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How Much Do Electric Drive Vehicles Matter to Future U.S. Emissions?

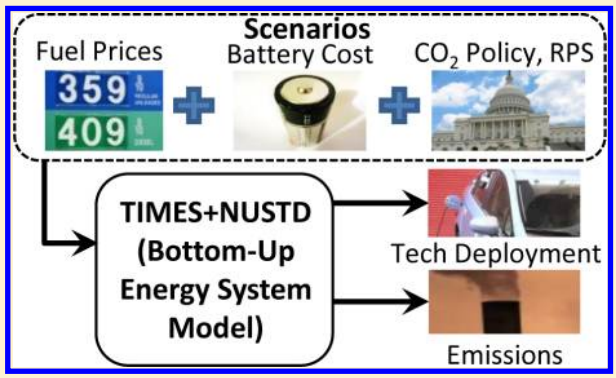
Samaneh Babaee,*[,†] Ajay S. Nagpure,[‡] and Joseph F. DeCarolis[†]

[†]Department of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, North Carolina 27695, United States

[‡]Hubert H. Humphrey School of Public Affairs, University of Minnesota, Minneapolis, Minnesota 55455, United States

Supporting Information

ABSTRACT: Hybrid, plug-in hybrid, and battery electric vehicles—known collectively as electric drive vehicles (EDVs)—may represent a clean and affordable option to meet growing U.S. light duty vehicle (LDV) demand. The goal of this study is 2-fold: identify the conditions under which EDVs achieve high LDV market penetration in the U.S. and quantify the associated change in CO_2, SO_2, and NO_X emissions through midcentury. We employ the Integrated MARKAL-EFOM System (TIMES), a bottom-up energy system model, along with a U.S. data set developed for this analysis. To characterize EDV deployment through 2050, varying assumptions related to crude oil and natural gas prices, a CO_2 policy, a federal renewable portfolio standard, and vehicle battery cost were combined to form 108 different scenarios. Across these scenarios, oil prices and battery cost have the biggest effect on EDV deployment. The model results do not demonstrate a clear and consistent trend toward lower system-wide emissions as EDV deployment increases. In addition to the trade-off between lower tailpipe and higher electric sector emissions associated with plug-in vehicles, the scenarios produce system-wide emissions effects that often mask the effect of EDV deployment.



INTRODUCTION

Increasing concerns over U.S. oil imports, anthropogenic climate change, and urban air quality motivate interest in alternative fuels and vehicles. Among existing options, electric drive vehicles (EDVs)—hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs)—are receiving increased attention from government, industry, and academia. Current U.S. policies designed to promote EDVs include President Obama's pledge to deploy 1 million BEVs by 2015,[1] a $7500 federal tax credit for BEVs and PHEVs,[2] and numerous state-level incentives.[3] In addition, the recent passage of aggressive new Corporate Average Fuel Economy (CAFE) standards that will roughly double fuel economy and halve the greenhouse gas emissions produced by cars and light duty trucks in model year 2025[4] make the prospect for EDV deployment even more promising.

EDVs offer three key benefits over competing vehicle technologies: (1) reduced consumption of petroleum-based fuels,[5] (2) lower refueling infrastructure costs compared to alternatives such as H_2 and compressed natural gas,[6] and (3) a shift in energy production from vehicles to the electricity grid, where emissions from large, centralized facilities are cheaper and easier to control.[7,8] While previous work has applied different methodologies and models to quantify the environmental benefits of EDVs, several consistent insights have emerged. First, HEVs produce less emissions than conventional vehicles.[9−11] Second, PHEVs with smaller battery packs are more likely to deliver emissions benefits and reduced gasoline consumption at lower lifetime cost compared to those with large battery packs in the short term.[12−15] Third, significant emissions benefits, particularly from vehicles with large battery packs, only begin to accrue with clean electricity.[9,11,12,16−18] Fourth, CO_2 prices as high as 100 $/t do not provide sufficient incentive for vehicle electrification.[9,10,12,14,16]

While these studies (along with others[19−22]) have made significant contributions to the literature, they only consider a single point in time or employ sector-specific models or calculations that ignore the interaction of EDVs with the rest of the energy system over time. Recent analyses based on energy system models mainly focus on CO_2 emissions and have been run with a limited set of scenarios,[6,23,24] which make it difficult to draw insight specific to EDVs.

This paper employs an energy system model to meet the following objectives: (1) identify the conditions under which EDVs achieve high market penetration in the U.S. light duty vehicle (LDV) sector through 2050 and (2) quantify the system-wide changes in CO_2, SO_2, and NO_X emissions at the

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national level. The model minimizes the system-wide cost of energy over time and links all sectors of the economy together through a consistent set of energy prices. Therefore, rather than characterizing the rest of the energy system through exogenous inputs and isolating the effects of EDV deployment, application of an energy system model can help characterize the broader impacts due to dynamic interactions across the energy system. As such, this paper adds to the existing literature by addressing a fundamental question: Does EDV deployment produce a consistent and measurable decline in emissions relative to other changes that may be induced throughout the system in response to a common set of scenario drivers? This analysis places particular emphasis on the long-run emissions changes that may be produced in the U.S. by 2050. To address future uncertainty, we examine the effect of 5 factors on EDV deployment: crude oil and natural gas prices, a federal CO_2 policy, a federal renewable portfolio standard (RPS), and EDV battery cost. To characterize possible EDV deployment over the next half century, assumed values associated with each factor are blended to create a large set of 108 scenarios that capture a wide range of potential outcomes. Given the highly uncertain role of consumer choice in future vehicle adoption, this analysis is focused on the economic and environmental performance of EDVs assuming minimal behavioral barriers to vehicle adoption. Strong and persistent reluctance on the part of consumers to adopt EDVs will dampen or eliminate the EDV-related effects presented here.

■ MODEL DESCRIPTION

The model used for this analysis consists of two components: The Integrated MARKAL-EFOM System (TIMES),[25] which serves as a generic energy optimization framework and operates on the National U.S. TIMES Data set (NUSTD), a TIMES-compatible data set constructed specifically for this analysis.

TIMES Model Generator. TIMES is a widely used bottom-up, technology rich energy system model, which represents an energy system as a network of technologies linked together via flows of energy commodities.[25] TIMES performs linear optimization to identify the least-cost way to satisfy end-use demands, subject to user-imposed constraints such as emissions limits and maximum growth rates on technology capacity. Model outputs by future time period include the optimal installed capacity and utilization by technology, marginal energy prices, and emissions. TIMES assumes rational decision-making, with perfect information and perfect foresight, and optimizes over an entire set of multiyear modeling periods simultaneously.

