 - 16:00
100 % of PHEV chargers on interruptible service	18,800	20:00 - 21:00
non-PHEV demand	18,400	15:00 - 16:00

In the case of half of PHEV chargers on interruptible service, the peak demand occurs between 3:00 and 4:00 pm, but the peak demand is 1.6% lower than with no interruptible service. The new second peak in demand occurs in the hour following restoration of power (between 8:00 pm and 9:00 pm), but is about 3.5% lower than the peak for the uncontrolled case. With all PHEV chargers on interruptible service, the new peak, occurring in the hour after power is turned back on, is 1.1% lower than the peak demand in the uncontrolled case. Demand during the broad peak around 3:00 pm is approximately 3% lower. This shows that interrupting PHEV charging can reduce peak demand, but this scenario is oversimplified, since restoring power to all PHEV chargers simultaneously, with no management of the non-transportation demand, would not provide a large reduction in peak demand, and it would result in a second peak with a high ramp rate (sudden increase in power). This scenario is not a credible example of the application of interruptible service to control peak demand, but it is of interest to examine the effect of such a severe interruption on the use of PHEVs.

For all three scenarios, the PHEV charging demand decreases to close to zero by 5:00 or 6:00 am. Since few drivers travel earlier than this, nearly all PHEV drivers have a fully charged vehicle before their first trip of the day, even with interruptible service. This can be seen by comparing the vehicle-miles traveled electrically for the three cases, and these values are listed in Table 3.15.

Table 3.15. Vehicle-miles traveled per day per PHEV and fraction of vehicle-miles traveled electrically by PHEVs with different fractions of PHEV chargers on interruptible service.

fraction of PHEV chargers on interruptible service	vehicle-miles per PHEV per day	fraction of miles driven electrically
0	34.7	0.363
0.5	34.8	0.361
1.0	35.0	0.358

Most PHEVs can complete charging in the hours after the power is switched on. However, this was not true for all PHEV drivers; some PHEV drivers did find their vehicles less than fully charged even though the vehicles had been plugged in for sufficient time to fully charge them, had power been on during the entire time the vehicle was plugged in. Naturally, a PHEV driver who has his vehicle plugged in for the time needed to bring the battery to a full charge would normally expect the battery to be charged at the end of this time. If power was interrupted during charging, this may not be so, in which case the driver may consume more gasoline. This would impact the economical operation of PHEVs for a small fraction of owners whose vehicle batteries are not fully charged due to interruption of electrical power.

To estimate the size of this fraction, the number of times each PHEV driver found their vehicle batteries less than 95% charged when the PHEV had been plugged in for sufficient time to fully charge the batteries was tracked. For the scenario in which all PHEV drivers were on interruptible service, approximately 19% of PHEV drivers found their batteries less than 95% charged after plugging in for the required charging time once per month. This happened more frequently for a smaller number of PHEV drivers. The frequency (times per month) of finding a battery less than 95% charged after plugging in for the required time for the five runs with all PHEV drivers on interruptible service is listed in Table 3.16 with the fraction of drivers experiencing less than a full charge with the stated frequency.

As seen in Table 3.16, only a very small fraction of drivers were impacted by interruptible service, and only about 6% of drivers found their vehicles less than 95% charged due to the interrupted power more than twice per month. The average fraction of miles driven electrically was slightly lower for these drivers, but their average operating cost savings per mile was not strongly affected. The observation that a complete interruption of charging between noon and 8:00 pm for all PHEV drivers in a population has such little impact on the economic operation of PHEVs indicates that utilities have considerable latitude in designing load control or demand-side management measures for managing peak demand. Presumably, participation by PHEV owners in such load control programs would be voluntary, but the results of the model suggest that few PHEV drivers would be averse to participating in these programs.

For PHEV drivers who found their vehicles less than fully charged after the vehicle was plugged in for sufficient time to fully charge the batteries would detract from the satisfaction of owning a PHEV. This would offset the satisfaction derived from operating cost savings that PHEV owners realize. To represent this in the model, a variable quantifying owner satisfaction tracked the difference between the operating cost savings and a monetized value of the dissatisfaction of experiencing less-than-fully charged batteries when a full charge was expected. A value of $1 was assigned to each occurrence of a less-than-fully charged battery.

As seen in Table 3.16, the case with all PHEV drivers on interruptible service, the number of occurrences per month of a less-than-fully charged battery is very unlikely to exceed 5 or 6 times per month. Assigning a value of $1 to each such occurrence would detract up to $5 or $6 per month from the monetized value of an owner’s satisfaction. This is less than 10% of the average monthly savings in operating costs, and therefore does not represent a significant effect on PHEV owner satisfaction.

Table 3.16. The frequency (number of times per month) that PHEV drivers found their vehicle batteries less than 95% charged after plugging in the vehicle for the required charging time. Less than full charge resulted from interruption of charging by the electricity supplier.

frequency of less than 95% charge [times per month]	number of drivers	fraction of drivers	average fraction of vehicle-miles electric	average cost savings per mile	average cost savings per month
0	1689	0.762	0.464	$0.061	$56.74
1	476	0.190	0.433	$0.060	$63.13
2	193	0.077	0.368	$0.056	$69.66
3	76	0.030	0.389	$0.059	$72.59
4	48	0.019	0.357	$0.054	$69.28
5	17	0.007	0.349	$0.051	$59.35
6	8	0.003	0.336	$0.050	$59.54
> 6	5	0.002	-	-	

An alternative to tracking dissatisfying occurrences per month is to add up the total number of occurrences weighted by a factor that decreases with elapsed time. This would more accurately represent "fading memory", i.e., events in the distant past having less influence than more recent events. Here, for simplicity, the number of times per month each PHEV driver found their vehicle batteries than 95% charged were equally weighted. Since these occurrences were less frequent than a few times per month, this simplification does not affect the conclusion that these occurrences do not significantly impact PHEV owner satisfaction.

In this Scenario, it is seen that interruptible electricity service for PHEVs, with PHEV chargers that can be switched off by the electric utility, can be used to control PHEV charging demand without significantly impacting the utility of PHEVs. For the scenario in which all PHEV charging was switched off between noon and 8:00 pm, some PHEV drivers did find their vehicles less than fully charged even though the vehicles had been plugged in for sufficient time to fully charge them (had power been on during the entire time the vehicle was plugged in). However, only a small fraction of PHEV drivers experienced less than fully charged batteries due to service interruption, and the effects on the operating cost per mile of the PHEVs and on the fraction of vehicle-miles traveled electrically was negligible. From a policy perspective, this implies that interruptible service may be used to control peak demand from PHEV charging without negatively impacting PHEV owners.

