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Influence of driving patterns on life cycle cost and emissions of hybrid and plug-in electric vehicle powertrains

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HIGHLIGHTS

- Electrified vehicle life cycle emissions and cost depend on driving conditions.
- GHGs can triple in NYC conditions vs. highway (HWFET), cost +30%.
- Under NYC conditions hybrid and plug-in vehicles cut GHGs up to 60%, cost 20%.
- Under HWFET conditions they offer few GHG reductions at higher costs.
- Federal tests for window labels and CAFE standards favor some technologies over others.

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ABSTRACT

We compare the potential of hybrid, extended-range plug-in hybrid, and battery electric vehicles to reduce lifetime cost and life cycle greenhouse gas emissions under various scenarios and simulated driving conditions. We find that driving conditions affect economic and environmental benefits of electrified vehicles substantially: Under the urban NYC driving cycle, hybrid and plug-in vehicles can cut life cycle emissions by 60% and reduce costs up to 20% relative to conventional vehicles (CVs). In contrast, under highway test conditions (HWFET) electrified vehicles offer marginal emissions reductions at higher costs. NYC conditions with frequent stops triple life cycle emissions and increase costs of conventional vehicles by 30%, while aggressive driving (US06) reduces the all-electric range of plug-in vehicles by up to 45% compared to milder test cycles (like HWFET). Vehicle window stickers, fuel economy standards, and life cycle studies using average lab-test vehicle efficiency estimates are therefore incomplete: (1) driver heterogeneity matters, and efforts to encourage adoption of hybrid and plug-in vehicles will have greater impact if targeted to urban drivers vs. highway drivers; and (2) electrified vehicles perform better on some drive cycles than others, so non-representative tests can bias consumer perception and regulation of alternative technologies. We discuss policy implications.

1. Introduction

The Obama Administration's New Energy for America agenda set a target of achieving 1 million plug-in vehicles on U.S. roads by 2015 (Obama and Biden, 2009–04–11). Plug-in vehicles, including plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), may play a key role in cutting national gasoline consumption, addressing global warming, and reducing dependency on foreign oil in the transportation sector. Plug-in vehicles operate partly or entirely on inexpensive electricity that can be potentially obtained from local, renewable, and less carbon-intensive energy sources than gasoline (Bradley and Frank, 2009; Samaras and Meisterling, 2008). Based on the 2009 National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2009), approximately 60% of U.S. passenger vehicles that drove on the day surveyed traveled less than 30 mi, a distance that could be powered entirely by electricity using plug-in vehicles. Thus, plug-in vehicles have the potential to offset a substantial amount of gasoline consumption even when charged only once per day.

The fuel economy and emissions of vehicles depend on the way they are driven, including daily driving distance (Shiau et al., 2010; Traut et al., 2012; Kelly et al., 2012; Neubauer et al., 2012, 2013; Raykin et al., 2012a,b) and driving conditions. Official fuel economy ratings are based on standard test driving conditions – called

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a driving cycle – but real-world driving patterns can vary substantially from standard test cycles (Patil et al., 2009; Berry, 2010), leading real-world costs and emissions to deviate from those estimated on window stickers or in life cycle studies. In the literature, vehicle life cycle assessment and design optimization studies are typically conducted using efficiency estimates from federal test cycles, with results that favor certain powertrains over others. In this paper, we investigate variation in life cycle cost and emission benefits of hybrid and plug-in vehicles under a range of driving conditions with a sensitivity analysis to critical factors such as gasoline prices, vehicle costs and electricity grid mix. Specifically, we compare conventional vehicle (CV), hybrid electric vehicle (HEV), PHEV, and BEV powertrain technologies and identify changes in all-electric range (AER), vehicle efficiency, and battery life, under a variety of driving patterns to determine the most cost effective and lowest GHG-intensive powertrains. Then we discuss the energy policy implications of our findings considering multiple scenarios related to market, vehicle technology, and electricity grid mix.

1.1. Electrified vehicle powertrain alternatives

Electrified powertrains include HEVs, which use a small battery to improve gasoline fuel efficiency but do not plug in; PHEVs, which use both gasoline and electricity; and BEVs, which use only electricity and not gasoline. All three powertrains share an advantage over conventional vehicles: each is capable of regenerative braking. When a conventional car brakes, the vehicle's kinetic energy dissipates mostly as heat. In contrast, an electrified vehicle with regenerative braking capability can capture and store some of this energy in its battery. In addition, HEVs and PHEVs are able to manage engine operating conditions to improve efficiency, turn off the gasoline engine at idle, and make use of higher efficiency, lower torque thermodynamic cycles.

Fig. 1 demonstrates the relationship between the battery and the different operation modes of plug-in vehicles. For safety, reliability, and longevity reasons, electrified vehicle powertrains use only a certain portion of the full energy capacity of its battery, limited by the specified maximum and minimum battery state of charge (SOC) values. Operation of PHEVs can be categorized into two modes as seen in Fig. 1: charge-depleting (CD) mode refers to the phase where the SOC is above the target SOC and the vehicle receives some or all of its net propulsion energy from the battery pack. Once the battery is depleted to a target SOC, the vehicle switches to charge-sustaining (CS) mode, in which gasoline is used to provide all net propulsion energy and the electrical system is used only as momentary storage to improve fuel economy, similar to a grid-independent HEV. Some PHEVs operate CD-mode using only electrical energy. Such a configuration, referred to as an all-electric control strategy or an extended-range electric vehicle (EREV), enables short trips to be driven without any gasoline consumption but requires electric motor and battery designs that can deliver the vehicle's maximum power demands. Other PHEV designs operate CD-mode using a mixture of gasoline and electrical energy. Such a configuration, referred to as a blended control strategy, does not eliminate gasoline consumption even for short trips, but power demands on electrical components are lower, allowing smaller, cheaper components to be used. We focus on EREV PHEVs, since the performance of blended-operation PHEVs varies substantially with control strategy parameters (Tulpule et al., 2009; Sciarretta et al., 2004; Sciarretta and Guzzella, 2007; Moura et al., 2011). Operation of a BEV is similar to that of an EREV PHEV in CD mode, and operation of an HEV is similar to that of a PHEV in CS mode.

Hybridization can be based on 3 specific powertrain architectures: (1) series, where the engine turns the generator which generates electricity to be used by the electric motor to turn the wheels; (2) parallel, which is capable of transmitting torque to the wheels from two different energy sources; and (3) split, which uses a planetary gear device to operate both in series and parallel. For greatest flexibility, we adopt the split powertrain for HEV and PHEV designs, as shown in Fig. 2, which is currently used in the Toyota Prius HEV and PHEV.

Current gasoline spark-ignition engine technology can typically provide 20% efficiency under urban driving with a maximum of 35% under the most optimal conditions (Heywood, 2006). These low efficiencies suffer even more under real world driving conditions, where closer to 10% of the chemical energy of each gallon of gasoline acts to turn the wheels. The rest of the energy is lost in the form of heat and sound. With the help of a planetary gear-based power-split device, hybridization allows the engine to operate near its most efficient torque and speed values while providing excess power to recharge the battery or drawing remaining power needs from the motor. In this way large amounts of fuel might be saved, depending on the drive cycle. The motor is supplied with the electric energy from the battery, which is

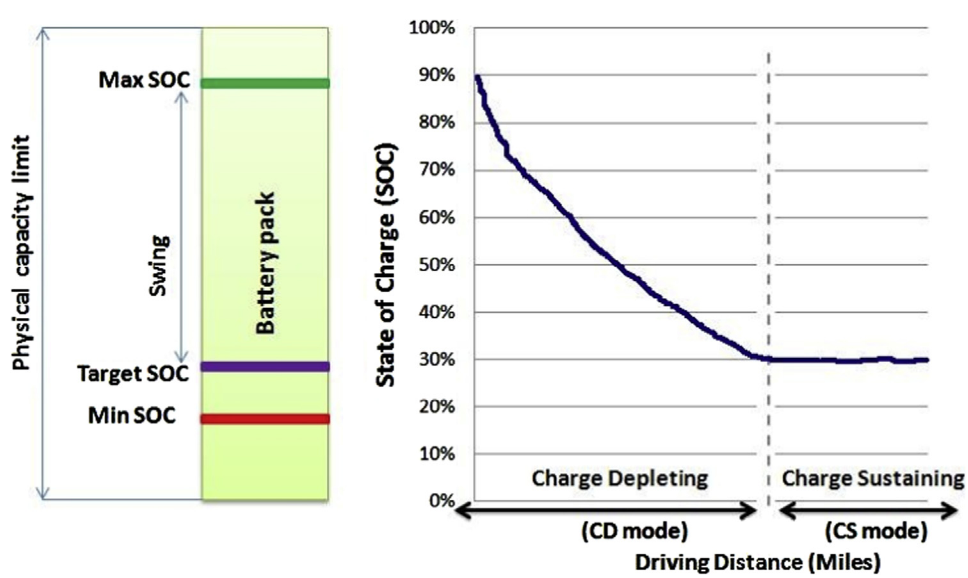

Fig. 1. Operation modes of a PHEV (figure adapted from Shiau et al. (2010).

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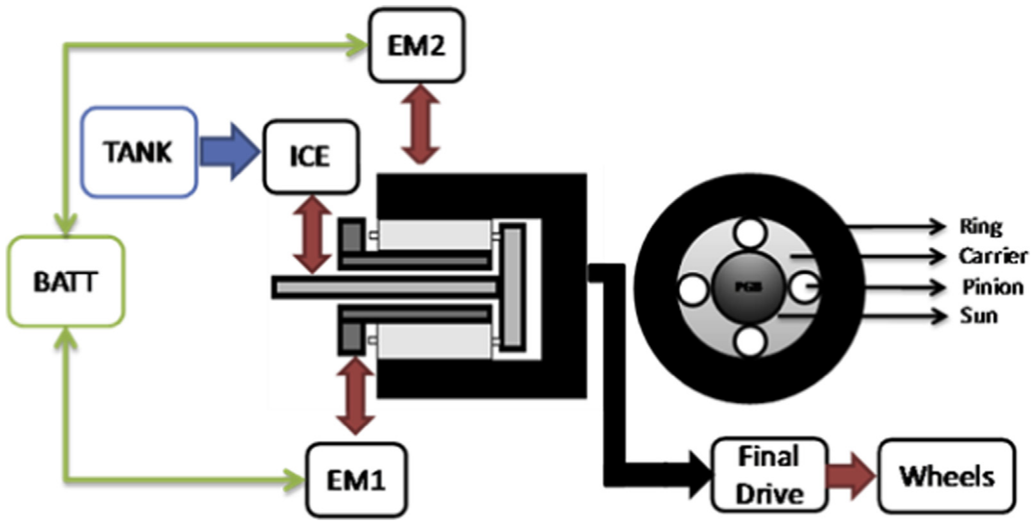

Fig. 2. Schematic of a split hybrid powertrain.

partially recharged during regenerative braking in HEV, PHEV and BEV powertrains and can be charged from an electrical outlet for PHEVs and BEVs.

HEV and PHEV vehicle models in this study are based on the Toyota Prius model year 2004 power split configuration (Fig. 2), modified to represent model year (MY) 2013 vehicles. This model has a planetary gear box (PGB), which splits road power demand between the internal combustion engine (ICE) and two electric motor/generators (EM1 and EM2). The EM2 is connected to the wheels over the ring gear, the outer gear of the PGB, and the final drive gear set. The ICE is directly connected to the carrier gear, while the EM1 is connected to the sun gear. The links between sun and ring is the pinion gear, which is set on the carrier. The chemical power source, the fuel tank, is attached to the ICE to create chemical and eventually mechanical power to propel the vehicle. The electrical power source, the battery pack, is connected to the electrical motor/generators to propel the vehicle or to be charged. All mechanical and electrical links are presented in Fig. 2 with thick and thin arrows, respectively. The planetary gear provides an effective continuously variable transmission and allows the power-split PHEV to run both in series and parallel, taking advantage of both configurations. We have adopted this split powertrain architecture in our HEV and PHEV vehicle powertrain models, using an EREV control strategy for PHEVs.