The National U.S. TIMES Data set (NUSTD). We developed NUSTD, a TIMES-compatible input data set containing fuel prices; technology cost and performance estimates; and end-use demands to represent the U.S. as a single region over the next four decades. We adhere to the adage that the best policy-relevant models are "small and simple" in order to maximize transparency.[26] As such, NUSTD represents a compromise between capturing enough technological detail to meet the goals of this analysis and eliminating superfluous information that makes the input data set unnecessarily complex and difficult to manage. We describe the basic design of NUSTD in this section, and provide detailed documentation in the Supporting Information (SI). In addition, the workbooks containing the complete set of input data are publicly available,[27] allowing verification of results by external parties.

The model time horizon is 2010 to 2050, with 5-year time periods. Intra-annual variation in demand and renewable resource availability is represented by specifying three seasonal (i.e., summer, winter, and intermediate) and four diurnal (i.e., morning, mid-day, afternoon/evening, and night) time segments. The U.S. is modeled as a single region with no interregional trade. A 5% social discount rate is used to convert future expenditures into present cost. As described below, a 10% hurdle rate is applied to all alternative vehicle technologies.

An overview of the energy system representation in NUSTD is provided in Figure S1 of the SI. Conceptually, NUSTD can be categorized into 4 parts: fuel supply, electric sector, transport sector, and the remaining end-use sectors (i.e., commercial, residential, industrial). Fuel supply is represented by a set of exogenously specified fuel prices drawn from the output to the Annual Energy Outlook (AEO) 2012.[28] This is in contrast to many other model data sets,[23,29−31] which specify supply curves that represent future fuel price and availability as a set of piecewise continuous steps. While the AEO utilizes supply curves, a retrospective analysis indicates that the fuel price prediction error more than 1 decade in the future is often greater than 40% compared to the realized value.[32] In addition, a review of the AEO[28] indicates low cross-price elasticities over the next 2 decades: an increase in one fuel price (e.g., coal) has a less than 10% effect on other fuel prices (e.g., oil, natural gas). Although the fuel price interaction effects are non-negligible, the fuel price prediction errors are significantly larger. As a result, we make the simplifying assumption that fuel price trajectories are independent of one another.

Given the focus on EDV deployment, the database contains significant technological detail in the transportation and electric sectors. The electric sector contains 32 generation technologies and 71 pollution control retrofits to reduce NO_X and SO_2 emissions from existing coal-fired power plants. Because the electric sector is modeled explicitly, the price of electricity is determined endogenously.

The transportation sector includes light duty, heavy duty, and off highway vehicles. There are 85 light duty vehicle technologies, which consist of 7 vehicle size classes, 6 fuel types, and 13 vehicle types. Much of the vehicle cost and performance data is derived from EPA,[30] but vehicle cost information is updated based on AEO,[28] and EDV performance data are drawn from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model.[5] The following EDV technologies, ordered by their all-electric range (AER) in kilometers, are modeled: HEV, PHEV20, PHEV60, and BEV160. Hurdle rates are used to adjust the amortized cost of alternative fuel vehicles relative to conventional gasoline vehicles in order to partially capture nonmarket factors that may affect their deployment. We allow alternative vehicle shares to reach the same levels as in the AEO reference case without a hurdle rate, but additional deployment beyond AEO levels requires the use of alternative vehicles with a hurdle rate.

Studies conducted using surveys have estimated hurdle rates for alternative vehicle purchases in the range 20−50%, with most estimates closer to the low end of this range.[13,33,34] However, applying a 20% hurdle rate to all alternative vehicle technologies resulted in zero EDV market share across the 108 scenarios tested. While interesting, we view this result as implausible, as hurdle rates are uncertain and likely to decrease over time as technology improves, market penetration increases, and recharging infrastructure becomes more

available. Therefore, in the absence of literature quantifying how hurdle rates may change over time, we simply employ a constant 10% hurdle rate, which is large enough to keep additional alternative vehicles out of the reference case (i.e., reference case fuel prices and battery cost as well as no new policy). As a result, we assume that consumers make decisions based largely on vehicle cost-effectiveness. Details on the hurdle rate calculation are provided in section S2 of the SI. We note that while sophisticated consumer choice models exist and are used to predict future vehicle deployment,[22,35,36] incorporation of such methodology into an energy system model is beyond the scope of the current analysis.

The remaining end-use sectors (commercial, industrial, residential) each contain a single aggregate energy demand with no explicit representation of demand devices. Instead, base year 2010 fuel consumption is constrained to historical shares, and the projected AEO[28] fuel shares serve as the basis for lower bound fuel share constraints that are gradually relaxed over time (Figures S2−S4 of the SI). Because there are minimum required electricity shares in these end-use sectors, the resultant price for electricity is affected not only by transportation demand, but by demand in the other end-use sectors as well. While the lack of technology detail is a key simplification, we assume that technology switching in these end use sectors will have a limited effect on vehicle deployment.

■ SCENARIO DESCRIPTION

For decades, scenario analysis has been used as a way to generate insights about the future that lead to improved strategic management.[37] Scenarios provide a way to systematically organize our perceptions about the future to see how they might play out.[37] The resultant model-based scenarios can then be used to challenge and inform our mental models about the future.[37,38]

While scenarios provide a self-consistent way to explore future outcomes, a small set of highly detailed scenarios can create compelling storylines that are prone to cognitive biases, which often leads to systematic overconfidence in the presented results.[39] We try to mitigate the effect of cognitive biases by examining a large number of composite scenarios based on five factors likely to affect the cost-effectiveness of EDVs relative to other vehicle technologies: natural gas price, crude oil price, EDV battery cost, a federal cap on CO_2 emissions, and a federal RPS. A key simplifying assumption is that these factors only interact weakly, and therefore can be treated independently. Figure S5 in the SI represents an influence diagram that illustrates how scenario parameters affect the marginal price of fuel and electricity, which affect technology deployment and utilization, and ultimately emissions. The total number of modeled scenarios is 108, which represents every combination of assumptions specified in Table 1. For example, 1 of the 108 scenarios involves low natural gas prices, high oil prices, a CO_2 policy, a federal RPS, and reference case EDV battery cost. The assumptions made in each set of scenarios are outlined in the subsections below. Table S16 in Supporting Information (SI) provides a complete enumeration of scenarios.