3.6 <u>Driving patterns</u>

3.6.1 Scenario 7: Arrival time distribution

In this scenario, changes in driving, energy consumption, and GHG emissions were estimated in response to changes in drivers' arrival times. The simulation was run with two different arrival time distributions. In one case, drivers tended to arrive an hour earlier than in the base case, and in the other case, drivers tended to arrive one hour later. In both cases, as in the base case, no drivers were scheduled to arrive at work between midnight and 4:00 am. Figure 3.25 shows the distribution of arrival times for all trips for these two cases, as well as for the base case. The base case arrival time distribution is the distribution used in the other scenarios, as shown in Figure 2.7.

Figure 3.26 shows the arrival time distributions for trips to work for these three cases, and Figure 3.27 shows the arrival time distributions for trips home for these cases. As can be seen, the morning and afternoon "rush hour" peaks in arrivals occur one hour earlier or later than in the base case.

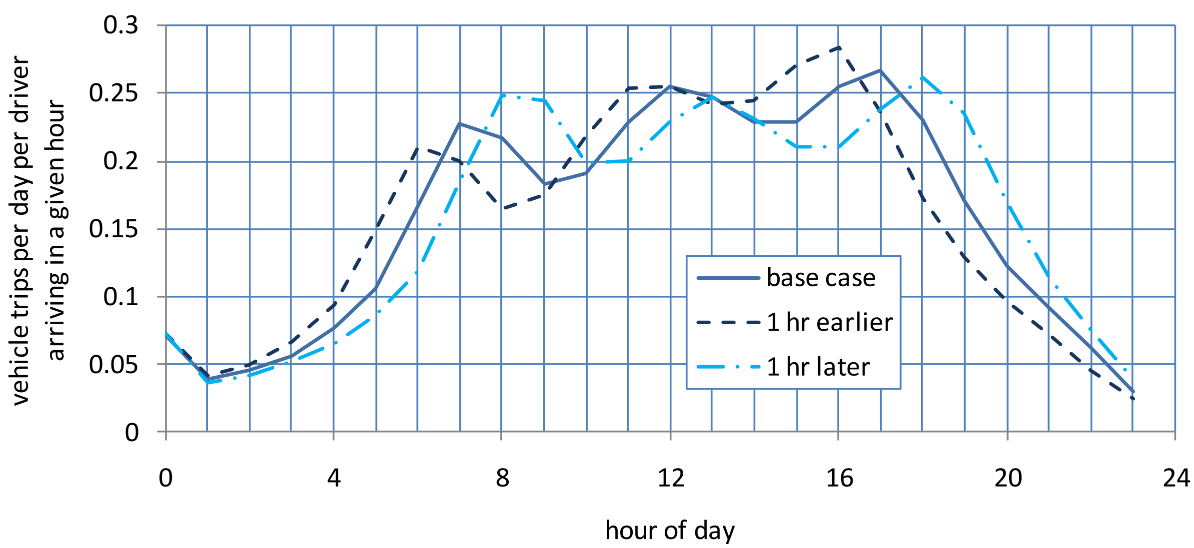

Figure 3.25. Distribution of arrival times of trips to all destinations for the base case (same as other scenarios, shown as a solid line), one hour earlier (dashed line) and one hour later (dash-dot line). Number of vehicle trips per driver per day arriving within a given hour.

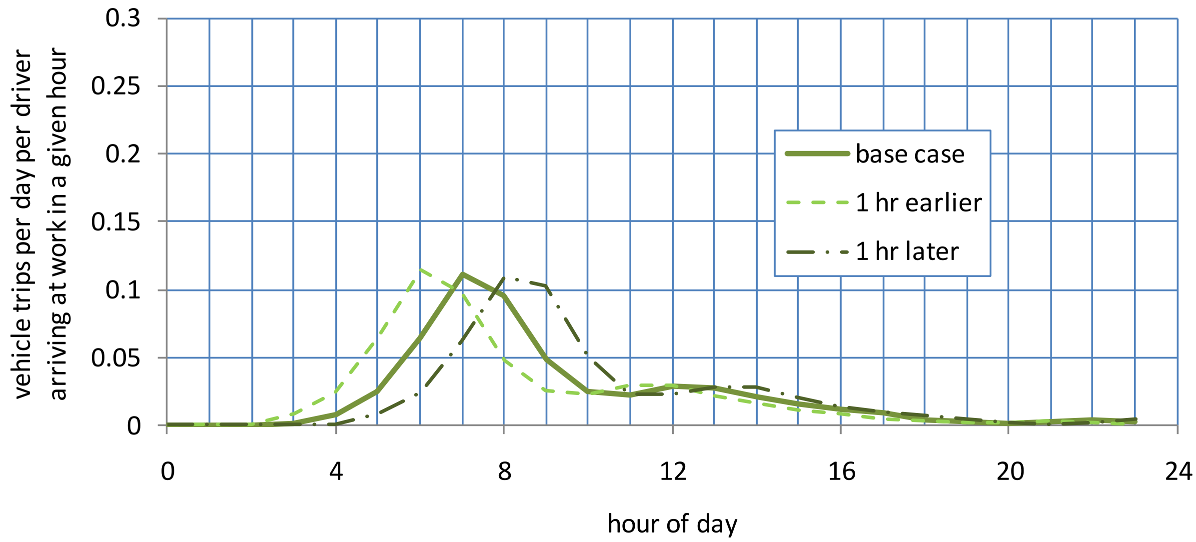

Figure 3.26. Distribution of arrival times of trips to work for the base case (same as other scenarios, shown as a solid line), one hour earlier (dashed line) and one hour later (dash-dot line). Number of vehicle trips per driver per day arriving within a given hour.