1.2. Vehicle comparison based on fuel economy and emissions

Fuel economy labels (window stickers) tell customers how far a vehicle is likely to travel on a gallon of gasoline under certain conditions. These labels are required by law to give customers the information they need to make informed vehicle purchase decisions. In the past, customers have typically observed lower fuel economy in practice than ratings state because test procedures are more gentle than typical driving conditions. This is in part because some of the fuel economy test procedures were developed under limitations of test equipment capabilities. The EPA updated its fuel economy test procedures in 2006, switching from the prior 2-cycle test to a 5-cycle test to more accurately reflect today's driving conditions. No single test can account for the different driving patterns of every driver. With new vehicle technologies such as hybrid powertrains now in the vehicle market, comparisons of the benefits of different vehicle technologies have become even more challenging. For example, the greenhouse gas (GHG) benefits of hybrid powertrains over conventional powertrains is more pronounced in aggressive driving and city driving with frequent stops, as we will show in our results.

The EPA working with the Department of Energy (DOE) has recently announced new fuel economy labels for a new generation of vehicles for 2013 and beyond (US Environmental Protection Agency, 2011). These labels will inform consumers about the vehicle's all-electric range (AER), fuel economy, estimated annual fuel cost, GHGs, smog rating, and how they compare to other vehicles. Fuel economy labels help guide consumer purchase decisions, aiming to provide a common ground to compare different vehicles. Although these new labels provide more information than before, there is also a risk of confusing consumers with too much information. On the other hand, the comparison metrics listed do not account for different representative driving patterns, effects of terrain, weather, changes in fuel price, electricity grid mix, and powertrain degradation, which introduces new costs later during the life of the vehicle (e.g.: reduced fuel efficiency, battery replacement, etc.). These factors have become more important for comparing vehicles as hybrid and plug-in powertrains are introduced. In this paper we analyze life cycle economic and environmental implications of conventional, hybrid, and plug-in vehicles under different driving patterns and daily driving distances, and we discuss the sensitivity of our findings to several parameters.

2. Literature review

Prior work has identified driving cycle as a significant factor in vehicle fuel efficiency, and several studies have compared standard driving cycles to regional data collected on vehicle fleets using GPS data. Moawad et al. (2009) used GPS data from Kansas drivers to compare the simulated fuel consumption of PHEVs and size vehicle components. They found that significant fuel economy improvements are achieved with HEVs compared to CVs; however these gains were lower than those usually estimated using standard drive cycles. Sharer et al. (2007) compared CVs and HEVs under a range of driving cycles and found that HEVs are more sensitive to aggressive driving. Fontaras et al. (2008) analyzed HEVs with European and real world driving cycles and found that under urban driving conditions, fuel consumption of HEVs are 40–60% lower than conventional vehicles. This benefit is even greater for low-average-speed driving with many stops, while at speeds over 95 km/h HEV fuel consumption is similar to that of CVs. Tate (2008) used GPS driving data from Southern California Association of Governments (2003), which consists of 621 samples, to study PHEV performance. The associated power and speed values of the driving samples are found to be higher than those associated with the UDDS driving cycle. The study also compares average energy consumption per unit distance to that of UDDS and HWFET drive cycles and finds that 94% of vehicles function at higher energy consumption under real-world driving conditions than they do under UDDS and HWFET cycles. A 2001 report (Energy and Environmental Analysis, Inc December, 2001) states that impact of aggressive driving in city conditions varies greatly depending on the type of vehicle: Powerful vehicles are robust, but low power vehicles show 6% reduction in efficiency compared to standard drive cycles. However in highway conditions, characterized by high speeds, impact of aggressive driving was much higher: 33% penalty for the average car, and 28% for the powerful car. Berry and Heywood (Berry, 2010) analyzed the effect of driving patterns on the fuel economy of CVs and found that the sensitivity of vehicle fuel economy to aggressive driving is a function of how wheel work and efficiency vary with driving patterns. Whitefoot et al. (2010) optimized HEVs under different driving cycles for minimal fuel consumption, finding that vehicles designed for one driving cycle show significantly lower performance on other drive cycles. Patil et al. (2010) optimized a series PHEV for naturalistic drive cycles and showed that the higher energy demands of real world cycles require larger batteries to meet AER targets. The required optimal battery size changed nonlinearly with desired AER. Fellah et al. (2009) found that if batteries of PHEVs are sized for the UDDS cycle, only 22% of 363 trips from Kansas City can be driven in all electric mode due to power limitations.

Despite the fact that standard cycles are not representative of real driving patterns, some of them can span a wide range. Patil et al. (2009) investigated the impact of real world driving cycles on PHEV component sizing using GPS data from southeastern Michigan. Simulations using the GPS driving data indicate that about 90% of the trips in the data are higher fuel-consuming per mile than the UDDS and HWFET standard cycles, while about 90% of the trips are lower fuel-consuming per mile than the US06 cycle. Similarly after examining the Southern California regional travel data (Southern California Association of Governments, 2003), Tate (2008) found that the vast majority of the energy demanded by the drive cycles of the dataset is bounded by the energy levels required by US06, a reasonable upper limit, and UDDS, a fair lower limit. Thus both studies agree that UDDS and US06 appear to provide reasonable bounds to characterize the effect of driving cycle variation over a population of drivers for conventional vehicles. The authors also emphasize the need for larger electrical components when real world driving is considered. All of these prior driving cycle studies focus on vehicle performance and efficiency but do not assess the full lifetime cost and life cycle implications of different powertrain technologies.

Life cycle assessment studies have shown that vehicle electrification has the potential to reduce GHGs; however, potential benefits depend on the source of electricity used to charge the vehicle. In 2009, the U.S. grid mix consisted of 45% coal, 23% natural gas, 20% nuclear, 7% hydroelectric, 4% other renewable, 1% petroleum, and 0.6% other (Administration, U.S.E.I. Annual Energy Review, 2009). Lipman and Delucchi (2010) provide a review of studies. Weber et al. (2010) show that determining regional grid mix is nontrivial, and dispatch studies such as Sioshansi and Denholm (2009) highlight that the mix associated with marginal demand for electricity varies widely depending on charge timing. Samaras and Meisterling (2008) find that under a high carbon-intensity electricity generation scenario life cycle GHGs of PHEVs are 9–18% higher than HEVs, while GHGs are 30–47% lower under a low-carbon scenario. The Electric Power Research Institute (EPRI) together with the National Resources Defense Council (NRDC) (Elgowainy et al., 2009) analyzed the GHG impacts of PHEVs over the 2010 to 2050 timeframe for several scenarios including different levels of CO_2 intensity in the electricity sector and fleet penetration of PHEVs. Some of the assumptions include projections of vehicle time-of-day charging, plant dispatch, plant retirement and construction, and public policy. Each of the EPRI scenarios showed significant GHG reductions, and PHEV adoption reduces petroleum consumption significantly. Argonne's well-to-wheels report (Argonne National Laboratory, 2009) states that PHEVs charging from the US average grid-mix produce 20% to 25% lower GHGs than CVs but 10% to 20% higher GHGs than gasoline HEVs. They suggest that to receive significant reductions in emissions, PHEVs and BEVs must recharge from a grid-mix which consists of largely non-fossil sources. According to their study, electric range decreases with real world driving. Michalek et al. (2011) estimate the economic value of life cycle oil consumption and air emissions externalities from conventional, hybrid and plug-in vehicles, finding that HEVs and PHEVs with smaller battery packs provide the greatest benefits per dollar spent. Hawkins et al. (2012) provide a life cycle inventory of CVs and BEVs and find that BEVs decrease global warming potential by 10–24% under a European grid mix.

A few studies have examined the role of driving patterns on life cycle implications, primarily assessing the importance of variation in driving distance. Shiau et al., (2010) constructed an optimization model to find the optimal allocation of CVs, HEVs, and PHEVs to drivers based on driving distance to minimize life cycle GHG emissions, finding that optimal allocation based on distance is a second order effect. Traut et al. (2012) extended Shiau's study to include BEVs and workplace charging infrastructure while accounting for day to day driving variability. They identify gasoline and battery prices needed for plug-in vehicles to enter the cost-minimizing solution. Neubauer et al. (2012, 2013) investigated the sensitivity of PHEV and BEV to driving distance and charging patterns, accounting for factors such as battery degradation and the need for a backup vehicle for BEVs when taking long trips. They find that changing the drive pattern can increase the PHEV-to-CV cost ratio by a factor of up to 1.6, and the cost of backup vehicles for BEVs can be substantial. Kelly et al. (2012) used NHTS data and examined the effects of charging location, time, rate, and battery size. Finally, Raykin et al. (2012a,b) analyzed the effect of driving patterns on tank-to-wheel energy use of PHEVs, using an estimated relationship between driving distance and drive cycle based on a travel demand model and vehicle driving simulation. They find that PHEVs result in greater GHG reductions relative to CVs in city rather than highway conditions.

With the exception of Raykin et al. (2012a,b), those studies that investigate variations in drive cycle focus on the effects on performance or efficiency without examining the larger system (e.g.: full life cycle), and those studies that investigate life cycle implications of electrified vehicles either ignore variation in driving conditions or confine scope to examining variation in driving distance and charge timing. Raykin et al. examine both drive cycle and distance in a study of the greater Toronto area, concluding that both matter in estimating life cycle implications. We build on this finding by examining a range of drive cycles and distribution of driving distances for the United States and estimating effects on life cycle emissions, gasoline consumption, lifetime ownership cost, battery degradation, and AER for CVs, HEVs, BEVs, and PHEVs of varying battery capacity.

3. Methodology

We use the Powertrain Systems Analysis Toolkit (PSAT) SP1 Version 6.2, developed by Argonne National Laboratory (2008), to model conventional, hybrid, plug-in hybrid, and battery electric vehicles with identical body characteristics, comparable control strategies, and comparable performance characteristics, and we simulate each vehicle over a range of drive cycles to compare vehicle efficiency and life cycle implications (Fig. 3). We account for battery degradation, different daily driving distances and different scenarios for costs, vehicle technology and electricity grid. In this section we explain each model and their interactions in detail. First, we discuss the choice and characteristics of driving cycles and travel patterns. Then we describe engineering, battery degradation, cost, and environmental models.