Baseline Assumptions. Several assumptions regarding the domestic U.S. energy market are consistent through all 108 scenarios. Twenty-nine states currently have legal binding renewable portfolio standards, which require a minimum percentage of electricity to come from renewable sources.[40] The overall minimum share of renewable energy for all states is 2% in 2010, and it gradually increases to 13% by 2025.[28] The new CAFE standard and the corresponding greenhouse gas (GHG) emissions rate limit[4] are included in the base case assumptions. LDVs are expected to reach a fleet-wide average fuel economy of 49.6 miles per gallon and GHG emissions of 163 g CO_2 per mile in model year 2025, per the NHTSA and EPA requirements, respectively.[6] Consistent with AEO,[6] the NHTSA standard of 49.6 miles per gallon is multiplied by a degradation factor of 80% to approximate on-road fuel economy. To factor out the effects of improved air conditioning that we do not model, the EPA standard is implemented as 185 g CO_2 per mile to only capture the effects of improved energy efficiency.

Table 1. Scenario Assumptions in 2050

factor	low	reference	high
natural gas prices ($/GJ)[a]	4.5	7.8	8.7
crude oil prices ($/bbl)[a]	62	145	200
battery cost ($/kWh)[a]	304	135	700
	No	Yes	
federal CO_2 cap[b]	NA	40% reduction below 2010 levels	
federal RPS[b]	NA	20% renewables	

[a]Drawn from AEO2012.[28] [b]See SI for more details.

The upper bound constraints on SO_2 and NO_X emissions from the electric sector are based on AEO[28] and include implementation of the Mercury and Air Toxics Standards (MATS)[41] and the Cross-State Air Pollution Rule (CSAPR).[42] The renewable fuel requirements in the transportation sector are based on the Energy Independence and Security Act of 2007.[43] The upper bound on cellulosic ethanol availability from 2015 to 2020 is obtained from the Renewable Fuel Standard[43] and held constant from 2025 to 2050, while the lower bound is based on AEO projections to 2035[28] and linearly extrapolated to 2050. Finally, the effect of existing fuel subsidies and tax credits for new vehicles, drawn from AEO,[6] are included in the baseline cost assumptions.

Natural Gas Prices. The future price of natural gas is a key factor that will affect future U.S. energy system development. In particular, the recent boom in shale gas exploration has dramatically increased the proved reserves of wet natural gas, rising from approximately 6 trillion m^3 in 2007 to 9 trillion m^3 in 2010.[6] In the AEO,[6] the impacts of total recoverable shale gas resources are examined by defining four scenarios in which the estimated ultimate recovery (EUR) and well density are varied. To limit the number of scenarios but also explore the full range of projected natural gas prices, we adopt the resultant AEO natural gas prices from the Low EUR, Reference, and High Total Recoverable Resources (TRR) scenarios. Additional information is provided in section S6 of the SI.

Oil Prices. A key determinant of future vehicle deployment in the U.S. will be the prevailing price of crude oil. To explore the effect of different oil price trajectories, we adopt the resultant crude oil price trajectories produced in the Low, Reference, and High Oil Price cases of the AEO.[28] The price differences between the three scenarios stem from demand uncertainty in non-OECD countries, the cost of non-OPEC supply, OPEC investment and production decisions, and the economics of alternative liquid fuel supplies.[6]

CO_2 Policy. A federal cap-and-trade system for greenhouse gas emissions has the potential to produce large impacts throughout the U.S. energy system. While several bills have been introduced in the U.S. Congress, none have been signed into law.[44] Based on a review of four proposed federal climate

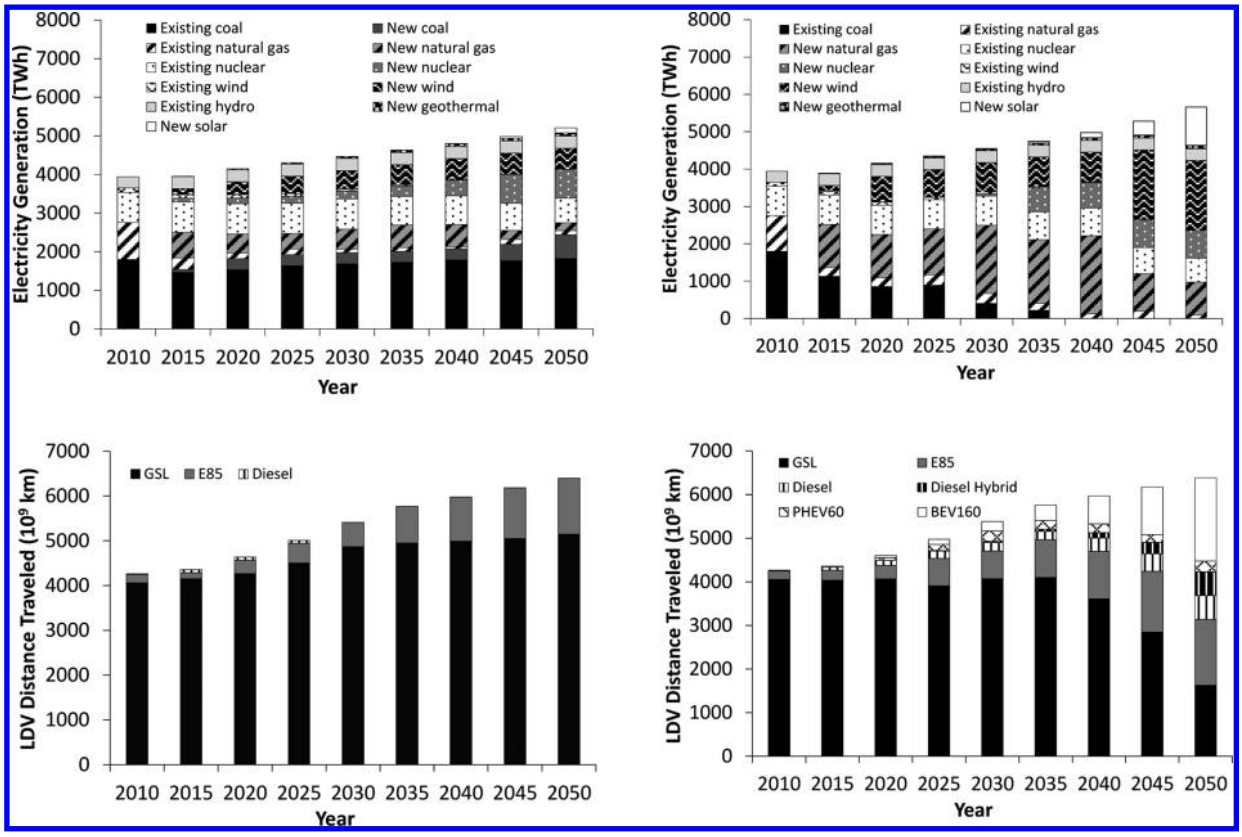

Figure 1. Electric generation by plant type (top) and travel demand met by different light duty vehicle types (bottom) over time for the lowest EDV deployment scenario (left) and the highest EDV deployment scenario (right). The lowest EDV deployment corresponds to low oil prices, high natural gas prices, no CO_2 cap or RPS, and high battery cost. The highest EDV deployment corresponds to high oil prices, low natural gas prices, a CO_2 cap and RPS, and low battery cost.

policies, which are outlined in the SI, we chose to model a cap on national CO_2 emissions level that requires a 40% reduction in the 2010 energy-related emissions level by 2050. For simplicity, we omit consideration of current state-level GHG targets such as California's AB32[45] or the Regional Greenhouse Gas Initiative (RGGI).[46] The federal CO_2 cap enters into force with a 5% reduction in the 2015 model period, and we assume uniform, linear reductions each 5-year period until a 40% reduction is achieved in 2050.