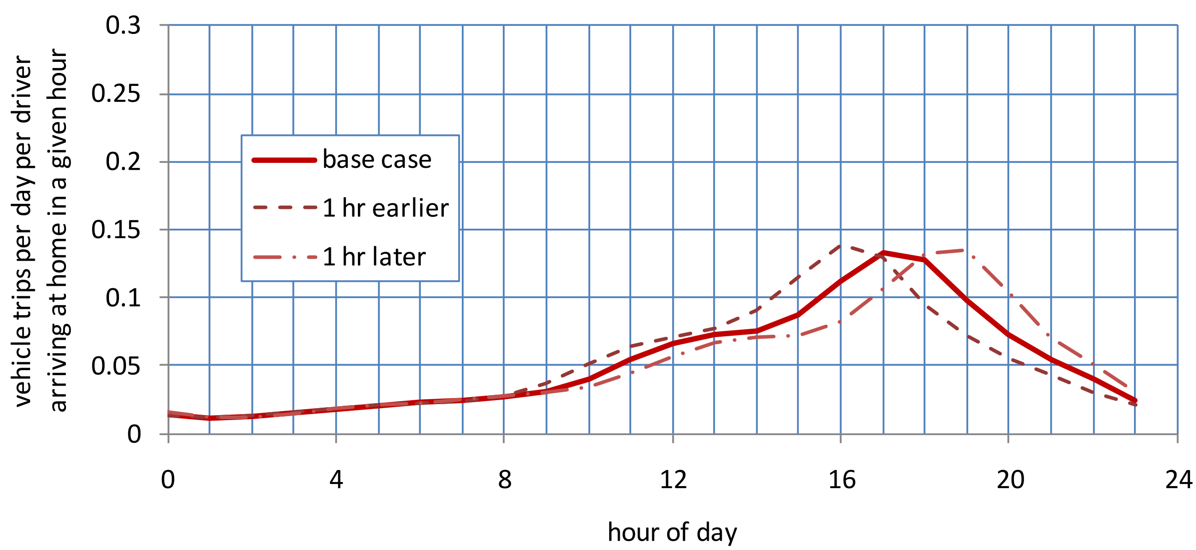

Figure 3.27. Distribution of arrival times of trips to home for the base case (same as other scenarios, shown as a solid line), one hour earlier (dashed line) and one hour later (dash-dot line). Number of vehicle trips per driver per day arriving within a given hour.

In all three cases, 50% of the fleet was PHEVs, with all drivers paying a flat electricity rate of \$0.10/kWh, and the gasoline price was \$2.50/gal. Drivers would choose to recharge their vehicles upon arriving at home if they planned to stay there for at least two hours. The resulting electricity demand for a fleet of 7.3 million vehicles (3.65 million PHEVs) as a function of time of day changed only slightly with the different arrival time distributions, as shown in Figure 3.28. Total demand for each hour was averaged over the week. PHEV charging demand occurred earlier or later when drivers arrived home earlier or later, respectively. This can be seen more clearly in Figure 3.29, which shows only the electricity demand for PHEV charging.

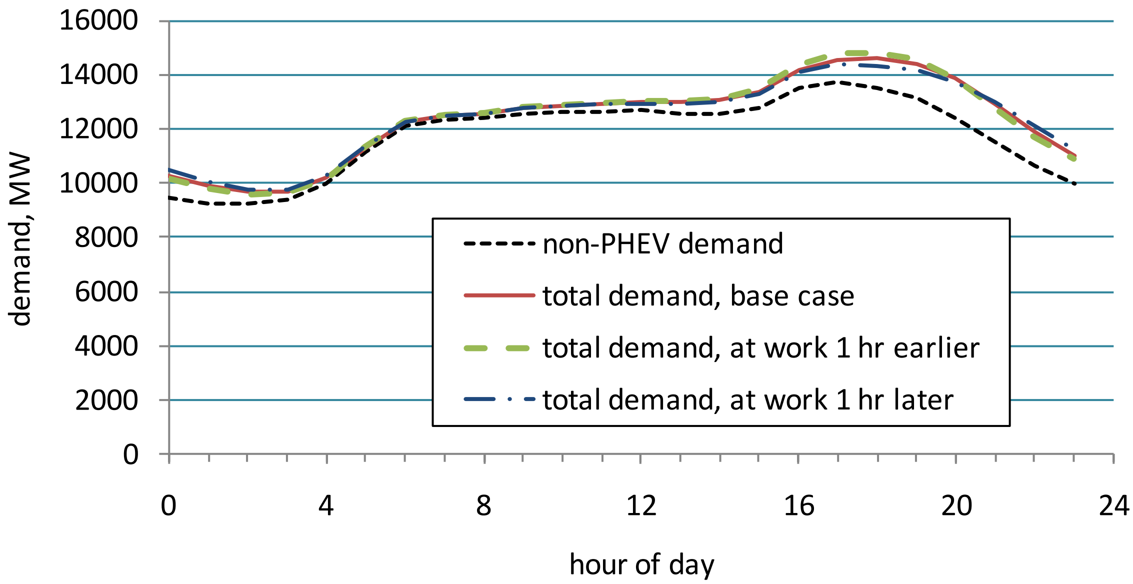

Figure 3.28. Electricity demand in Michigan with 50% of the fleet PHEVs, arriving one hour earlier (dashed line) or later (dash-dot line) than in the base case (solid line). Non-PHEV electricity demand is shown as a dotted line.

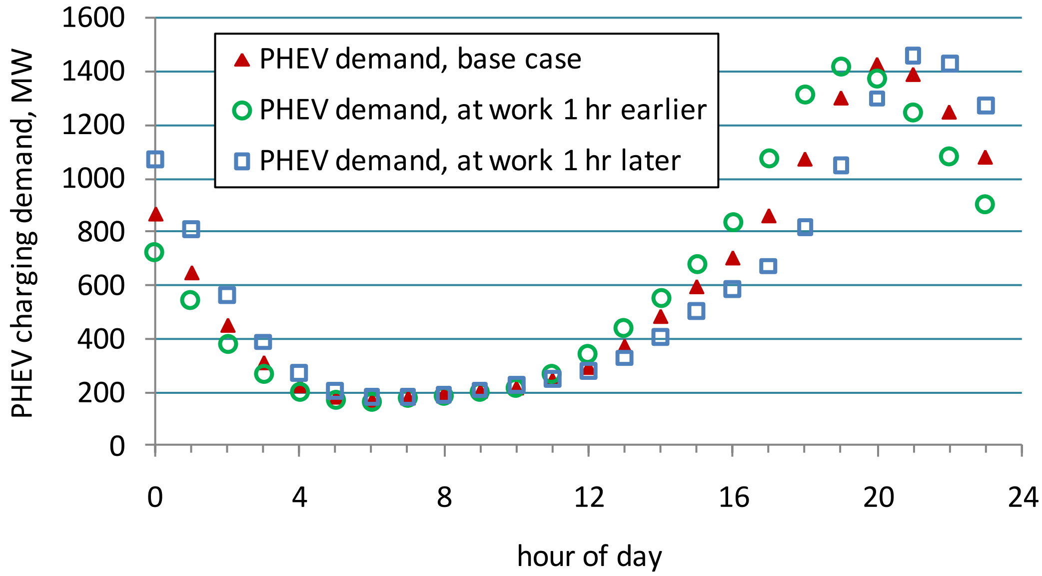

Figure 3.29. Electricity demand for PHEV charging in Michigan with 50% of the fleet PHEVs, arriving one hour earlier (circles) or later (squares) than in the base case (triangles).