3.1. Driving cycles

Efforts to assess and improve the fuel economy and emissions of vehicles are typically not conducted under real-world driving, since multiple noise factors such as various driving patterns, traffic conditions, weather, and terrain might affect the results. Instead, tests are done in a laboratory under controlled and repeatable conditions so that even small fuel economy improvements are not lost due to the noise in the environment. This enables designers, analysts and regulators to compare different vehicle designs to each other on a common basis. A chassis dynamometer is the device used to simulate driving in laboratory conditions: the wheels are placed on rollers that simulate the road load by matching the inertia of the car so that the propulsion system of the vehicle needs to work to rotate the wheels at a certain reference speeds. The speed reference used in this test is taken from a given drive cycle (test cycle) in the form of a series of target vehicle speed values over time. During the test a driver tries to match the vehicle's speed to the reference speed at each moment in time using visual feedback by a computer screen. An emission analyzer is connected to the exhaust pipe of the vehicle to track emissions and estimate fuel consumption. Different driving cycles used during this test result in different performance demands and thus different fuel consumption and emissions. The performance of some powertrain designs may be more sensitive to driving cycle than others. EPA has been using standard driving cycles (FTP and HWFET) to report the fuel consumption and emissions of vehicles. When these test cycles were designed, chassis dynamometer technology was not capable of simulating high acceleration and deceleration (Austin et al., 1993), and the test cycles were constrained to conditions less aggressive than observed in practice. Also because traffic patterns have changed since the 1960s and 1970s, when the FTP and HWFET drive cycles were created, they may fail to represent typical driving conditions today. In 2006, EPA announced a new method to measure fuel economy based on a five-cycle testing method in an effort to better reflect real world performance. According to this method, vehicles are tested on aggressive (US06), air conditioning on (SC03) and cold weather (Cold FTP) drive cycles in addition to city (FTP) and highway (HWFET). Characteristics of these drive cycles are given in Table 1 (Berry, 2010). Weighted combinations of these test results are used to calculate the city and the highway fuel economy values (EPA, 2006). Alternatively, automakers could use unadjusted FTP and HWFET test results in some regression equations to approximate the 5-cycle city and highway fuel economies, with some restrictions during 2008–2010. EPA (2006):

$$\text{Five}-\text{cycle city fuel economy} = \frac{1}{0.003259 + (1.1805)/(\text{FTP fuel economy})} \tag{1}$$

$$\text{Five}-\text{cycle highway fuel economy} = \frac{1}{0.001376 + (1.3466)/(\text{HWFET fuel economy})} \tag{2}$$

EPA combined MPG[2008+]

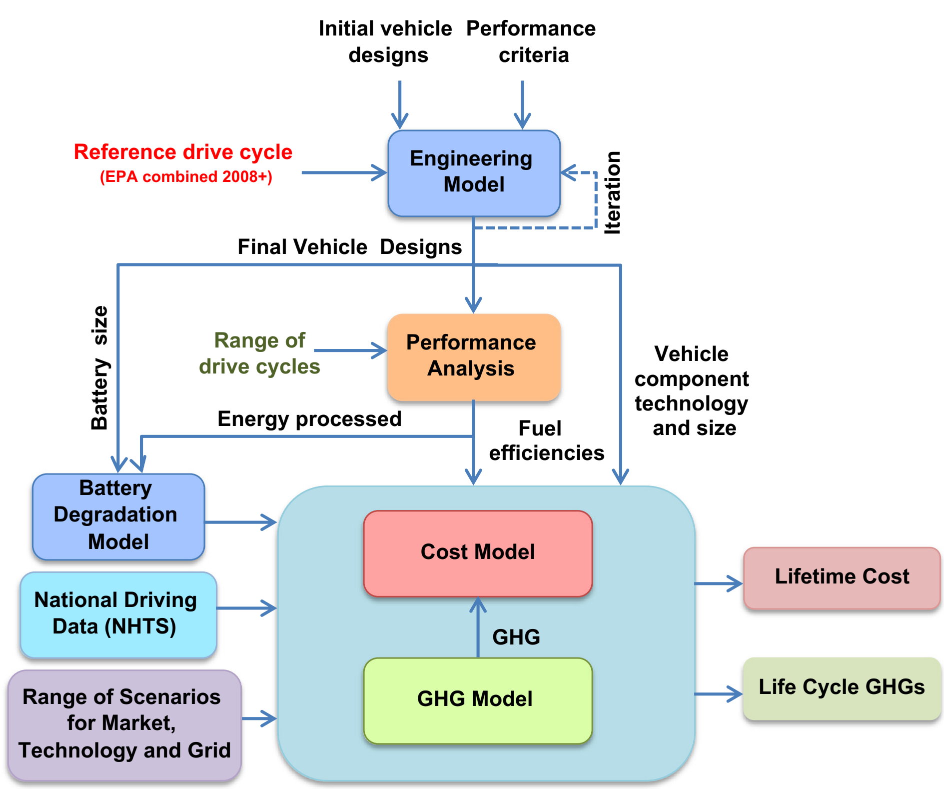

Fig. 3. Framework of vehicle life cycle benefit comparison for different driving patterns.

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$$= \frac{1}{0.43/(5\text{–cycle city MPG}) + 0.57/(5\text{–cycle highway MPG})} \quad (3)$$

For MY2011 and beyond, the 5-cycle fuel economy method is required to be used; however, if the five-cycle city and highway fuel economy results of a test vehicle group are within 4% and 5% of the regression line, respectively, then the automaker is permitted to continue using the regression estimates. These regression equations may be optimistic or pessimistic estimates of measured 5-cycle fuel economy, depending on vehicle and powertrain design. The equations were developed for gasoline vehicles; however, we also apply them to estimate reductions in electrical efficiency of plug-in vehicles for the 5-cycle fuel economy estimates.

While the new standards offer an improvement in estimating real-world fuel economy, test estimates can still differ from real-world driving, favoring certain vehicle designs and powertrains over others and representing some driver habits and driving conditions better than others. We can understand the effects of different driving styles by considering approximate upper and lower bounds on those styles. To evaluate how the relative benefits of different vehicle technologies change with respect to driving cycles, we examine five different driving cycles plus the EPA combined estimate: (1) the Urban Dynamometer Driving Schedule (UDDS) represents city driving conditions for light duty vehicles which are characterized by relatively slow speed. UDDS is also called LA4, FTP72 and FUDS and is related to the FTP cycle; (2) the Highway Fuel Economy Test (HWFET) which represents highway driving conditions under 60 mph; (3) the US06 cycle is an aggressive driving cycle with high acceleration and high engine loads; (4) the NYC cycle represents low speed urban driving with frequent stops; (5) the LA92 cycle is an aggressive driving cycle in city conditions; and (6) the combined MPG computed by the EPA by weighting city and highway efficiency. We use regression Eqs. (1)–(3) to adjust fuel and electrical efficiency values of FTP, HWFET, and combined fuel economy. Table 1 and Table 2 summarize the characteristics of these driving cycles for comparison, and Fig. 4 shows the statistics normalized to unadjusted UDDS, which is adopted by several life cycle and optimization studies in the literature. We will summarize the adjusted and unadjusted efficiencies of vehicles in Table 4.

Patil et al. (2009) find that the US06 is more fuel-consuming than 90% of real-world GPS cycles collected in southeast Michigan. The NYC cycle is low speed with frequent stops and relatively high acceleration and deceleration, serving as a reasonable bound on urban driving conditions. LA92 represents somewhat more aggressive and higher speed driving in city conditions. A recent study by Aymeric et al. (2008) claims that this cycle is closer to real-world driving than the standard test cycles, partially due to the fact that it was designed using data collected in 1992, after dynamometer technology had improved.

3.2. Distribution of daily distance driven

Daily driving distance is an important factor in estimating the real benefits of electrified vehicles since EREV PHEVs have the potential to power daily trips entirely on electricity if the distance between charge points is shorter than the AER of the PHEV. If daily distance driven is longer than the AER, there will be additional gasoline consumption.

Table 2
Driving cycle characteristics (Argonne National Laboratory, 2008).

Statistics	Units	UDDS	HWFET	US06	NYC	LA92
Distance	mi	7.45	10.27	8.01	1.17	9.82
Max. speed	mi/h	56.70	59.90	80.29	27.53	67.20
Avg. speed	mi/h	19.58	48.28	47.96	7.05	24.61
Avg. acceleration	m/s^2	0.50	0.19	0.67	0.62	0.67
Avg. deceleration	m/s^2	−0.58	−0.22	−0.73	−0.60	−0.75
Time at rest (%)	%	18.92	0.65	7.5	35.12	16.31
Stop freq. (#/mi)	mi^{-1}	2.28	0.10	0.62	15.38	1.63

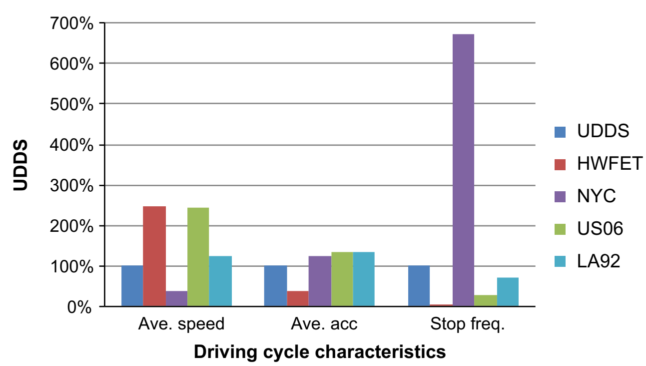

Fig. 4. Driving cycle characteristics.

Table 1
Characteristics of U.S. certification drive cycles (Berry, 2010).

Drive cycle	FTP	HWET	US06	SC03	C-FTP
Description	Urban/city	Free-flow traffic on highway	Aggressive driving on highway	AC on, hot Ambient temp.	City, cold Ambient temp.
Regulatory use (2010)	CAFE & label	CAFE & label	Label	Label	Label
Data collection method	Instrumented vehicles/ specific route	Chase-car/naturalistic driving	Instrumented vehicles/ naturalistic	Instrumented vehicles/ naturalistic	Instrumented vehicles/ specific route
Year of data collection	1969	Early 1970s	1992	1992	1969
Top speed	90 kph (56 mph)	97 kph (60 mph)	129 kph (80 mph)	88 kph (54 mph)	90 kph (56 mph)
Avg. velocity	32 kph (20 mph)	77 kph (48 mph)	77 kph (48 mph)	35 kph (22 mph)	32 kph (20 mph)
Max. accel.	1.48 m/s^2	1.43 m/s^2	3.78 m/s^2	2.28 m/s^2	1.48 m/s^2
Distance	11 mi (17 km)	10 mi (16 km)	8 mi (13 km)	3.6 mi (5.8 km)	11 mi (18 km)
Time (min)	31 min	12.5 min	10 min	9.9 min	31 min
Stops	23	None	4	5	23
Idling time	18%	None	7%	19%	18%
Engine start	Cold	Warm	Warm	Warm	Cold
Lab. temp.	68–86 °F	68–86 °F	68–86 °F	95 °F	20 °F
Air conditioning	Off	Off	Off	On	Off

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The second implication of daily driving distance is that vehicle life depends on use. Typical vehicle life is assumed to be approximately 150,000 mi (EPA, 2005). Daily driving distance determines the life of the vehicle and the amount of time over which the purchase cost is spread, which is important for computing net present value of lifetime vehicle ownership.

The average daily distance driven by US drivers is estimated using data from the 2009 National Household Travel Survey (NHTS) (U.S. Department of Transportation, 2009). Data is collected on daily trips taken in a 24-h period by over 150,000 interviewed households and 300,000 people. The dataset provides information about the characteristics of the trips such as length, duration, and the type of the vehicles used. Fig. 5 shows the weighted daily driving distance distribution for automobiles.

These data were obtained from the post-processed NHTS 2009 dataset of 294,407 automobiles which only include cars, vans, SUVs, and pickup trucks, where 14 data points were removed since the daily distance reported was not plausible. Considering only the vehicles which drive that day, average daily distance driven is found to be 37.1 mi, implying an average annual distance of 13,500 mi per vehicle. When we include the vehicles that did not drive, the average distance driven that day is found to be 22.0 mi, implying an average annual distance of 8050 mi, lower than EPA estimates.

3.3. Engineering model

Vehicle designs and performance analysis takes place in the engineering model of the proposed framework (Fig. 3). PHEVs have several important performance characteristics that affect their economic and environmental benefits. One of them is the distance the vehicle can be driven using only electricity, s_{AER}. Change in driving patterns results in change in s_{AER}. We calculate s_{AER} as

$$s_{AER} = Zk\eta_{CD} \quad \text{(mi)}$$
$$k = \frac{C_{BAT}V_{BAT}K_{BAT}}{1000} \quad \text{(kW h)} \tag{4}$$

where Z is the battery swing window (%) shown in Fig. 1, k is the total battery energy capacity (kW h), $\eta_{CD}$is the vehicle fuel efficiency in CD mode (mi/kW h), C_{BAT} is the number of cells in the battery pack, V_{BAT} is the nominal cell voltage and K_{BAT} is the battery capacity (Ah).