Renewable Portfolio Standard (RPS). The federal renewable portfolio standard modeled in this study is based on a recent proposal contained in Title I of the American Clean Energy and Security Act of 2009 (H.R. 2454), which sets forth renewable energy purchase requirements.[47] Because the proposed federal standard is more aggressive than the aggregation of existing state policies,[48] we adopt the percentages associated with H.R. 2454 as the lower bound constraint on renewable electricity generation in the RPS scenario and extend the required renewable share in 2039 to 2050.[47] See the SI for more details.

Battery Development. Assumptions about the pace and scale of battery innovation will be a key determinant of EDV cost-effectiveness relative to other vehicle technologies. We adopt high, reference, and low battery cost assumptions. The high battery cost scenario assumes constant EDV cost over the entire model time horizon. The reference battery cost scenario is drawn from the AEO Reference case, which assumes a battery cost of 304 $/kWh in 2035.[6] The low cost battery scenario considers attainment of program goals set forth by the DOE's Office of Energy Efficiency and Renewable Energy, which assumes a battery cost of 135 $/kWh in 2035.[49] We only include effects on battery investment cost, not increased efficiency or reduced EDV weight over time, given the uncertainty inherent in such estimates.

■ RESULTS AND DISCUSSION

The insights discussed below are drawn from analysis of the 108 scenario results. For reference, the scenario-specific EDV deployment as well as CO_2, SO_2, and NO_X emissions are included in the SI (Table S16).

Technology Deployment in Two Extreme Scenarios. Figure 1 displays results from the electric and LDV sectors for 2 of the 108 scenarios: the lowest EDV deployment (left) and the highest EDV deployment (right). The lowest EDV deployment corresponds to high natural gas prices, low oil prices, no RPS, no CO_2 policy, and high battery cost. Without a CO_2 policy or RPS, the electric sector is driven largely by generation from combined-cycle natural gas, coal steam, and light water nuclear reactors. The combination of low oil prices and high battery cost prevent EDV deployment.

By contrast, the highest deployment of EDVs corresponds to low natural gas prices, high oil prices, the RPS, the CO_2 policy, and low battery cost. In the electric sector, the existing coal power plants are retired by 2040 in favor of natural gas and renewables due to the combined effect of the CO_2 cap and the RPS. In the LDV transportation sector, a combination of E85, BEV160, diesel, and diesel hybrids meet growing demand and replace retired vehicles by 2050. In this scenario, dramatic reductions in battery cost coupled with low electricity prices

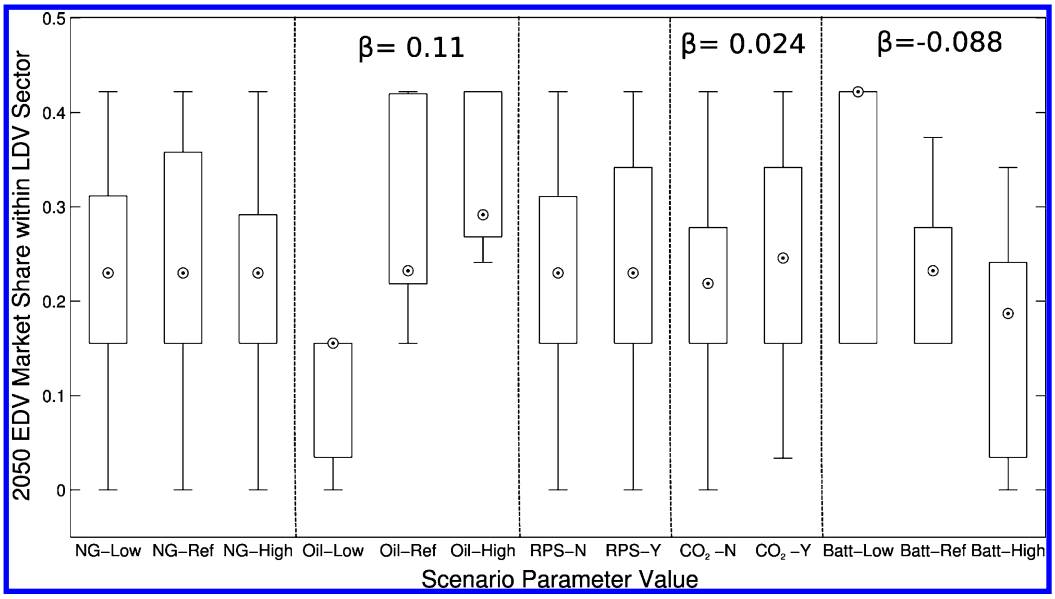

Figure 2. Projected range of 2050 EDV market share for each scenario parameter value. Each boxplot represents the variation in EDV market share when the given parameter value is held fixed but the others are allowed to vary. When the boxplots appear similar across all values for a given scenario parameter (i.e., natural gas price, RPS), it indicates that the effect of that scenario parameter is minimal. The β values represent the linear regression coefficients and express the fractional change in the EDV market share per unit change in each scenario parameter selected during the stepwise regression.

relative to liquid fuels make BEV160s and PHEV60s the most cost-effective EDV alternatives in the long run. In the remaining end use sectors (i.e., commercial, industrial, and residential), the fuel shares gradually shift from fossil fuel combustion to low carbon electricity.

Effects of Scenario Drivers on EDV Deployment. One metric to assess the role of EDVs is the total share of the LDV market in 2050 met by a combination of hybrid, plug-in hybrids, and electric vehicles. Figure 2 summarizes the results across all scenarios as a series of boxplots that represent the total EDV share within the LDV market when a particular scenario parameter is held fixed. For example, the box representing 'NG-Low' represents the EDV deployment across the 36 scenarios in which natural gas prices are assumed low. For each box, the circle represents the median, the edges of the box represent the 25th and 75th percentiles, and the whiskers extend to the maximum and minimum EDV deployment levels. The effects of oil price, battery cost, and CO_2 policy are clearly discernible because the median, quartiles, and range shift as the associated parameter values change. By contrast, the range and median values associated with natural gas (NG) prices and the RPS do not change.