As neither the average trip distance nor numbers of trips per day changed, the vehicle miles driven and energy consumed were the same in all three cases. However, with the peak in PHEV charging demand occurring an hour earlier, it coincided more nearly with the peak in non-PHEV demand. With later arrival times, the peak in PHEV charging occurred slightly later than the peak in non-PHEV demand. Thus, the magnitude of the total peak demand depends on the time of the peak in PHEV demand. This is to be expected; when the afternoon rush hour occurs close to or just before the peak in non-PHEV demand, the peak in PHEV charging coincides with other electricity demand, and the resulting peak in total demand is higher. The maximum total demand for the three cases is shown in Table 3.17.

The magnitude of the difference in total demand is a few hundred MW, which is not large, but is significant in comparison to the magnitude of the peak PHEV charging demand (1400 MW, as seen in Figure 3.29).This suggests that congestion management measures such as rush hour road pricing or other policies that affect timing of the afternoon rush hour may affect peak electricity demand at the high levels of PHEV fleet penetration considered here.

Table 3.17. The peak average total demand with PHEV drivers arriving as in the base case, one hour earlier, or one hour later.

arrival times	Peak average total demand [MW]	Daily charging electrical energy per PHEV [kWh/day]	GHG per PHEV-mi. [g CO_2 eq/mi]
base case	14,700	4.04	281
one hour earlier than base case	14,900	4.05	280
one hour later than base case	14,300	4.00	279

Since miles driving patterns are unchanged, vehicle miles traveled and the fraction of vehicle-miles traveled electrically are unchanged. Greenhouse gas emissions are unchanged, due to the nearly constant marginal emission rate of the power plants included in the model for the range of electricity demand in this scenario.

In this scenario, it is seen that modest changes in the time of day of the morning and afternoon rush hour peaks in arrival frequency can change the magnitude of peak electricity demand, even though the total electrical energy for PHEV charging is unchanged. The coincidence of the peak in PHEV charging demand with the peak in non-PHEV charging demands depend on the time of day of the afternoon rush hour. The more these peaks overlap, the greater is the peak in total electricity demand. This suggests that at high levels of PHEV fleet penetration, policies that influence the time of day that PHEV drivers travel may be useful in managing the electricity demand for PHEV charging. On the other hand, in communities with large numbers of PHEVs, municipal planning organizations developing policies to control congestion should consider the potential impacts on electric utilities that such polices might have.

3.6.2 Scenario 8: Distance between home and work

To examine the effects of longer distances between home and work, in this scenario drivers who work have home-to-work distances 80% longer on average than in the base case. The distribution of distances between home and work used in this scenario is compared with that of the base case in Figure 3.30. Also shown is the commute distance distribution estimated from the 2001 NHTS. The base case distribution is the distribution used in the other scenarios, as shown in Figure 2.8. In this scenario, arrival times at work were distributed the same as in the base case, but the departure times for trips to work and the arrival times for trips to other destinations differed due to the longer travel times for commute trips.

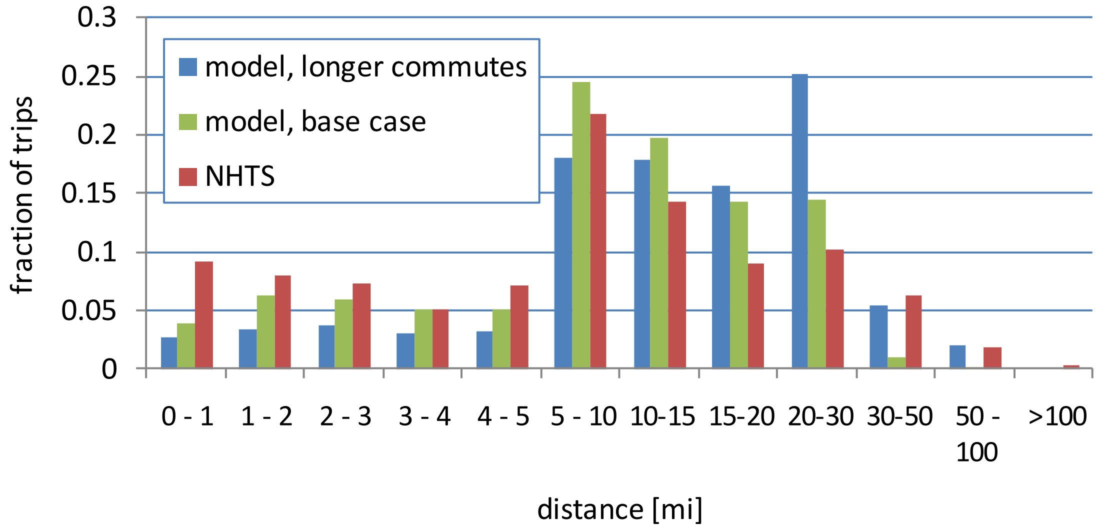

Figure 3.30. Distribution of distance between home and work for this scenario (longer commutes), other scenarios (base case), and the distribution estimated from the 2001 NHTS.

For this scenario, the average home-to-work distance was 22.1 mi, while in the base case, it was 12.1 mi. The average travel time for a 22.1 mi trip is 28 minutes, and the average travel time for a 12.1 mi trip is 21 minutes, so the additional travel time is only 7 mints, on average. The arrival time distribution for the longer commute case is only slightly different from the base case, as shown in Figure 3.31.

Arrival times at work are the same, as this is fixed. Arrival times for trips to home or other destinations are slightly later, but the difference is too small to significantly change the timing of electricity demand for PHEV charging. The PHEV charging demand is basically unchanged by longer commuting distances, as is seen in Figure 3.32.