For this study, we designed several vehicles including a CV, an HEV, three PHEVs and a BEV. The primary design variables for plug-in vehicles are engine size, motor size, and battery size. Vehicle mass is accounted by adding the mass of each component to the vehicle glider based on their energy and power densities. We assume 1 kg of additional structural weight for each kg of battery cells added to the battery pack for plug-in vehicles (Shiau et al., 2009). Vehicles are designed for the EPA 5-cycle to meet certain criteria: (1) the desired s_{AER} is satisfied within 1% and (2) the 0–60 mph acceleration time is less than 10.3 s (the reference set by the HEV model) in both CS and CD modes. The CV in our study is designed using the PSAT Honda Accord configuration with an altered vehicle body and tires to match Prius MY13 specifications; the HEV is the MY13 Toyota Prius configuration; the PHEVs use the MY13 PHEV configuration with a switch to a Li-ion battery and increased battery size; and the BEV uses a modified mid-size electric powertrain in PSAT with a Prius body and tires. F/R weight ratio is 06/04, drag coefficient is 0.26, frontal area is 2.25 m^2. Constant power loss due to electric load is the default value of 0.3 kW for all vehicles. HEV initial SOC and target SOC are set to 60%. For PHEVs and BEVs, in CD mode the initial SOC is set to 90% and target SOC is set to 30%, and for CS mode the initial and target SOC are set to 30%. Control variables are adjusted from the default to enable regenerative braking when SOC is less than maximum allowable SOC value. Following PSAT defaults, the braking control strategy is set to capture 90% of the braking energy when vehicle deceleration is less than 2 m/s^2 (in practice more or less braking energy may be lost, depending on the brake system design). Argonne's Advanced Powertrain Research Facility has validated the conventional and mild-hybrid vehicles in PSAT within 2% and full hybrid vehicles within 5% for both fuel economy and battery state-of-charge on several driving cycles (Plotkin and Singh, 2009). Vehicle component sizes are summarized in Table 3 and efficiencies are given in Table 4. More detail on component specifications and vehicle performance can be found in Appendix and PSAT (Argonne National Laboratory, 2008).

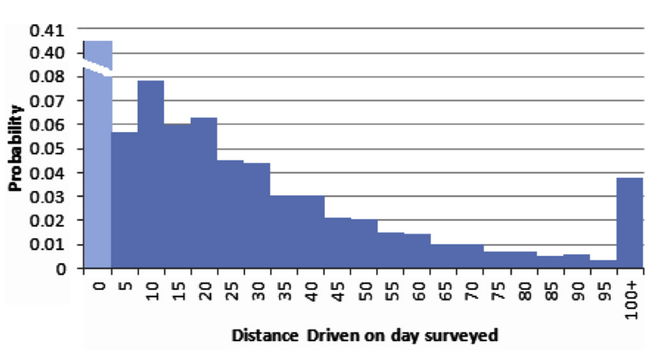

Fig. 5. NHTS Distribution of daily distance driven.

Final vehicle designs used in our study, including a CV, an HEV, PHEVs sized for 20 mi, 40 mi, and 60 mi AER, and a BEV sized for 100 mi AER, are summarized in Table 3, and fuel economy results are given in Table 4. By convention the AER of a plug-in vehicle is indicated with a number x shown as PHEVx or BEVx. For example, $PHEV_{20}$ indicates a PHEV with a 20 mi AER under the EPA combined test procedure. Here, vehicle efficiency is a function of drive cycle and will change depending on the vehicle's mass, thus matching the AER of electrified vehicles to the specifications is an iterative process. Also we have sized the components to satisfy performance constraints both in CD and CS mode. Sizing components for blended control would result in smaller components but an inability to operate as an EREV and greater sensitivity to control strategy parameters. We leave investigation of blended operation PHEVs for future work. Efficiency estimates for each vehicle type could vary for different vehicle and component designs as well as for on-road tests vs. simulation.

3.4. Fuel consumption

For a distance s driven between charges in a vehicle with a specific s_{AER}, the distance driven in CD mode s_{CD} and CS mode s_{CS}, measured in miles, is calculated as follows:

$$s_E(s) = \begin{cases} s & \text{if } s \le s_{AER} \\ s_{AER} & \text{if } s > s_{AER} \end{cases}$$

Table 3
Vehicle configurations.

Vehicle type	Engine (kW)	Motor (kW)	Battery (kW h)	Mass (kg)
CV (Corolla engine)	110			1371
HEV (2013 Prius)	73	60	1.3	1424
PHEV20	73	78	9.9	1569
PHEV40	73	88	19.9	1793
PHEV60	73	98	30.2	2027
BEV100		120	54.0	2265

Table 4
Efficiency and AER of each vehicle under each driving cycle. The label "2008+" refers to the regression-based adjusted fuel economy calculations used by the EPA between 2008 and 2011 and beyond 2011 under some specific conditions (Eqs. (1)–(3)).

Vehicle type		UDDS	HWFET	US06	NYC	LA92	FTP	EPA city(2008+)	EPA highway(2008+)	EPA Combined MPG (2008+)
CV	mi/gal	32.1	52.8	29.8	16.4	28.9	32.8	25.4	37.2	31.0
HEV	mi/gal	69.5	59.7	43.9	48.0	54.1	67.8	48.4	41.8	44.4
PHEV20										
CD eff	mi/kW h	6.2	5.7	3.2	4.2	4.2	6.0	3.3	3.6	3.4
CD-mpg-eq	mpg-eq	207.9	193.0	108.4	142.0	142.2	202.3	110.0	119.7	115.3
CS eff	mi/gal	69.4	58.6	41.0	45.7	52.3	67.3	48.1	41.1	43.8
AER	mi	36.8	34.1	19.2	25.1	25.2	35.8	19.5	21.2	20.4
PHEV40										
CD eff	mi/kW h	6.0	5.7	3.2	4.1	4.1	5.8	3.2	3.5	3.4
CD-mpg-eq	mpg-eq	201.2	192.1	106.9	138.2	138.1	196.2	107.8	119.3	114.0
CS eff	mi/gal	68.0	58.2	40.2	43.1	50.0	66.0	47.3	40.8	43.4
AER	mi	71.2	68.0	37.8	48.9	48.9	69.4	38.1	42.2	40.3
PHEV60										
CD eff	mi/kW h	5.7	5.6	3.1	3.8	3.9	5.6	3.1	3.5	3.3
CD-mpg-eq	mi/kW h	192.2	190.0	104.0	129.6	132.2	188.0	104.8	118.1	112.0
CS eff	mi/gal	65.8	57.8	39.2	40.3	48.0	64.0	46.1	40.5	42.7
AER	mi	103.5	102.3	56.0	69.8	71.2	101.2	56.4	63.6	60.3
BEV100										
CD eff	mi/kW h	4.8	5.2	3.4	3.1	4.1	4.8	2.8	3.3	3.1
CD-mpg-eq	mi/kW h	162.2	176.4	113.5	103.8	136.9	160.9	94.4	111.0	103.2
AER	mi	155.9	169.6	109.1	99.8	131.6	154.7	90.7	106.7	99.2

$$s_G(s) = \begin{cases} 0 & \text{if } s \le s_{AER} \\ s - s_{AER} & \text{if } s > s_{AER} \end{cases} \tag{5}$$

The NHTS-averaged distance driven on electricity $\bar{s}_E$ and average distance driven on gasoline$\bar{s}_G$ is given by

$$\bar{s}_E = \int_{s=0}^{\infty} s_E f_S(s) ds$$
$$\bar{s}_G = \int_{s=0}^{\infty} s_G f_S(s) ds \tag{6}$$

where $f_S(s)$ is the probability distribution function (PDF) of distance driven for a randomly selected vehicle on a random driving day in the NHTS 2009 data, including those vehicles that were not driven on the day surveyed. We discretize this distribution into 1-mi bins for numerical integration.

Average distance driven per day $\bar{s}$ is given as

$$\bar{s} = \int_{s=0}^{\infty} s f_S(s) ds \tag{7}$$

Gasoline consumption $g(s)$, given in gallons, and electricity consumption $e(s)$, given in kW h, on a day with s miles of driving is calculated by

$$g(s) = \frac{\max(0, s - s_{AER})}{\eta_{CS}}$$
$$e(s) = \frac{\min(s, s_{AER})}{\eta_{CD}} \tag{8}$$

where η_{CS} and η_{CD} values are fuel efficiencies in CD and CS modes, respectively, summarized in Table 4.

The average gasoline $\bar{g}$ and electricity $\bar{e}$ consumption in the NHTS data set given as

$$\bar{g} = \int_{s=0}^{\infty} g(s) f_S(s) ds$$
$$\bar{e} = \int_{s=0}^{\infty} e(s) f_S(s) ds \tag{9}$$

Typical vehicle life, s_{LIFE} is assumed to be approximately 150,000 mi (EPA, 2005). D is the number of days in the year (365). Vehicle life $T_{VEH}(s)$ in years is given by:

$$T_{VEH}(s) = \frac{s_{LIFE}}{Ds} \tag{10}$$

and the NHTS average vehicle life is:

$$\bar{T}_{VEH} = \frac{s_{LIFE}}{D\bar{s}} \tag{11}$$

3.5. Battery degradation model

We follow Peterson et al. (2010a) and Shiau et al. (2010) in modeling battery degradation as a function of energy processed, based on data collected from A123 $LiFePO_4$ cells. Energy processed w_{DRV} in kW h while driving a distance s is:

$$w_{DRV}(s) = \mu_{CD} s_E + \mu_{CS} s_G \tag{12}$$

where μ_{CD} and μ_{CS} are the energies processed per mile (kW h/mi) in CD and CS modes, respectively. Energy processed, given in kW h, while charging is:

$$w_{CHG}(s) = s_E (\eta_{CD} \eta_B)^{-1} \tag{13}$$

where η_B is the battery charging efficiency, assumed to be 95%. The relative energy capacity fade can be calculated as

$$r_P(s) = \frac{\alpha_{DRV} w_{DRV} + \alpha_{CHG} w_{CHG}}{k} \tag{14}$$

where $\alpha_{DRV} = 3.46 \times 10^{-5}$ and $\alpha_{CHG} = 3.46 \times 10^{-5}$ are the relative energy capacity fade coefficients derived from the data set in (Peterson et al., 2010a). We define battery end of life (EOL) as the point when the portion of the remaining energy capacity equals the energy within the swing window under the original capacity. The relative energy capacity fade r_{EOL} at the EOL becomes the original total capacity minus swing ($r_{EOL} = 1 - Z$).

The NHTS average computed battery life, given in years, is found by:

$$\bar{T}_{BAT} = \frac{k(1-Z)}{(\alpha_{DRV}(\mu_{CD}\bar{s}_E + \mu_{CS}\bar{s}_G) + \alpha_{CHG}\bar{s}_E(\eta_E \eta_C)^{-1})D} \tag{15}$$

We assume that the functional battery life in the vehicle $\bar{\theta}_{BAT}$ is never longer than vehicle life:

$$\bar{\theta}_{BAT} = \min(\bar{T}_{BAT}, \bar{T}_{VEH}) \tag{16}$$

We ignore degradation effects for NiMH cells in the HEV because HEV performance is far less sensitive to capacity fade (effectively an AER of zero); HEV economics are less sensitive to possible battery replacement; and our Li-ion degradation model predicts no replacement for the HEV configuration and use

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patterns. For Li-ion cells in PHEVs and BEVs we use the battery degradation model described above.