No EDV deployment occurs with high battery costs, low oil prices, and no CO_2 policy. At least 1 of these 3 scenario assumptions must change in order for EDVs to achieve some level of market penetration in 2050. As the scenario parameters shift to values more favorable to EDVs (i.e., 'low' to 'high' oil prices, 'no' to 'yes' on CO_2 policy, 'high' to 'low' on battery cost), the median market shares increase. The maximum EDV market penetration is 16% with the low oil price assumption versus 42% with reference or high oil prices. Similarly, high and reference battery costs limit EDV penetration to a maximum of 34% and 37%, respectively, whereas low battery costs enable the maximum market penetration of 42%. The maximum EDV market share is 42% because EDV deployment is largely limited to the compact and full size vehicle classes. EDVs in larger size classes are generally not cost-effective under the broad range of scenario assumptions we tested. The CO_2 cap results in marginal CO_2 prices of 37−125 $/tCO_2$, which all else equal, only increase EDV deployment by approximately 3%. This result is consistent with other studies demonstrating that CO_2 prices less than 100 $/tCO_2$ have little effect on EDV deployment.[9,10,12,14,16]

A multivariate linear regression model was developed to further quantify the relative degree of scenario parameter influence on EDV deployment in 2050. All scenario parameters were converted into integer scores, starting with values of 0 for scenario parameters designated by 'low' or 'no'. A stepwise linear regression was performed to identify the scenario parameters that improve model fit by increasing R^2. The regression coefficients are presented in Figure 2. The order of parameter selection in the stepwise regression was oil price, battery cost, and CO_2 cap, which were all significant at the 5% level. The resultant linear regression equation had an adjusted R^2 of 0.86. The CO_2 policy, however, increased the R^2 value by less than 1% when included. These results are consistent with Kammen et al.[16] who found that battery cost and oil price are the two most significant factors driving EDV deployment. The natural gas price and RPS scenarios do not have a statistically significant influence on EDV deployment.

Across all scenarios, the total EDV deployment ranges from 0−42% of the LDV market with an average value of 24%, which is broadly consistent with other projections. For comparison, AEO[28] projects 7.5−19% EDVs in 2035, Yeh et al.[23] project 32−100% EDVs in 2050, and Wu et al.[21] predict 100% EDVs in 2050. Within the EDV category, the average market share of HEVs, PHEVs, and BEVs in 2050 is 5%, 1%, and 18%, respectively, across the 108 scenarios in this analysis. The relatively low HEV adoption rate is due in part to the use of conservative GREET EDV efficiency data compared to the higher AEO[6] efficiencies used for conventional gasoline vehicles.

While the average market share of PHEVs and BEVs is roughly the same through 2030, BEV deployment begins to

dominate post-2030. The long-run model preference for BEVs over PHEVs and HEVs is due to several factors: higher BEV efficiency, the generally lower cost for electricity compared to liquid fuels, and larger proportional benefits to BEVs associated with battery cost reductions. While the long-term trend toward BEVs differs somewhat from studies that focus on near term deployment,[12−15] it is consistent with modeling studies that make projections to 2035 and beyond and show appreciable shares of BEVs.[21,28]

Effect of EDV Deployment and Scenario Drivers on Emissions. Figure 3 illustrates how 2050 EDV deployment relates to the total system-wide CO_2, NO_X, and SO_2 emissions across the 108 scenarios. While the scenario parameters influence EDV deployment, the EDV deployment does not in turn produce a discernible effect on total system-wide emissions. There are three reasons for this lack of observed effect: at present the overall share of emissions from the LDV sector is only 20% of U.S. CO_2 emissions;[28] EDV charging can still produce comparable emissions to conventional vehicles depending on the grid mix; and the effect of other sectors on emissions is significant. Because the CO_2 policy has a large and direct effect on system-wide emissions, the emissions in the CO_2 and no-CO_2 policy cases are discussed in turn.

In the 54 scenarios without a CO_2 policy, the horizontal position of the 2050 emissions levels are determined largely by the prevailing oil price and battery cost, while the vertical spread is determined largely by the natural gas price and the RPS. Although low natural gas prices and the presence of the RPS do not produce an effect on EDV deployment, they do affect system-wide emissions. The RPS reduces electric sector emissions by forcing a minimum share of renewables, which produces a modest reduction in system-wide emissions. Similarly, lower natural gas prices lead to higher shares of new natural gas rather than coal capacity in the electric sector. The result is uniformly lower system-wide SO_2, NO_X, CO_2 emissions at lower natural gas prices.

By contrast, the CO_2 policy imposes a binding constraint on system-wide CO_2 emissions, which results in 54 scenarios with 2050 emissions of approximately 3500 $MtCO_2$. In these cases, the SO_2 and NO_X also decrease because much of the conventional coal capacity in the electric sector is retired.

Since oil price and battery cost have the largest effect on EDV deployment, we can better isolate the effect of EDV deployment on emissions by varying these scenario parameters while holding the others constant. Figure 4 presents the sector-specific differences in 2050 emissions between high and low EDV deployment scenarios without the CO_2 cap (top panel) and with the CO_2 cap (bottom panel). The high deployment scenario assumes high oil prices and low battery cost, while the low deployment scenario assumes low oil prices and high battery cost. All four scenarios assume reference case natural gas prices and no RPS. Without the CO_2 cap, there is no change in electric sector SO_2 and NO_X emissions because the air pollution constraints remain binding. The system-wide net decrease in SO_2 and NO_X (approximately 3% for each) is largely unrelated to EDV deployment: higher oil prices lead to fuel switching in the fuel supply, heavy duty vehicle (HDV), and end-use sectors. Also without the CO_2 cap, high EDV deployment creates a 21% reduction in LDV CO_2 emissions but a 13% increase in electric sector CO_2 emissions. Accounting for additional changes across the remaining sectors, the net system-wide effect is a slight 0.9% decrease in total CO_2 in 2050. EPRI[18] similarly finds little change in electric sector SO_2 and NO_X emissions due to PHEV deployment, and an 11% increase in electric sector CO_2 emissions in 2030. The CO_2 cap is binding when in effect, so lower tailpipe CO_2 emissions from high EDV deployment are compensated by higher CO_2 emissions in the electric sector. As a result, high EDV deployment can enable the retention of some existing coal in the electric sector, which increases both electric sector SO_2 and NO_X emissions by approximately 24% and 7% respectively in 2050, because the air pollution limits are no longer binding.