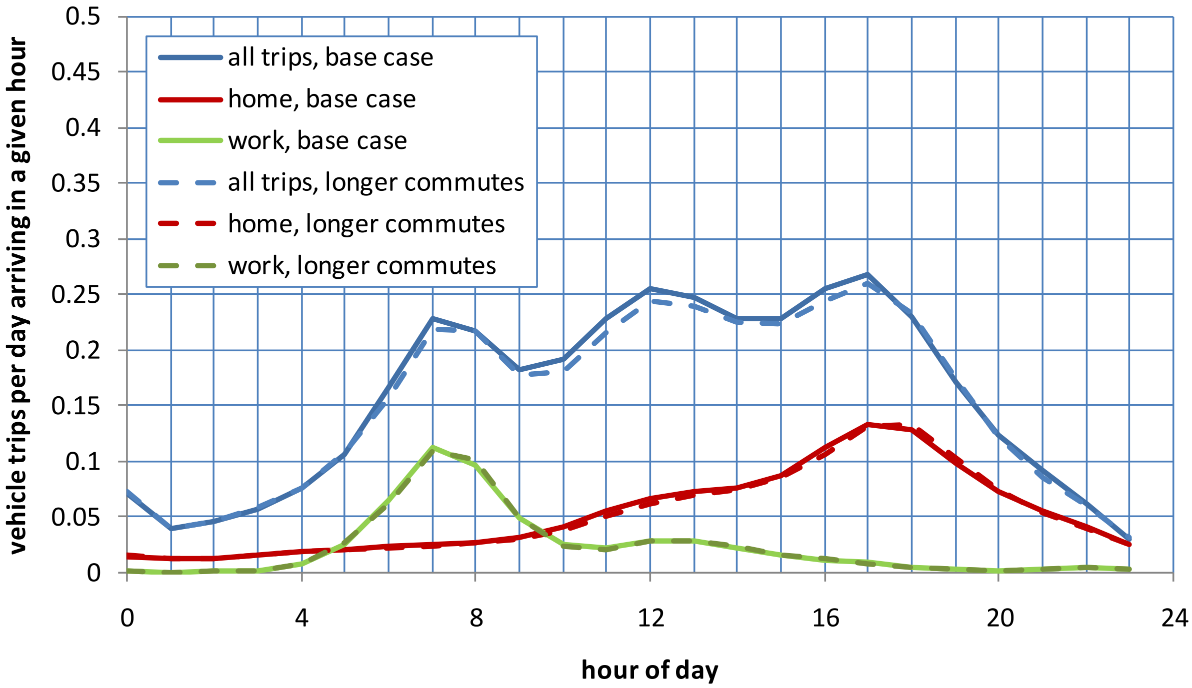

Figure 3.31. Distribution of arrival times of trips to work (green), home (red) and to all destinations (blue) for the base case (same as other scenarios, shown as a solid line), and for 80% longer commute distances (dashed lines).

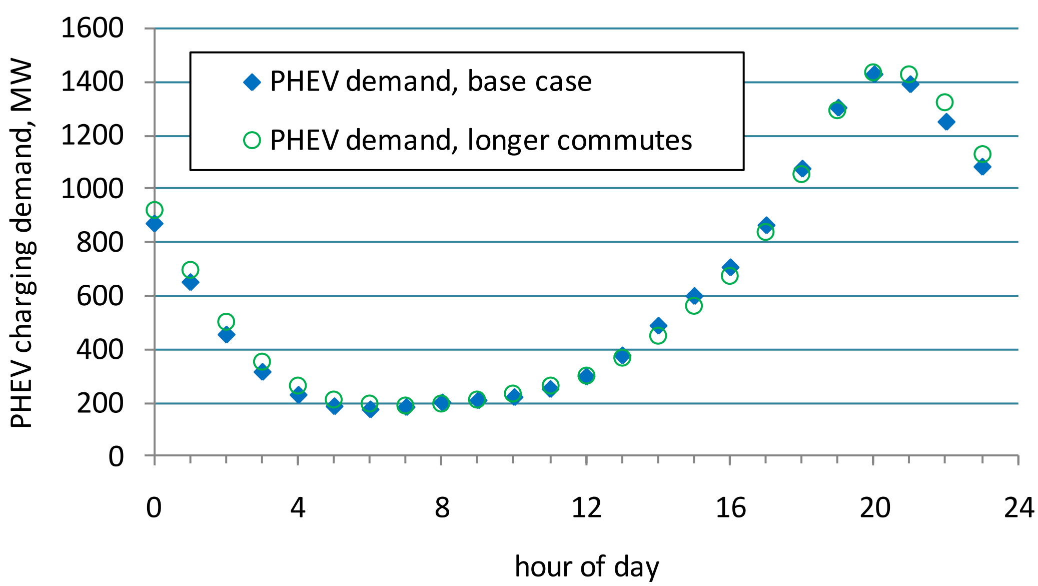

Figure 3.32. Electricity demand for PHEV charging in Michigan for 50% of the fleet PHEVs, with an average commute distance of 12.1 mi (base case, diamonds) and 22.1 mi (circles).

Charging demand and therefore power plant emissions are the same for the two cases, but the average distances driven and fraction of miles driven electrically are different, as expected. Table 3.18 lists the vehicle-miles traveled, gasoline consumed, and GHGs emitted by vehicles for the two cases.

Table 3.18. Vehicle miles traveled, gasoline consumed, and GHGs emitted by vehicles for an average commute distance of 22.1 mi compared with the base case with an average commute distance of 12.1 mi.

average commute distance [mi]	12.1 (base case)	22.1
daily VMT per vehicle (all vehicles)	33.6	40.6
daily VMT per PHEV [mi/day]	34.7	41.9
daily elect-powered VMT per PHEV [mi/day]	12.6	13.0
fraction PHEV-miles elec	0.363	0.310
daily CV gasoline use per vehicle [gal/ day]	1.453	1.75
daily PHEV gasoline use per vehicle [gal /day]	0.539	0.70
GHG per CV-mi [g/mi]	500	500
GHG per PHEV-mi [g/mi]	283	281

With longer commute distances, PHEV drivers tend to drive greater distances on gasoline power, but electricity demand is basically unchanged. The timing of vehicle charging is the same to within a few minutes for the range of commute distances considered here, since the increase in travel time for commutes is small, only 7 minutes. In general, driving longer distances per trip will decrease the fraction of miles traveled electrically for PHEV drivers and increase fuel consumption, vehicle emissions, and operating costs per mile.