3.6. Environmental model

Life cycle GHG emissions $\nu(s)$ for a vehicle that travels s miles per day and NHTS-averaged emissions $\overline{\nu}$ are computed in kg CO_2-equivalent per year:

$$\nu(s)=\nu_{\mathrm{VEH}}(T_{\mathrm{VEH}}(s))^{-1}+\nu_{\mathrm{BAT}}k(\theta_{\mathrm{BAT}}(s))^{-1}+g(s)\nu_{\mathrm{G}}D+e(s)\eta_{\mathrm{C}}^{-1}\nu_{\mathrm{E}}D$$
$$\overline{\nu}=\nu_{\mathrm{VEH}}(\overline{T}_{\mathrm{VEH}})^{-1}+\nu_{\mathrm{BAT}}k(\overline{\theta}_{\mathrm{BAT}})^{-1}+\overline{g}\nu_{\mathrm{G}}D+\overline{e}\eta_{\mathrm{C}}^{-1}\nu_{\mathrm{E}}D \tag{17}$$

where ν_{VEH} is the life cycle emissions from producing the base vehicle, ν_{BAT} is the life cycle emissions from producing the battery pack (Table 5) (Samaras and Meisterling, 2008), $\nu_{\mathrm{G}}=11.34$ kg-CO_2-eq per gallon is the life cycle emissions per gallon of gasoline consumed (Wang et al., 2007), $\nu_{\mathrm{E}}=0.752$ kg-CO_2-eq per kW h is the life cycle emissions per kW h of electricity consumed (Wang et al., 2007), and $\eta_{\mathrm{C}}=88\%$ for battery charging efficiency (EPRI, 2007).

3.7. Cost model

Equivalent annualized cost (EAC) of vehicle ownership is the value of the recurring fixed annual payment whose net present value (NPV) is equal to NPV of vehicle ownership over the vehicle lifetime. This metric makes it possible to compare the ownership cost of vehicles over different lifetimes. The net present value of vehicle ownership includes costs of vehicle production, battery, and vehicle operation plus any carbon price costs, assuming that a carbon tax would be levied equally on all GHG emissions released over the life cycle and that upstream costs would be passed down to the consumer. We define a nominal discount rate r_{N} and inflation rate r_{I}, implying a real discount rate $r_{\mathrm{R}}=(1+r_{\mathrm{N}})/(1+r_{\mathrm{I}})-1$ (Neufville, 1990). The capital recovery factor $f_{\mathrm{A|P}}$ for a general discount rate r and time period N in years is given by de Neufville (1990):

$$f_{A|P}(r,N)=\left(\sum_{n=1}^{N}\frac{1}{(1+r)^{n}}\right)^{-1}=\frac{r(1+r)^{N}}{(1+r)^{N}-1}; \tag{18}$$

the annualized cost $c(s)$ for a vehicle that travels s mi/day is:

$$\begin{aligned}c(s)=&\,c_{\mathrm{VEH}}f_{\mathrm{A|P}}(r_{\mathrm{N}},T_{\mathrm{VEH}})+c_{\mathrm{BAT}}f_{\mathrm{A|P}}(r_{\mathrm{N}},T_{\mathrm{BAT}}(s))\\&+p_{\mathrm{GAS}}g(s)D\frac{f_{\mathrm{A|P}}(r_{\mathrm{N}},T_{\mathrm{VEH}}(s))}{f_{\mathrm{A|P}}(r_{\mathrm{R}},T_{\mathrm{VEH}}(s))}+p_{\mathrm{ELEC}}e(s)\eta_{\mathrm{C}}^{-1}D\frac{f_{\mathrm{A|P}}(r_{\mathrm{N}},T_{\mathrm{VEH}}(s))}{f_{\mathrm{A|P}}(r_{\mathrm{R}},T_{\mathrm{VEH}}(s))}\\&+p_{\mathrm{CO_2}}\nu(s)\frac{f_{\mathrm{A|P}}(r_{\mathrm{N}},T_{\mathrm{VEH}}(s))}{f_{\mathrm{A|P}}(r_{\mathrm{R}},T_{\mathrm{VEH}}(s))}\ (\$/\mathrm{year})\end{aligned} \tag{19}$$

and the NHTS average annualized cost $\overline{c}$ is:

$$\begin{aligned}\overline{c}=&\,c_{\mathrm{VEH}}f_{\mathrm{A|P}}(r_{\mathrm{N}},\overline{T}_{\mathrm{VEH}})+c_{\mathrm{BAT}}f_{\mathrm{A|P}}(r_{\mathrm{N}},\overline{T}_{\mathrm{BAT}})+p_{\mathrm{GAS}}\overline{g}D\frac{f_{\mathrm{A|P}}(r_{\mathrm{N}},\overline{T}_{\mathrm{VEH}})}{f_{\mathrm{A|P}}(r_{\mathrm{R}},\overline{T}_{\mathrm{VEH}})}\\&+p_{\mathrm{ELEC}}\overline{e}\eta_{\mathrm{C}}^{-1}D\frac{f_{\mathrm{A|P}}(r_{\mathrm{N}},\overline{T}_{\mathrm{VEH}})}{f_{\mathrm{A|P}}(r_{\mathrm{R}},\overline{T}_{\mathrm{VEH}})}+p_{\mathrm{CO_2}}\overline{\nu}\frac{f_{\mathrm{A|P}}(r_{\mathrm{N}},\overline{T}_{\mathrm{VEH}})}{f_{\mathrm{A|P}}(r_{\mathrm{R}},\overline{T}_{\mathrm{VEH}})}\quad(\$/\mathrm{year})\end{aligned} \tag{20}$$

where c_{VEH} is the vehicle cost and c_{BAT} is the battery cost specified in Tables 6 and 7 for each vehicle and battery type, (cost estimates are taken from Plotkin and Singh (2009) and based on 2015 literature review and 2030 DOE program goals to provide a range for sensitivity–battery cost for PHEV20 and 60 have been interpolated), $p_{\mathrm{GAS}}=\$2.75$/gal is the average price of gasoline during the 2008–2010 period (Energy Information Administration, 2011), $p_{\mathrm{ELEC}}=\$0.114$/kW h is the average price of electricity during the 2008–2010 period (Energy Information Administration, 2011), and $P_{\mathrm{co_2}}$ is the carbon price, which we vary from \$0–\$100/tCO_2e (Peterson et al., 2010b). The real discount rate r_{R} is used for future commodity purchases under the assumption that prices follow inflation $(f_{\mathrm{A|P}}(r_{\mathrm{R}},\overline{T}_{\mathrm{VEH}})^{-1}$ computes NPV of future payments for a commodity whose prices follow inflation, and $f_{\mathrm{A|P}}(r_{\mathrm{N}},\overline{T}_{\mathrm{VEH}})$

Table 6
Battery cost given in \$ per kW h for 2015 LR and 2030 PG cases (Plotkin and Singh, 2009).

	Chemistry	Size (kW h)	2015 LR (\$)	2030 PG (\$)
HEV	NiMH	1.3	1310	717
PHEV20	Li-ion	6.4	549	171
PHEV40	Li-ion	11.1	500	160
PHEV60	Li-ion	20.0	490	157
BEV100	Li-ion	30.0	472	154

Table 7
Vehicle and battery cost given in \$ for 2015 LR and 2030 PG cases.

Vehicle	Battery Size (kW h)	Cost component	2015 LR	2030 PG
PHEV20	9.9	Vehicle	24369	22643
		Battery	7635	2427
PHEV40	19.9	Vehicle	24429	22671
		Battery	14904	4769
PHEV60	30.2	Vehicle	24429	22671
		Battery	21984	7001
BEV100	54.0	Vehicle	20607	18197
		Battery	35360	11932
HEV	1.3	Vehicle	23547	22206
		Battery	1964	717
CV	0	Vehicle	21857	21857

Table 5
Parameter levels for base case and sensitivity analysis.

Parameters	Lower	Base case	Upper	Units
Cost of gasoline	\$1.59	\$2.75	\$4.05	per gallon
Cost of electricity	\$0.06	\$0.114	\$0.30	per kW
CO_2 tax	\$0	\$0	\$100	t-CO_2-eq
GHGs for electricity emission	0.066	0.73	0.9	kg CO_2 eq per kW h
GHGs for gasoline emission	–	11.34	–	kg CO_2 eq per gal
Battery charging efficieny	–	0.88	–	%
Vehicle life	–	150000	–	mi
Number of driving days per year	–	365	–	days/year
Nominal discount rate	5	8	15	%
Inflation rate for future fuel prices	–	3	–	%
Real discount rate	–	5	–	%
GHGs for Li-ion battery production	–	120	–	kg CO_2 eq
GHGs for NiMH battery production	–	230	–	kg CO_2 eq
GHGs for vehicle production	–	8500	–	kg CO_2 eq
Battery swing	–	60	–	%

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converts NPV to EAC). In the next section, we analyze the results and discuss their engineering and policy implications.

4. Results and discussion

4.1. All electric range

Our analysis shows that driving patterns affect AER significantly. An aggressive driving cycle (US06) can reduce AER by 45% relative to a gentle cycle (UDDS) (see Fig. 6). For example, a PHEV with a split powertrain designed to achieve a 70-mi AER on the UDDS drive cycle provides only a 40 mi AER under the US06 drive cycle. Reduced range is particularly important for BEVs, which have no gasoline backup, but reduced range also affects life cycle cost and emissions of PHEVs and can negatively affect customer satisfaction and perception of plug-in vehicle technology. The vehicles components of this study have been sized to satisfy the target AER under the EPA combined mpg(2008+) which adjusts FTP and HWFET test results to estimate outcomes from a 5-cycle test, which results in lower efficiency estimates and thus AER.

4.2. Life cycle cost

Fig. 7 summarizes base case equivalent annualized cost for each vehicle type and each driving cycle. 2015 battery price estimates from Plotkin and Singh (2009) are used for the base case. Vehicle and battery cost of each vehicles is constant across driving cycles, since vehicle design is given; however gasoline and electricity costs are functions of driving patterns. Under HWFET, US06 and the EPA-5 cycle, the CV is the cost minimum followed closely by the HEV; under the UDDS and NYC driving cycles the HEV minimizes cost. CV is the most sensitive to driving cycle, especially stop-and-go driving and traffic conditions. Electrified vehicles are less sensitive to drive cycle. In the base case, plug-in vehicles are consistently more expensive than HEVs over the life, primarily due to the cost of larger battery packs, and only in NYC conditions is the $PHEV_{20}$ lower cost than the CV.

The BEV powertrain cost is least sensitive to drive cycle because electricity consumption is a small portion of overall cost, and regenerative braking together with the lack of an idling gasoline engine makes electrified powertrains less sensitive to stopping frequency. The cost associated with CV is 30% higher under NYC conditions than under HWFET conditions.

4.3. Life cycle greenhouse gas emissions

Fig. 8 shows the breakdown of average annual GHG emissions for each vehicle and driving cycle. Increased battery size results in greater displacement of gasoline with electricity; however, battery production emissions also increase, and vehicle efficiency decreases with vehicle mass. This accounts for the increased GHG emissions of longer-range PHEVs with average U.S. electricity.

Under HWFET conditions all powertrains produce comparable life cycle emissions. In all other conditions, hybrid and electric vehicles release significantly lower GHGs than CVs—in particular, HEVs reduce emissions by 60% relative to CV in the NYC cycle. In the base case, plug-in vehicles do not provide substantial GHG reductions relative to HEVs except for the BEV100 in the EPA 5-cycle, which may be optimistic due to application of EPA regression equations to electric operation.