To quantify the benefit of EDV deployment, the model was run again in the CO_2 constrained scenarios exhibiting the

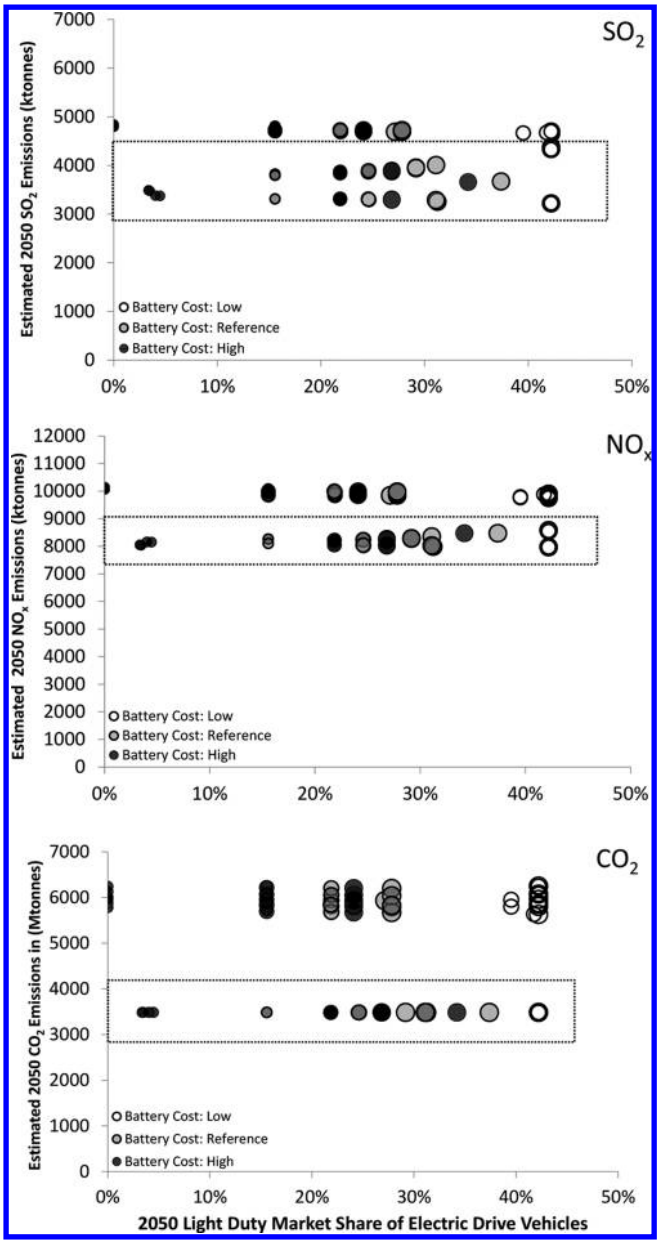

Figure 3. The estimated total system-wide SO_2 (top panel), NO_X (middle panel), and CO_2 (bottom panel) emissions in 2050 associated with the 2050 market share of light duty travel demand met by EDVs in each of the 108 scenarios. Scenarios with higher oil prices and lower battery costs are presented with larger bubbles and lighter colors, respectively. Scenarios with a CO_2 policy are enclosed by the dashed boxes. The horizontal spread is largely related to the oil price and battery cost, while the vertical spread is determined by the natural gas price and RPS.

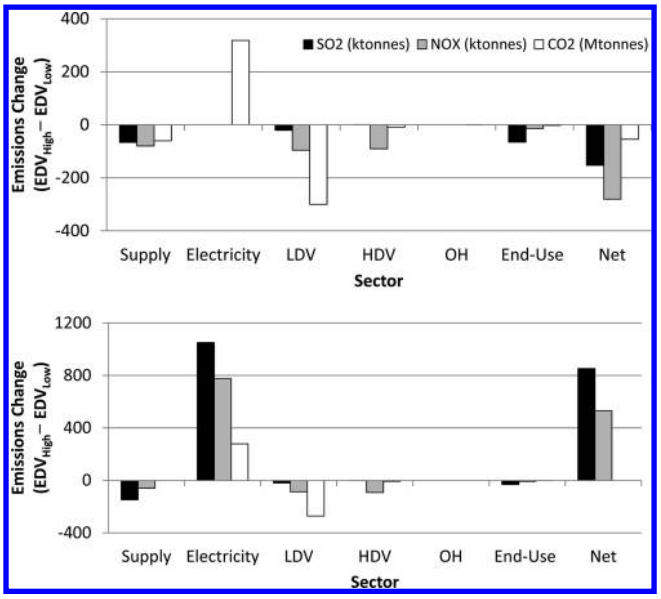

Figure 4. Year-2050 sectoral differences in SO_2, NO_X, and CO_2 emissions between high and low EDV deployment scenarios without the CO_2 cap (top panel) and with the CO_2 cap (bottom panel). High EDV deployment assumes high oil prices and low battery cost; low EDV deployment assumes low oil prices and high battery cost. Both sets of scenarios assume reference case natural gas prices and no RPS. 'HDV' represents the heavy duty vehicle sector, 'OH' represents off highway vehicles, and 'End Use' represents the end use sectors other than transport (i.e., commercial, industrial, residential). 'Net' represents the net emissions change across the whole system.

highest and lowest EDV deployment, but without the availability of EDVs. Comparing the difference in the marginal CO_2 price between the EDV and no-EDV runs in both scenarios, the cost savings associated with EDV deployment ranges from approximately 30−200 \$/t CO_2 in 2050. While there is much uncertainty associated with these price estimates, they nonetheless suggest that EDVs can provide an economic benefit under a CO_2 policy, though their deployment must be driven by other factors such as oil price and battery cost.

Policy Implications. The model results do not demonstrate a clear and consistent trend toward lower system-wide emissions as EDV deployment increases. Differences in net emissions among scenarios do not stem exclusively from the trade-off between lower vehicle tailpipe emissions and higher electric sector emissions; rather, the scenarios can produce systemic effects that mask the effect of EDVs, as shown in Figure 4. Therefore, it is not enough to simply incentivize the purchase of EDVs and wait for emissions benefits to accrue. The emissions benefits—if any—will depend on a broad set of future conditions. Therefore, public policies that target EDV deployment should be formulated, reviewed, and revised with careful attention paid to evolving changes to the broader energy system over time.

If the primary objective is to reduce emissions, policy makers should focus on implementing targeted emissions policy rather than the promotion of specific technologies or fuels. Among the scenario variables tested, the CO_2 cap produced the largest and most consistent drop in CO_2, SO_2, and NO_X emissions. Although the observed marginal CO_2 prices do not drive significant EDV deployment, the results indicate that EDVs can help lower the marginal price of CO_2, particularly if scenario variables favorable to EDVs (high oil prices, low battery cost) prevail.