CHAPTER 4

Discussion and conclusions

4.1 Modeling approach

Predicting energy use by future PHEV drivers is made difficult by the fact that the decisions of many individuals in a large, heterogeneous population determine the electricity demand as a function of the time of day, which determines their demand for gasoline. An agent-based model, the Driver Vehicle Use Decision (DVUD) model, was developed that uses simple assumptions about travel demand and statistical information on travel by U.S. drivers. From these, and data on the GHG emissions from fuel supply and electric utilities, electricity and fuel demand and the resulting GHG emissions are estimated for a population of drivers. These estimates can be made for different assumptions about travel demand, and driver sensitivity to travel costs.

This demonstrates that agent-based modeling can be used to represent a population of drivers who respond to changes in energy prices and to constraints on the location and time of day for vehicle charging. Tracking vehicle energy use and greenhouse gas (GHG) emissions for each driver's vehicle trip-by-trip allows accurate estimation of energy consumption and emissions by hour without having to assume a value for the fraction of distance traveled electrically or having to assume a charging profile (electricity demand as a function of time of day) for the fleet. In the model developed here, estimates of energy use and emissions are made from the drivers' trips. In turn, driver agents in the model make trips according to their travel needs (when they need to be where) and time constraints (when they cannot travel), and the frequency of trips shows the expected response to travel costs. This permits modeling of scenarios in which energy prices change or there are constraints on where or when PHEV drivers can charge their vehicles. Furthermore, the ABM approach permits examination of the distribution of responses of drivers and of the effects of prices and constraints on segments of the population. Values for quantities such as the fraction of miles driven electrically and operating cost savings can vary widely between drivers, and averages of these quantities may not be representative of values realized by many individuals.

For the scenarios modeled here, changes in driving patterns due to changes in the price of gasoline, the electricity rate, or changes in where or when PHEV could charge their vehicle batteries were very small. This was due to the low sensitivity of drivers to operating costs. Drivers agents in the DVUD model were limited in the behavior changes they exhibited. They could change the frequency of driving, but could not change vehicles or choose to carpool or to chain trips in response to higher operating costs. However, U.S. drivers show a low sensitivity to the price of gasoline, and typically, these behavioral responses do not result in a large change in gasoline consumption. Therefore, a deterministic (non-adaptive) model of drivers based on a static driving pattern would provide estimates of energy use and emissions close (within a few percent) to the projections of the DVUD model, at least for modest ranges of gasoline price and electricity rate.

4.2 Electricity and gasoline consumption and GHG emissions

From estimates made using the DVUD model for a fleet penetration of 50% by PHEVs in Michigan, with a total fleet of 7.3 million vehicles, gasoline consumption is projected to decrease from 11.4 million gallons per day to 7.4 million gallons per day. Peak electricity demand for PHEV charging is projected to reach about 1400 MW. If future PHEV drivers drive trips with travel patterns similar to current U.S. drivers, then most PHEV charging will occur overnight, and the peak in charging demand will occur soon after the majority of drivers get home in the evening. The electrical energy demand may not be large with respect to the total electrical demand, but if the peak demand for charging coincides with the peak in total electricity demand, new generating capacity may be required unless drivers can be induced to charge during off-peak hours. The charging profile produced by the model is similar to profiles assumed in many earlier studies of PHEV electricity demand, with demand by PHEVs high in the evening when most drivers arrive at home. However, the profile produced by the model shows significant demand at all hours, depending on whether drivers can charge only at home or both at home and at work.

The fraction of miles driven electrically by PHEV drivers estimated by the DVUD model is close to estimates made by others, with the same dependence on PHEV charge-depleting range, giving some confidence in the consistency of the approach taken here with that of other the studies. The estimated reductions in gasoline consumption and in GHG emissions achieved by substitution of conventional vehicles by PHEVs are close to estimates made in other studies. In this study, the electricity was assumed to be supplied by the power plants in the state of Michigan, which on average, have a higher GHG emission rate (900 g CO_2 eq/kWh) than the U.S. nation-wide average (587 g CO_2 eq/kWh), Hence, Michigan GHG reductions were not predicted to be as large as for regions with lower electric generation emissions.

4.3 PHEV driver response to energy costs

If future PHEV drivers exhibit the same price elasticity of demand for energy for their vehicles as U.S. drivers currently exhibit for gasoline, PHEV drivers will probably be less responsive to changes in gasoline prices than current drivers of conventional vehicles... This is for two reasons: 1) PHEVs consume less gasoline per mile than comparable conventional vehicles, so PHEV owners are less exposed to changes in gasoline prices, and 2) PHEVs are likely to be owned preferentially by higher-income drivers, who have a lower price elasticity of demand for gasoline. The first reason will be true even for low-income PHEV owners. The driver agents in the DVUD reduce their trips frequency in response to an increase in gasoline price, but PHEV drivers decrease trip frequency by only about 70% as much as conventional vehicle drivers in the same income bracket. Response of PHEV drivers to changes in electricity rates may be even lower than to changes in fuel prices due to the fact that at foreseeable gasoline prices and electricity rates, PHEVs will cost less to operate per mile on electric power than on gasoline power. Therefore, even if electricity rates increase, it will be more economical for PHEV owners to use electricity than gasoline, and PHEV owners will not change their charging behavior.

However, at very high electricity rates, (or very low gasoline prices), PHEV owners will find it more economical not to charge their vehicle batteries and simply drive on gasoline. The electricity rate at which this occurs depends on the efficiency of the PHEV, the relative prices of electricity and gasoline, and the fraction of miles the PHEV travels under electric power, which in turn depends on the driving pattern. These dependencies may make it difficult for electric utilities to use electricity rates to influence the time of day that PHEV owners charge their vehicles, since the response of PHEV drivers will be difficult to predict. Additionally, it is difficult to predict whether PHEV drivers who are faced with high peak rates and low off-peak rates will compare the cost of electric power per mile of travel to the cost of gasoline per mile, or compare the cost of peak-rate electricity to that of off-peak-rate electricity. PHEV drivers who do not plan to drive their vehicles during several hours of the off-peak period may choose to defer charging their vehicles until the off-peak hours. If they can do so and be confident that their batteries will be fully charged before their next trip, they may choose to wait to recharge until the off-peak hours. This requires drivers to have some sensitivity to travel costs, to know when off-peak hours are, and to plan their future trips. For just how many future PHEV drivers this will be the case is highly uncertain. This again makes the use of electricity rates to influence when PHEV drivers charge their vehicles difficult to implement without some trial and error or pilot studies.