4.4. Base case cost and GHG comparison

Fig. 9 summarizes the life cycle annualized cost and GHG emissions for each vehicle and drive cycle using our base case assumptions. Drive cycles with more aggressive acceleration demands and more stops increase both cost and emissions simultaneously. The CV (diamond) is much more sensitive to drive cycle, whereas the electrified powertrains experience less variation with drive cycle. A move from CV (diamond) to HEV (square) with larger battery packs reduces GHG emissions at no cost or at

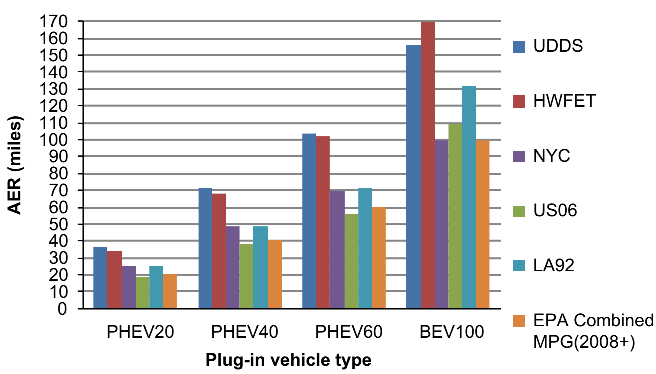

Fig. 6. All electric range under different driving cycles.

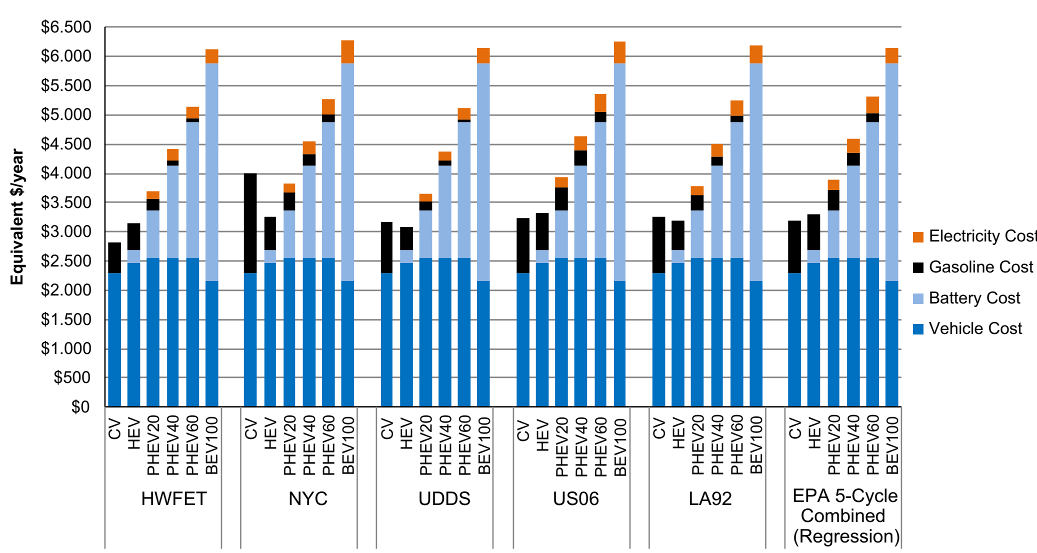

Fig. 7. NHTS Averaged Annualized Cost Breakdown per Vehicle (Base Case).

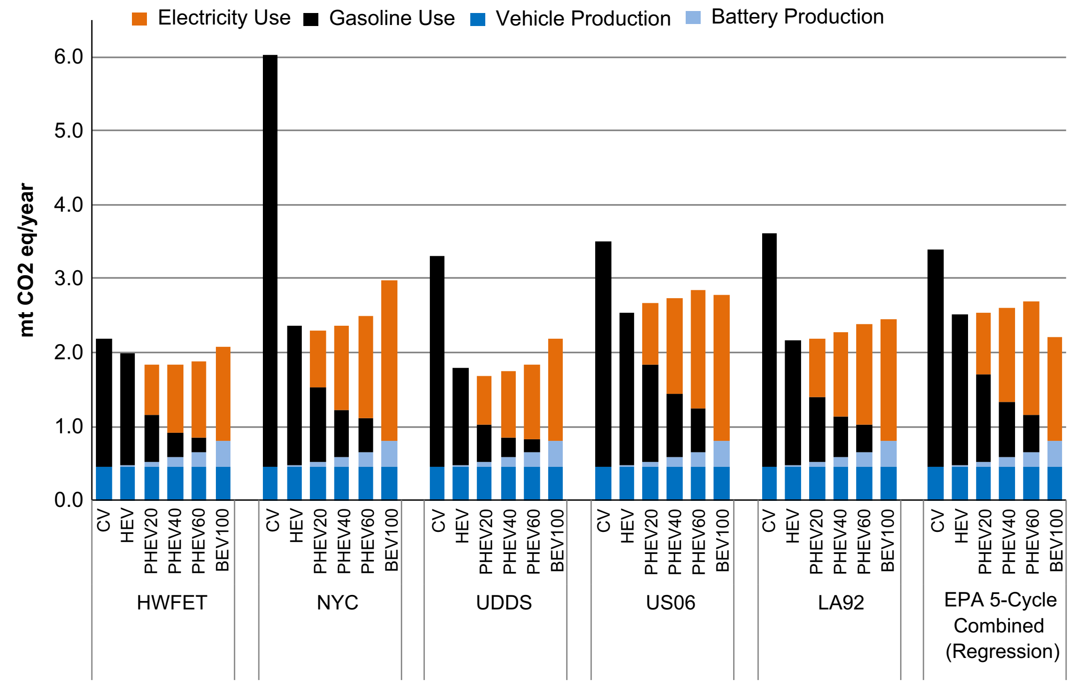

Fig. 8. NHTS-Averaged Annual GHG Emissions per Vehicle (Base Case).

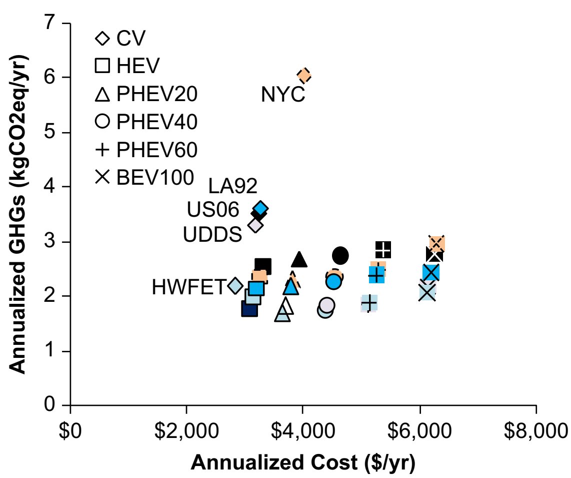

Fig. 9. Annualized cost vs. annual GHG emissions for various vehicles and drive cycles. Shapes indicate vehicle powertrain. Colors indicate drive cycle.

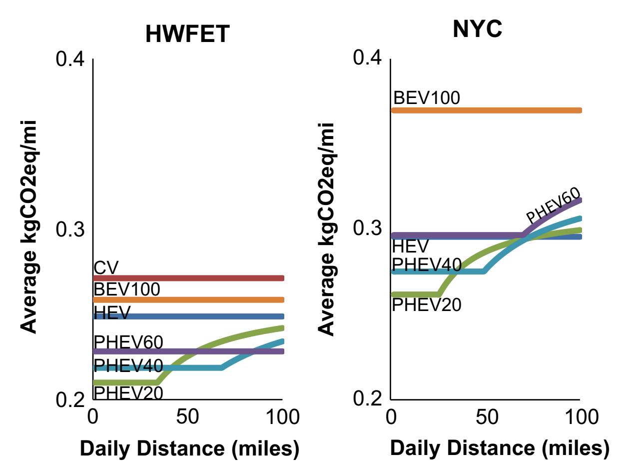

Fig. 10. Life cycle GHG per mile under HWFET and NYC driving patterns for a variety of daily driving distances (to show detail, *y*-axis does not cross at zero). The CV has 0.75 $kgCO_2$ eq/mi on the NYC cycle.

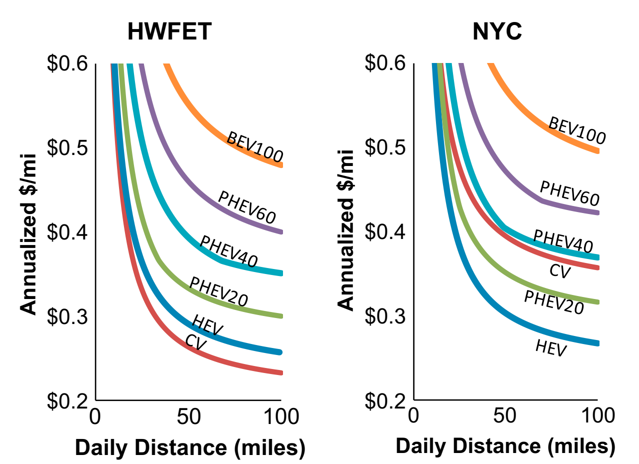

Fig. 11. The net annualized cost per mile under HWFET and NYC driving patterns for a variety of daily driving distances (to show detail, *y*-axis does not cross at zero).

modest cost, depending on the drive cycle. A move from HEV to the plug-in powertrains with larger battery packs reduces or increases GHGs, depending on the vehicle and drive cycle, but comes at a substantial increase in costs.

4.5. Cost and GHGs per mile for different daily driving distances and patterns

Fig. 10 shows average life cycle GHG emissions per lifetime mile and annualized cost per annual mile traveled as a function of daily distance traveled for the two contrasting driving conditions: HWFET and NYC, assuming one charge per day and the same driving distance every day. GHG emissions per mile vary with daily distance traveled for PHEVs because distance driven between charges affects the portion of travel that can be propelled using electricity in place of gasoline. If a PHEV is driven further than its AER, it will begin to consume gasoline. The resulting trends are similar to the trends identified by Shiau et al. (2009): PHEVs with small battery packs have lower emissions when charged frequently and driven primarily in CD mode but may have higher emissions if charged infrequently.

The cost curves in Fig. 11 show a decline of annualized cost/mile with daily driving distance, which results from capital cost of initial vehicle and battery purchase comprising a larger portion of total cost for short daily driving distances, which imply long vehicle life and discounted future fuel costs. The curves have less overlap in this case, and dominant vehicles align with NHTS-averaged estimates in Fig. 7. Under HWFET conditions the ranking of cost competitive vehicles (CV, HEV, PHEV20, PHEV40, PHEV60, BEV100) follows increasing battery capacity. Under NYC conditions, HEV and PHEV20 are lower cost than CV. In both cases, BEVs increase the costs significantly.

5. Sensitivity analysis

Fig. 12 summarizes sensitivity of annualized cost to gasoline price, electricity price, vehicle and battery price, carbon tax price (GHG value), and discount rate. We focus on comparing two contrasting cases: HWFET which consists of high speed and low acceleration, and NYC which consists of low speed and stop-and-go city driving. Fig. 10a shows the HWFET and NYC EAC breakdown from the base case (Fig. 7). All other cases show the base case as faded bars and display how the results would change under alternative assumptions using error bars. Fig. 10b shows that increasing gasoline prices affect CV cost most dramatically and makes plug-in technology more cost competitive; however, large battery pack vehicles remain higher cost. Fig. 10c shows that electricity price affects the cost of plug-in vehicles with large battery packs most; however, a five-fold increase in electric price has a notably smaller overall effect that does not change ranking. Fig. 10d emphasizes that vehicle and battery costs have a critical impact on the cost benefits of plug-in vehicles. Near term 2015 vehicle costs estimated by Plotkin and Singh of Argonne National Laboratory (ANL2015) suggest that plug-in vehicles with large battery packs are more expensive than HEVs regardless of driving cycle, but Department of Energy targets for costs in 2030 (DOE2030), which ANL calls “very optimistic” (Plotkin and Singh, 2009), would result in more comparable costs. Fig. 10e reveals that while high carbon prices would have non-negligible effects on life cycle costs, they would do little to change the relative costs of the powertrain options except for the relatively large penalty to CVs in NYC conditions. Fig. 10f examines the effect of varying consumer discount rate. Higher discount rates are less favorable to plug-in vehicles, whose savings are delayed to future years, but do not change rank ordering.