In the absence of a CO_2 policy, the promotion of clean electricity can provide direct emissions reductions and also lower the emissions footprint from vehicle charging. The new EPA proposed carbon pollution standard[50] and the forthcoming proposed rule on existing coal-fired power[50] (due out in 2014) could have a significant impact on national emissions and eliminate some of the potential emissions increases associated with vehicle charging.

Finally, other alternative vehicles are worth a mention. First, compressed natural gas (CNG) vehicles are not cost-effective in any scenario, including those with low natural gas prices, because low CNG prices are not enough to overcome the higher investment costs. Second, the model deploys diesel and diesel hybrids in many scenarios, which may be a cost-effective way to reduce CO_2 emissions given their higher efficiency compared to conventional gasoline vehicles.

Caveats. While this analysis provides useful insight into the role that EDVs may play in the future, a few caveats should be noted. First, we do not capture the potential air quality benefits due to shifting emissions out of dense urban areas to more remotely located power plants where emissions from large point sources are easier to control. Second, we do not explicitly map the all electric range (AER) for plug-in vehicles to the annual distribution of daily trip lengths. However, we note that the highest penetration of BEV160 in the model results is 30%, which can be assumed to meet 87% of the daily trips less than 160 km in length[51] in the 59% of households with 2 or more vehicles.[52] Third, as noted above, the 10% hurdle rate applied to alternative vehicle technologies is relatively low compared to the 20−40% rates published in the literature, so EDV deployment should be considered optimistic. We conducted a sensitivity analysis of hurdle rates in the highest EDV deployment scenario and found there is a significant drop in EDV deployment as the hurdle rate increases from 12 to 14%, with no deployment of hurdle rate EDVs at 15%. While hurdle rates are a crude proxy of consumer choice, the results nonetheless indicate that prevailing consumer preferences pose a potentially serious challenge to large scale EDV deployment. Fourth, we assume vehicle charging is constant throughout the day. As a next step, we plan to investigate the effects of time-of-day charging on system-wide emissions.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

Documentation of the National U.S. TIMES Data set (NUSTD), additional information on scenario assumptions, and enumeration of key scenario results. This material is available free of charge via the Internet at http://pubs.acs.org.

■ AUTHOR INFORMATION

Corresponding Author

*Phone: 919-264-1744. Fax: 919-515-7908. E-mail: sbabaee@ncsu.edu.

Notes

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REFERENCES

(1) *Blueprint for a Secure Energy Future*; The White House: Washington, DC, 2011; http://www.whitehouse.gov/sites/default/files/blueprint_secure_energy_future.pdf.

(2) U.S. Department of Energy (DOE). Federal Tax Credits for Plug-in Hybrids; http://www.fueleconomy.gov/feg/taxphevb.shtml (accessed Feb. 1, 2013).

(3) U.S. Department of Energy (DOE). Alternative Fuels Data Center; http://www.afdc.energy.gov/laws/matrix/tech (accessed Feb. 3, 2013).

(4) *Federal Register*; Environmental Protection Agency and Department of Transportation: Washington, DC, 2012; http://www.gpo.gov/fdsys/pkg/FR-2012-10-15/pdf/2012-21972.pdf.

(5) *The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET)*; 2012; http://greet.es.anl.gov/ (accessed Feb. 3, 2013).

(6) *Annual Energy Outlook 2012 with Projections to 2035*; DOE/EIA-0383(2012); U.S. Energy Information Administration: Washington, DC, 2012; http://www.eia.gov/forecasts/aeo/pdf/0383(2012).pdf.

(7) Sioshansi, R.; Fagiani, R.; Marano, V. Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power systems. *Energy Policy* **2010**, *38*, 6703−6712.

(8) Peterson, S.; Whitacre, J.; Apt, J. Net air emissions from electric vehicles: The effect of carbon price and charging strategies. *Environ. Sci. Technol.* **2011**, *45* (5), 1792−1797.

(9) Traut, E.; Hendrickson, C.; Klampfl, E.; Liu, Y.; Michalek, J. Optimal design and allocation of electrified vehicles and dedicated charging infrastructure for minimum life cycle greenhouse gas emissions and cost. *Energy Policy* **2012**, *51*, 524−534.

(10) Shiau, C. N.; Kaushal, N.; Hendrickson, C. T.; Peterson, S. B.; Whitacre, J. F.; Michalek, J. J. Optimal plug-in hybrid electric vehicle design and allocation for minimum life cycle cost, petroleum consumption, and greenhouse gas emissions. *J. Mech. Des.* **2010**, *132* (9), 091013−1−13.

(11) Samaras, C.; Meisterling, K. Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy. *Environ. Sci. Technol.* **2008**, *42* (9), 3170−3176.

(12) Michalek, J. J.; Chester, M.; Jaramillo, P.; Samaras, C.; Shiau, C. N.; Lave, L. B. Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proc. Natl. Acad. Sci. U.S.A.* **2011**, *108* (40), 16554−16558.

(13) Peterson, S. B.; Michalek, J. J. Cost-effectiveness of plug-in hybrid electric vehicle battery capacity and charging infrastructure investment for reducing US gasoline consumption. *Energy Policy* **2013**, *52*, 429−438.

(14) Shiau, C. N.; Samaras, C.; Hauffe, R.; Michalek, J. J. Impact of battery weight and charging patterns on the economic and environmental benefits of plug-in hybrid vehicles. *Energy Policy* **2009**, *37* (7), 2653−2663.

(15) *Multi-Path Transportation Future Study: Vehicle Characterization and Scenario Analyses*; ANL/ESD/09-5; Argonne National Laboratory: Argonne, IL, 2009; http://www.ipd.anl.gov/anlpubs/2009/11/65560.pdf.

(16) Kammen, D.; Arons, S.; Lemoine, D.; Hummel, H. Cost-effectiveness of green-house gas emissions reductions from plug-in hybrid vehicles. *Plug-In Electric Vehicles: What Role for Washington?*; Brookings Institution Press: Washington, DC, 2009; pp 170−189.

(17) Hawkins, T. R.; Singh, B.; Majeau-Bettez, G.; Strømman, A. H. Comparative environmental life cycle assessment of conventional and electric vehicles. *J. Ind. Ecol.* **2012**, *17* (1), 53−64.

(18) *Environmental Assessment of Plug-in Hybrid Electric Vehicles, Volume 1: Nationwide Greenhouse Gas Emissions*; 1015325; Electric Power Research Institute (EPRI): Palo Alto, CA, 2007; http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000000001015325.

(19) Wang, J.; Liu, C.; Ton, D.; Zhou, Y.; Kim, J.; Vyas, A. Impact of plug-in hybrid electric vehicles on power systems with demand response and wind power. *Energy Policy* **2011**, *39*, 4016−4021.