4.4 Availability of electricity for PHEV charging

Interruptible service may be a very feasible means to manage PHEV charging demand. If future PHEV drivers have similar travel patterns to current U.S. drivers, charging at home overnight will allow nearly all PHEV drivers to charge their vehicle batteries overnight as long as electricity service is not interrupted too late at night. Nearly all PHEV owners will be able to completely charge their vehicles after power is restored. Electric utilities will have to manage the peak in PHEV charging demand when power is restored, since at night there will probably be a large number of vehicles plugged in with batteries at a low state of charge.

Allowing PHEV owners to charge at work in addition to charging at home increases the electrical energy consumed by almost 30% and decreases the fuel consumed by PHEVs by about 15%. When PHEV drivers can charge at both work and at home the electricity demand for charging is significantly higher in mid-morning hours, after many PHEV drivers arrive at work. In months with high total electricity demand, electricity demand tends to peak in the early afternoon, and the additional demand for PHEVs being charged at work may add to the peak in total demand. DVUD model projects that PHEV charging demand in the evening, when most PHEV drivers are arriving at home is very nearly the same as in the case of charging only at home. This indicates that even if drivers charge their batteries at work, most PHEV drivers will discharge their batteries before returning home after work. In the model, many PHEV drivers made trips between leaving work and arriving at home. Additional charging at work did not decrease their demand for charging at night, but increased the fraction of distance they could drive electrically. Since at reasonable values of electricity rates and gasoline prices traveling electrically costs less per mile than traveling under gasoline power, enabling PHEV drivers to charge at work as well as at home will increase the operating cost savings realized by PHEV drivers.

4.5 Suggestions for future work

Linking driver decisions to their energy consumption and emissions offers opportunities to explore other questions about PHEVs. Improvements to the DVUD model, such as more realistic vehicle energy consumption and emissions modeling would increase the accuracy of energy and emissions estimates. This could also include models for blended, parallel drivetrain PHEVs, in order to estimate fraction of miles traveled electrically for these vehicles, which is difficult to estimate without travel details at the trip level.

Giving driver agents the ability to choose to allow the electric utility to use their vehicle battery for storage for a fee (payable to the PHEV owner), would permit modeling vehicle-to-grid scenarios which could examine conditions and prices under which drivers might decide to allow a utility to use energy in their vehicle batteries. Other scenarios could include use of vehicle batteries for residential backup power in the case of power outages.

Further work examining economic benefit of owning a PHEV would be aided by integrating the DVUD model with a consumer vehicle choice model, or at least assigning vehicles to drivers in a manner more consistent with realistic vehicle purchase decisions. The current DVUD model assigns vehicles to drivers with a realistic correlation with driver income, but owners should have the ability to trade their vehicle for another model if their vehicle does not suit them, which may be influenced largely by operating costs and purchase price. This would permit more realistic analysis of the economics of PHEV ownership under different energy prices, rebates, or other incentives.

More fundamentally, a more realistic approach to modeling travel demand by drivers would increase confidence in the model projections. This might require an explicit 2-dimensional representation of the area that drivers travel in, as well as modeling driver agents as members of households rather than one driver per vehicle. Driver agents in households, who negotiate vehicle use based on their activities as do actual drivers, would permit modeling a wider range of more realistic driver responses to changes in energy prices, constraints on charging or other conditions.