Fig. 13 summarizes the effect of electricity source on life cycle GHG emissions. Electricity source varies substantially with location and charge timing (Sioshansi and Denholm, 2009), is difficult to know regionally with certainty (Weber et al., 2010), and is typically not under the consumer's control. Electricity from coal-fired power

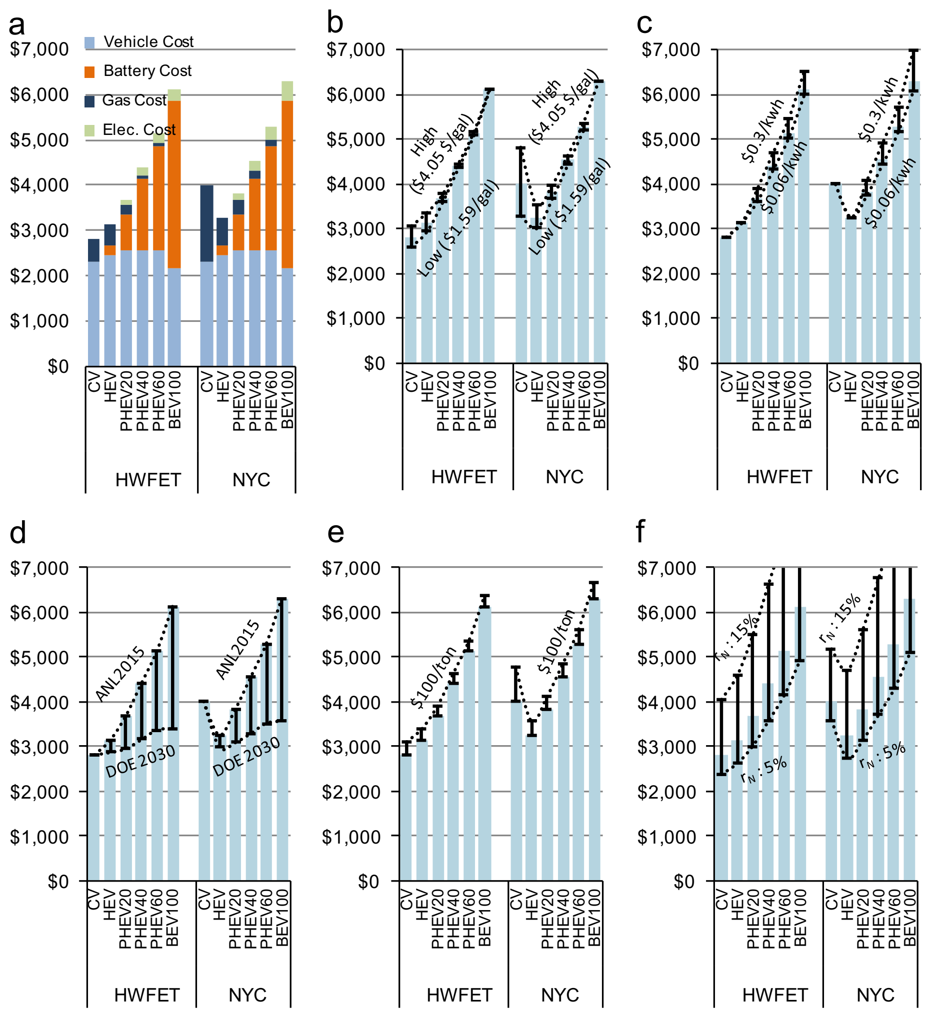

Fig.12. Sensitivity analysis for life cycle equivalent annualized cost under HWFET and NYC drive cycles. (a) Base case, (b) Gasoline price, (c) Electricity price, (d) Vehicle data, (e) GHG value and (f) Discount rate.

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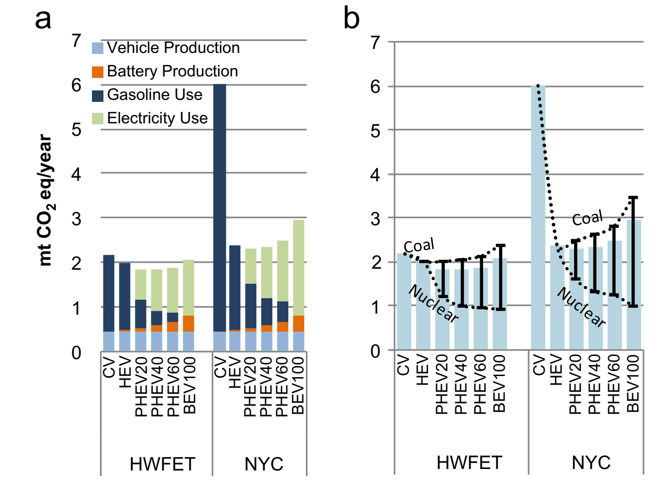

Fig. 13. Sensitivity analysis for life cycle GHG emissions. (a) Base case and (b) Grid mix.

plants lead to increased emissions from plug-in vehicles, whereas low-carbon electricity sources such as nuclear, wind, hydro, and solar power, result in substantial reductions in life cycle GHG emissions from plug-in vehicles relative to today's U.S. average grid mix. The marginal electricity used to charge plug-in vehicles will typically not be nuclear, which is usually run as base load generation, and use of renewable energy is subject to constraints from the intermittent and variable nature of renewable energy sources, so the zero-emission cases (labeled "Nuclear") serve as lower bounds.

6. Conclusions

Customer vehicle purchasing decisions are in part guided by EPA fuel economy and AER estimates based on standard laboratory test driving cycles. However, diverse real-world driving conditions can deviate substantially from laboratory conditions, affecting which vehicle technologies are most cost effective at reducing GHG emissions for each driver. As such, the choice of driving cycle for testing necessarily preferences some vehicle designs over others. This effect has become more pronounced with the introduction of hybrid and plug-in powertrains because factors like regenerative braking and engine idling affect the relative importance of aggressive and stop-and-go driving conditions on system efficiency. Compared to cycles like NYC, test drive cycles UDDS and HWFET, used for corporate average fuel economy (CAFE) tests, underestimate relative cost and GHG benefits of hybrid and plug-in vehicles.

With the introduction of hybrid and plug-in vehicles, it has become more important that the right vehicles are targeted to the right drivers. Drivers who travel in NYC conditions could cut lifetime costs by up to 20% and cut GHG emissions 60% by selecting hybrid vehicles instead of conventional vehicles, while for HWFET drivers conventional vehicles provide a lower cost option with a much smaller GHG penalty. CV owners observe more variability in cost and emissions subject to driving conditions, while HEVs offer the most robust, cost effective configuration across the driving patterns tested.

When comparing HEVs to PHEVs under the average U.S. grid mix, it is clear that most of the GHG-reduction benefit of PHEVs comes from hybridization, and relatively little additional benefit can be achieved through plugging in. HEVs provide an optimal or near optimal economic and environmental choice for any driving cycle. However, given a substantially decarbonized electricity grid plug-in vehicles could reduce life cycle GHG emissions across all driving cycles, and lower battery costs combined with high gasoline prices would make plug-in vehicles more economically competitive.

7. Policy implications

These results have several key policy implications. First, the benefits of plug-in vehicles vary dramatically from driver to driver depending on drive cycle (driving style, traffic, road networks, etc.). While hybrid and plug-in vehicles offer little GHG benefit at higher cost for highway driving (HWFET), they can offer dramatic GHG reductions and cost savings in NYC driving with frequent stops and idling. Electrification will have more positive impact if targeted to drivers who travel primarily in NYC-like conditions rather than HWFET-like conditions. Government could play a role through information campaigns, driver education, as well as modification to fuel economy labels. The new labels already contain a lot of information, but several possibilities could help target the right drivers: First, the label could report several additional characteristic driving cycles besides the city and highway mileage reported now. The label design would need to balance the need to avoid overwhelming the consumer, and more research on this would be needed to determine the best balance. Second, the smartphone QR code available on the new labels currently takes the consumer to a general website that describes the label in more detail. This website could instead offer interactive information for a wider range of driving conditions and even potentially use in-vehicle or smartphone GPS to measure the consumer's driving style, VMT, and local gasoline prices, using this information to give customized estimates for individual drivers. Privacy concerns would need to be addressed in such a system. Adoption by urban drivers may be limited by lower access to dedicated off-street parking and a higher proportion of renters who lack authority to install charging infrastructure (Traut et al., 2013; Axsen and Kurani, 2012a,b).

Second, our results suggest that the choice of standardized test used to assess vehicle efficiency for window labels and for CAFE standards can have an important effect on the measured benefit of hybrid and plug-in vehicles relative to conventional vehicles. While choice of testing protocol has always had impact on the relative benefits of vehicles, the unique features of hybrid and electric vehicle powertrains and their importance in certain types of driving amplify this impact and the potential for bias that could systemically underestimate the benefits of hybridization and electrification, influencing adoption rates and corporate strategy for compliance with CAFE standards. Furthermore, vehicles optimized to score well on EPA tests may score less well in real-world driving. Our results suggest that with the presence of hybrid and electric vehicles in the marketplace, the test cycles used to assess fuel efficiency – while substantially improved from the old tests that are still used for CAFE standards – should be reexamined to minimize bias. This could be accomplished, for example, using a national collection of representative GPS data to assess a distribution of driving conditions, followed by simulation, testing, and optimization to identify a set of tests that produces fuel efficiency estimates across powertrain types that most closely matches estimates using a representative distribution of on-road GPS data. In particular, CAFE standards are still based on old UDDS and HWFET tests that produce estimates with about 20% lower fuel consumption for CV, 30% lower for HEV, and 40% lower for plug-in vehicles than the EPA 5-cycle regression tests. The CAFE measurement is about 60% lower fuel consuming for CVs and 30% lower for hybrid and electric vehicles than the NYC test. The CAFE tests artificially inflate fuel economy estimates and do so unevenly for different vehicle technologies. Using a common test for CAFE standards and window labels – one that is as representative as possible of the resulting efficiency experienced by US drivers across vehicle technologies – would help reduce bias against certain technologies as well as confusion about why the high fuel efficiency standards cited by politicians fail to match the reality of the vehicle fleet observed by consumers.

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Third, as suggested in prior studies (Shiau et al., 2010, 2009; Michalek et al., 2011; Traut et al., 2012; Peterson and Michalek, 2013), HEVs and small-battery PHEVs provide comparable GHG reductions at lower cost than large-battery PHEVs or BEVs with today's electricity grid. This holds true across the driving cycles we tested. In particular, in NYC conditions HEVs show the lowest cost and GHG emissions. This is because hybridization (regenerative braking, efficient engine operation, Atkinson cycle, engine off at idle, etc.) offers most of the GHG benefit, and additional benefits of using electricity rather than gasoline as the energy source are dependent on grid decarbonization. Current federal and state policy favors large battery packs, but this is misaligned with potential for GHG reductions (Michalek et al., 2011). In fact, given binding CAFE standards plug-in vehicle subsidies may produce no net benefit unless they succeed in stimulating a breakthrough that leads to cost competitive plug-in vehicles and sustainable mainstream adoption that would not have happened otherwise (Peterson and Michalek, 2013; Congressional Budget Office, 2012).

Finally, government fleet purchases should account for the anticipated driving conditions of vehicles when selecting powertrain type.

8. Limitations and future work

There are many factors that may affect the lifetime cost and life cycle emissions of vehicles. In this work we have addressed drive cycle and distance. Climate may also have a substantial effect on vehicle efficiency, range, and battery life due to climate control, battery thermal management, and sensitivity of battery degradation to temperature (Barnitt et al., 2010). Terrain may also affect electrified powertrain designs differently, although all driving cycles presented here are on flat ground.

Vehicle design choices could also influence results. We focus on EREV PHEVs because the broad space of control parameters for defining a blended operation PHEV makes results too dependent on assumptions (each control strategy will perform better on some

Table A1
Vehicle component specifications.

Mass breakdown	Units	HEV	PHEV20	PHEV40	PHEV60	BEV100	CV
Vehicle glider/body mass	kg	815	815	815	815	815	815
Powertrain mass	kg	609	754	978	1212	1450	556
Vehicle curb mass	kg	1424	1569	1793	2027	2265	1371
Driver mass	kg	80	80	80	80	80	80
Total mass	kg	1504	1649	1873	2107	2345	1451
Engine							
Max. power	kW	73	73	73	73		110
Engine scale		1	1	1	1		1.5
Block mass	kg	108	108	108	108		166
Radiator mass	kg	6	6	6	6		6
Tank mass	kg	20	20	20	20		20
Fuel mass	kg	43	43	43	43		43
Total mass of engine block	kg	177	177	177	177		234
Motor							
Max. power	kW	60	78	88	98	120	
Motor scale		1.0	1.3	1.5	1.6	2.0	
Motor mass	kg	35	46	51	57	70	
Controller mass	kg	5	7	7	8	10	
Total mass of motor block	kg	40	52	59	65	80	
Motor 2							
Max. power	kW	30	30	30	30		
Motor mass	kg	20	20	20	20		
Controller mass	kg	5	5	5	5		
Total mass of motor 2	kg	25	25	25	25		
Battery							
Technology		NiMH	Li-ion	Li-ion	Li-ion	Li-ion	
Parallel cell array		1	5	10	14	25	
Number of cells in series		168	92	92	100	100	
Total # cells		168	460	920	1400	2500	
Cell capacity	Ah	7	6	6	6	6	
Nominal output voltage	V	1.2	3.6	3.6	3.6	3.6	
Output voltage	V	202	331	331	360	360	
Energy capacity	kW h	1.3	9.9	19.9	30.2	54.0	
Packaging factor		1.3	1.3	1.3	1.3	1.3	
SOC min	%	30	30	30	30	30	
SOC max	%	90	90	90	90	90	
SOC init	%	60	90/30	90/30	90/30	90/30	
SOC target	%	60	30	30	30	30	
Battery swing	%		0.6	0.6	0.6	0.6	
Mass of each cell	kg	0.4	0.4	0.4	0.4	0.4	
Total mass of battery block	kg	84	217	435	662	1182	22
Other Components							
Electrical accessories	kg	18	18	18	18	18	18
Exhaust mass	kg	30	30	30	30		30
Planetary gear mass/gear mass	kg	40	40	40	40		75
Mechanical accessories	kg	35	35	35	35		0
Wheel mass	kg	140	140	140	140	140	140
Final drive mass	kg	20	20	20	20	20	20
Torque coupling	kg					10	10
Alternator and controller	kg						7

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drive cycles than others). But blended operation PHEVs could be more competitive in some cases, especially for low-range PHEVs. The battery degradation model used in this study is based on laboratory-tested A123 $LiFePO_4$ cells at room temperature. The data ignore temperature variation and calendar fade, they do not account for the higher c-rate implied by more aggressive driving cycles, and they do not examine other chemistries, which can have degradation characteristics more sensitive to state of charge and other factors. Degradation also affects vehicle performance (Markel and Simpson, 2006), which can prevent the vehicle from satisfying some drive cycles and acceleration tests later in the vehicle's life.

We assume a single charge per day for the PHEV simulations, and we ignore range limitations of the BEV100, which in practice can be substantial (Neubauer et al., 2012). Multiple daily charges would increase the benefits of PHEVs and extend the applicability of BEVs. Further, we ignore differences in maintenance, insurance and charging infrastructure costs across vehicle types and focus only on the split hybrid drivetrain—results for series and parallel designs and for blended control strategies may vary somewhat. We also ignore any salvage value of the battery pack at end of life as well as opportunities for energy arbitrage in vehicle to grid applications, which are expected to be small (Peterson et al., 2010). We account only for GHG emissions and ignore other life cycle emissions and impacts, and we assume that CO_2 tax costs are passed through the supply chain to the vehicle customer. We ignore government subsidies, which reduce costs observed by consumers but transfer these costs to taxpayers rather than eliminating them. With government subsidies, plug-in vehicles are somewhat more attractive purchase options for consumers. Finally, advancements in technology and other changes, such as gasoline prices, grid mix, vehicle efficiency, driving patterns, and public policy will affect cost and environmental comparisons in the future.

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Appendix

Tables A1 and A2
Figs. A1–A5

Table A2
Performance of vehicles.

	Acceleration time (s)	
CV		10.2
HEV		10.3
PHEV20	CD mode	10.2
	CS mode	9.3
PHEV40	CD mode	10.1
	CS mode	8.1
PHEV60	CD mode	10.1
	CS mode	8.3
BEV100	CD mode	10.1

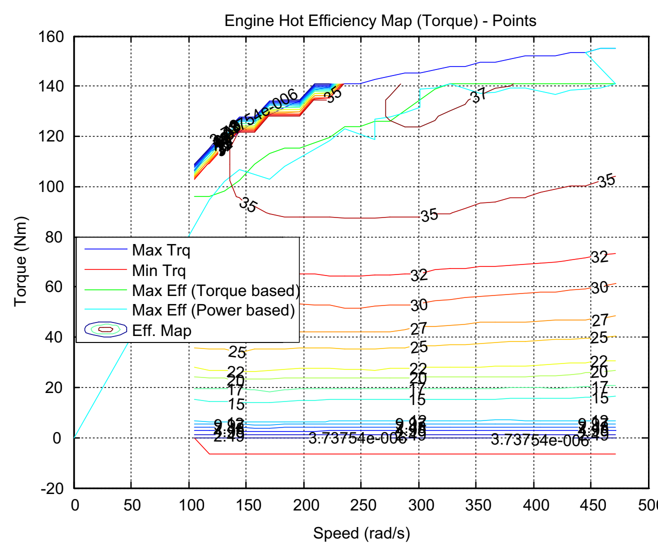

Fig. A2. Engine efficiency map of HEV (%) (Argonne National Laboratory, 2008).

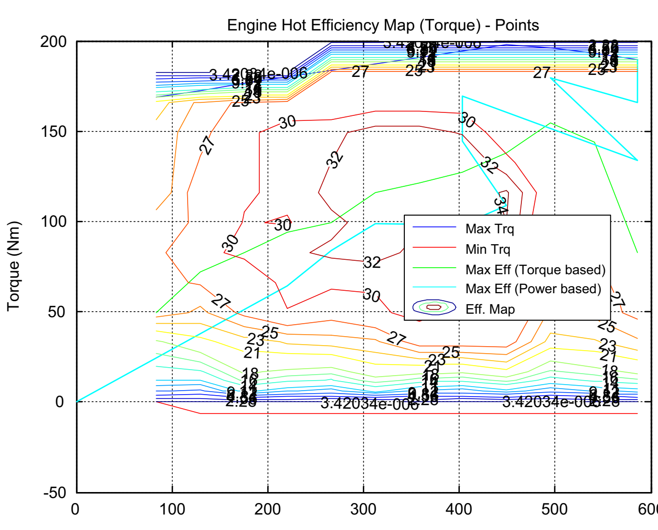

Fig. A1. Engine efficiency map of CV (%) (Argonne National Laboratory, 2008).

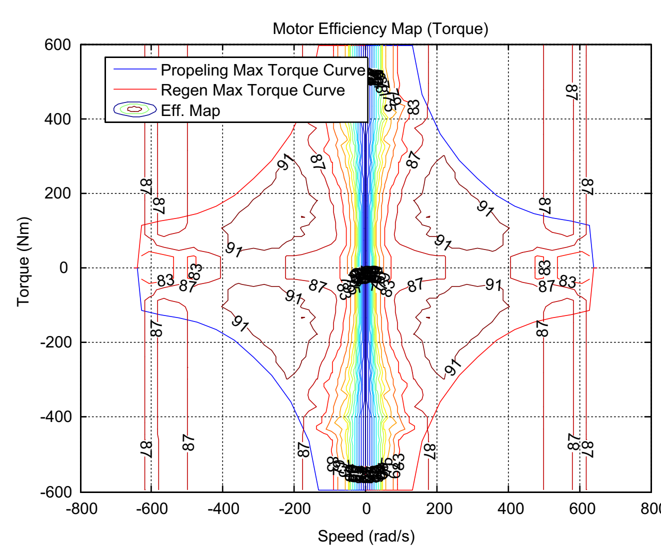

Fig. A3. Motor efficiency map of HEV and PHEVs (%) (Argonne National Laboratory, 2008).

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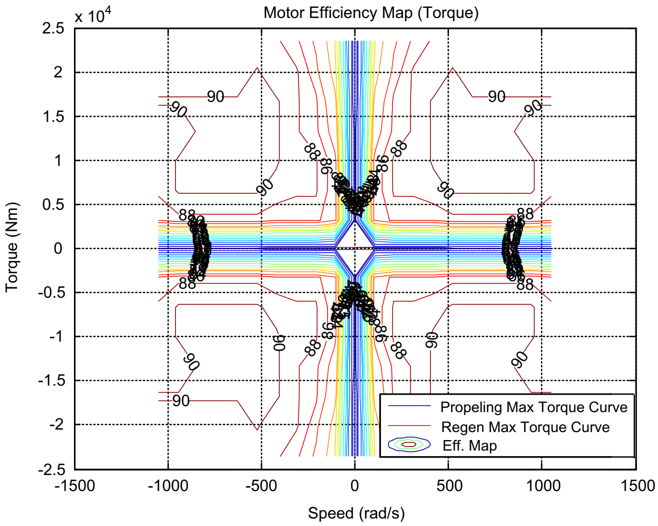

Fig. A4. Motor 2 (generator) efficiency map of HEV and PHEVs (%) .

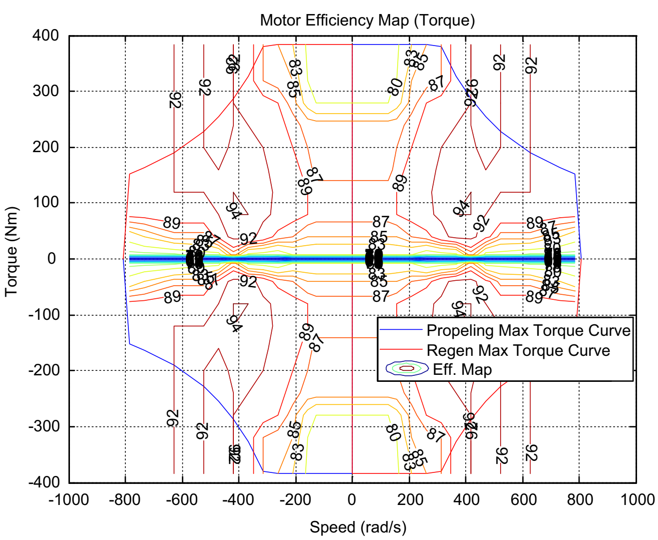

Fig. A5. Motor efficiency map of BEV (%) (Argonne National Laboratory, 2008).

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