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Appendix A

Model Flowcharts

Figure A1. Driver Vehicle and Use Decision (DVUD) model flowchart

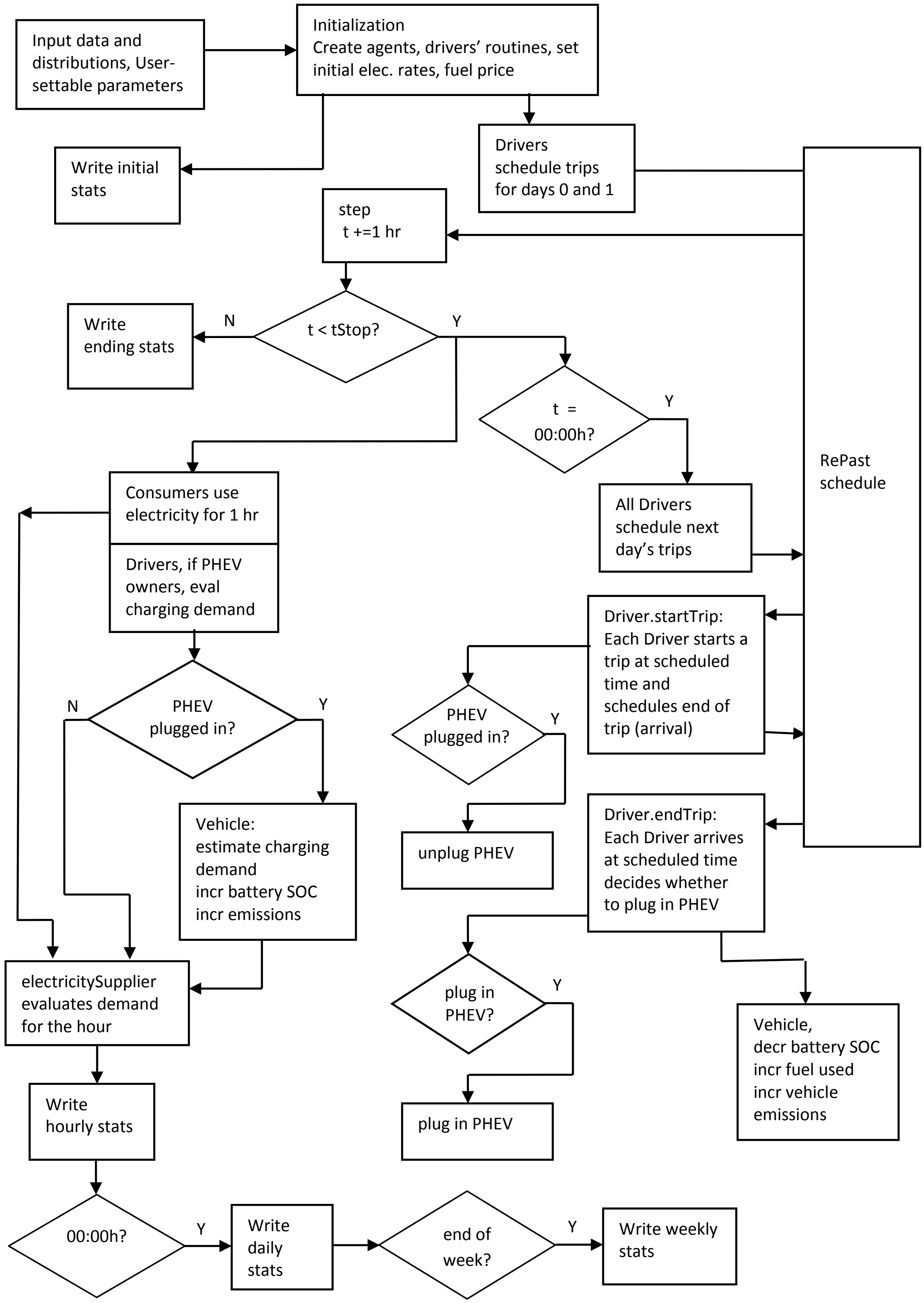
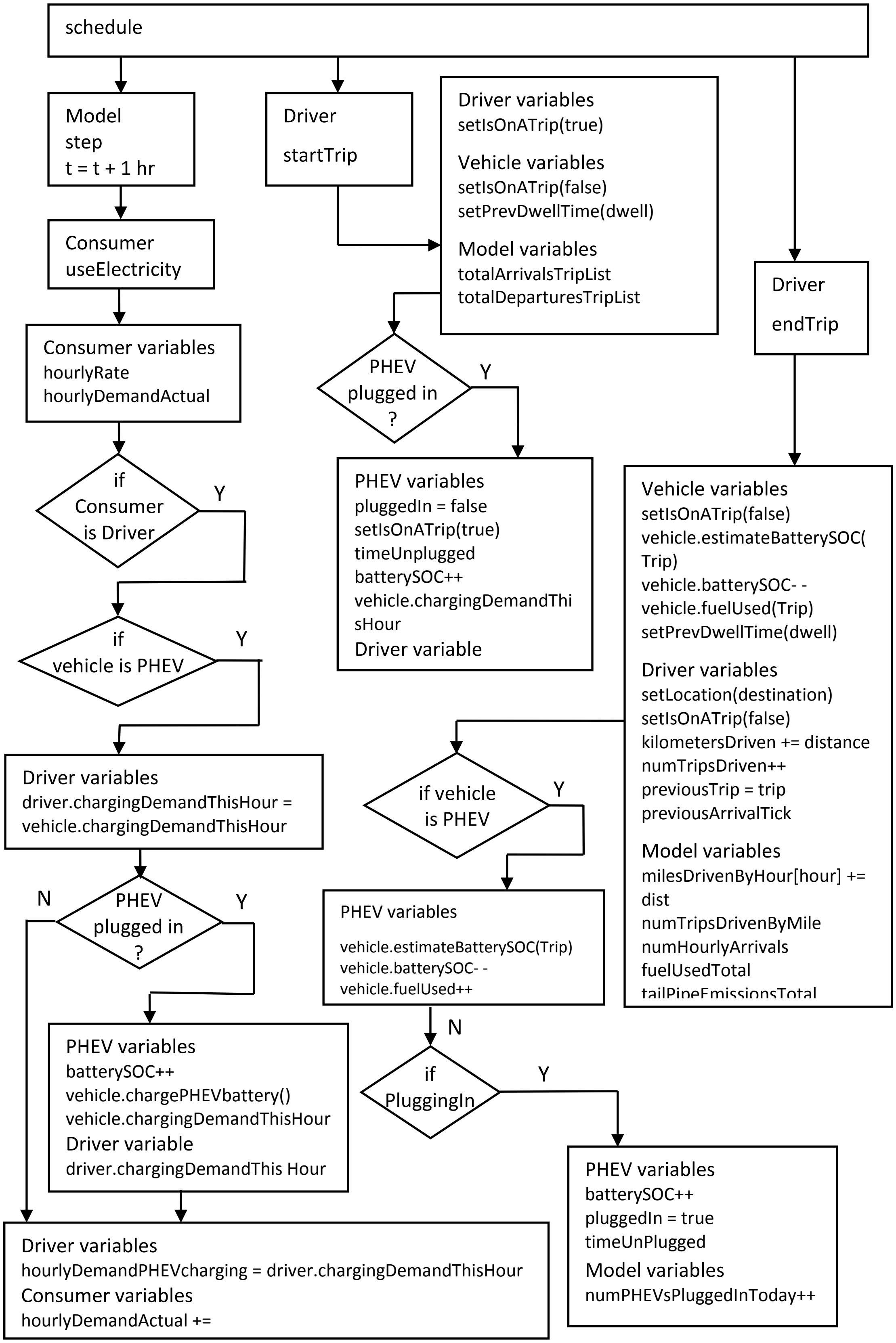


Figure A2. Driver decisions and actions flowchart



Appendix B

Installing and running the DVUD model

To set up folders to run program on a Windows (Vista) machine, create a directory named phevDrivers containing a subdirectory phevDrivers. In phevDrivers\phevDrivers, there must be:

- a subdirectory bin
- a subdirectory src
- the following files:
    - cscs530.jar
    - elecDemandInput3.txt
    - elecInput.txt
    - tripDistanceDistr.txt
    - vehicleDistr4.txt
    - workDayTripDistr4.txt

The file cscs530.jar is a jar file containing Java code. It was developed by Michael Bommarito in the Center for the Study of Complex Systems at the University of Michigan.

Another file is also required: repast.jar.

If this file is in a directory with a pathname C:\Program Files\Repast 3\Repast J\repast.jar then the program can be compiled from the directory phevDriver\phevDriver with the command (typed into a DOS command prompt window, or in a DOS bat file that is in the phevDrivers\phevDrivers directory):

```
javac -d bin\ -cp "C:\Program Files\Repast 3\Repast J\repast.jar" src\phevDrivers\*.java
```

The compiler may issue a warning statement:
"Note: src\phevDrivers\Driver.java uses unchecked or unsafe operations."
This is due to data structures that are not type-checked, but it will not result in errors.

To run the program, type the command:

```
java -cp bin/;"C:\Program Files\Repast 3\Repast J\repast.jar" phevDrivers.BatchModel D=0
S=531117 T=1441 nD=1000 sF=1.37 fPV=0.5 fNW=0.2 dSD=250.0 aDFN="agentDemogr"
pRFN="moReport" fLO=0.5 dRFN="dayReport" dSD=0.0 pP=1.0 fE=1.0 rN=0
```

To run the program and have it print out the parameters (but not execute the model) type the command:

```
java -cp bin/;"C:\Program Files\Repast 3\Repast J\repast.jar" phevDrivers.GUIModel -h
```