(20) Hadley, S. W.; Tsvetkova, A. A. Potential impacts of plug-in hybrid vehicles on regional power generation. *Electricity J.* **2009**, *1040*, 56−68.

(21) Wu, D.; Aliprantis, D. C. Modeling light-duty plug-in electric vehicles for national energy and transportation planning. *Energy Policy* **2013**, in press.

(22) Committee on Transitions to Alternative Vehicles and Fuels, Board on Energy and Environmental Systems, Division on Engineering and Physical Sciences, National Research Council. *Transitions to Alternative Vehicles and Fuels*; The National Academic Press; Washington, DC, 2013; http://www.nap.edu/catalog.php?record_id=18264.

(23) Yeh, S.; Farrell, A.; Plevin, R.; Sanstad, A.; Weyant, J. Optimizing U.S. mitigation strategies for the light-duty transportation sector: What we learn from a bottom-up model. *Environ. Sci. Technol.* **2008**, *42* (22), 8202−8210.

(24) Karplus, V. J.; Paltsev, S.; Reilly, J. M. Prospects for plug-in hybrid electric vehicles in the United States and Japan: A general equilibrium analysis. *Transportation Res., Part A* **2010**, *44*, 620−641.

(25) Loulou, R.; Remne, U.; Kanudia, A.; Lehtila, A.; Goldstein, G. *Documentation for the TIMES Model PART I*; Energy Technology Systems Analysis Programme: Paris, 2005; http://www.iea-etsap.org/web/Docs/TIMESDoc-Intro.pdf.

(26) Morgan, M. G.; Henrion, M. *A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*; Cambridge University Press: Cambridge, U.K., 1992; pp 289−306.

(27) *Energy Modeling*; http://www.energy-modeling.org/ (accessed Feb. 5, 2013).

(28) The U.S. Energy Information Administration (EIA). Annual Energy Outlook (AEO) 2012: Annual Projections to 2040 (online data); http://www.eia.gov/analysis/projection-data.cfm#annualproj (accessed Feb. 13, 2013).

(29) The U.S. Energy Information Administration (EIA). The national energy modeling system: An overview; http://www.eia.gov/oiaf/aeo/overview/ (accessed Feb. 3, 2013).

(30) Shay, C. L.; DeCarolis, J.; Loughlin, D.; Gage, C.; Yeh, S.; Wright, E. L. *National MARKAL Database Documentation*; U.S. Environmental Protection Agency: Research Triangle Park, NC, 2006.

(31) Sarica, K.; Tyner, W. E. Analysis of US fuels policies using a modified MARKAL model. *Renewable Energy* **2013**, *50*, 701−709.

(32) The U.S. Energy Information Administration (EIA). AEO Retrospective Review: Evaluation of 2011 and Prior Reference Case Projections; http://www.eia.gov/forecasts/aeo/retrospective/ (accessed Feb. 3, 2013).

(33) Mau, P.; Eyzaguirre, J.; Jaccard, M.; Collins-Dodd, C.; Tiedemann, K. The neighbor effect: Simulating dynamics in consumer preferences for new vehicle technologies. *Ecological Economics* **2008**, *68*, 504−516.

(34) Horne, M.; Jaccard, M.; Tiedemann, K. Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions. *Energy Economics* **2005**, *27*, 59−77.

(35) Lin, Z.; Greene, D. L. A plug-in hybrid consumer choice model with detailed market segmentation. *Transportation Research Board 89th Annual Meeting*, Washington, DC; 2010.

(36) Heckmann, C. G.; Michalek, J. J.; Morrow, W. R.; Liu, Y. Sensitivity of vehicle market share predictions to alternate discrete choice model specifications. *Proceedings of the ASME 2013 International Design Engineering Technical Conferences*, Portland, OR; 2013.

(37) Schwartz, P. *The Art of the Long View: Planning for the Future in an Uncertain World*; Random House Digital, Inc.: New York, 1996; pp 1−24.

(38) Lave, L. B.; Epple, D. Scenario analysis. In *Climate Impact Assessment: Studies of the Interaction of Climate and Society*; ICSU/

SCOPE Report No.27; Kates, R. W., Ausubel, J. H., Berberian, M., Eds.; John Wiley: New York, 1985; p 150.
(39) Morgan, M. G.; Keith, D. W. Improving the way we think about projecting future energy use and emissions of carbon dioxide. *Climatic Change* **2008**, *90*, 189−215.
(40) DSIRE. Renewable Portfolio Standard Policies; http://www.dsireusa.org/documents/summarymaps/RPS_map.pdf (accessed Feb 3, 2013).
(41) US EPA. Mercury and Air Toxics Standards; http://www.epa.gov/airquality/powerplanttoxics (accessed Feb. 16, 2013).
(42) US EPA. Cross-State Air Pollution Rule (CSAPR); http://epa.gov/airtransport/ (accessed Feb. 16, 2013).
(43) US EPA. Renewable fuel standard (RFS); http://www.epa.gov/otaq/fuels/renewablefuels/regulations.htm (accessed Feb. 3, 2013).
(44) US EPA. Legislative analyses; http://www.epa.gov/climatechange/EPAactivities/economics/legislativeanalyses.html (accessed Feb. 3, 2013).
(45) California Environmental Protection Agency (Air Resources Board), Assembly Bill 32: Global Warming Solutions Act; http://www.arb.ca.gov/cc/ab32/ab32.htm (accessed Oct. 9, 2013).
(46) *Regional Greenhouse Gas Initiative, an Initiative of the Northeast and Mid-Atlantic States of the U.S.*; http://www.rggi.org/ (accessed Oct. 9, 2013).
(47) American Clean Energy and Security Act of 2009 (H.R. 2454); http://thomas.loc.gov/cgi-bin/query/z?c111:H.R.2454.PCS: (accessed Feb. 3, 2013).
(48) DSIRE. Database of state incentives for renewables and efficiency; http://www.dsireusa.org/rpsdata/index.cfm (accessed Feb. 3, 2013).
(49) U.S. Energy Information Administration (EIA). Today In Energy; http://www.eia.gov/todayinenergy/detail.cfm?id=6930 (accessed Oct. 9, 2013).
(50) Environmental Protection Agency (EPA). Carbon Pollution Standards, 2013 Proposed Carbon Pollution Standard for New Power Plants; http://www2.epa.gov/carbon-pollution-standards/2013-proposed-carbon-pollution-standard-new-power-plants (accessed Oct. 9, 2013).
(51) Bradley, T. H.; Quinn, C. W. Analysis of plug-in hybrid electric vehicle utility factors. *J. Power Sources* **2010**, *195*, 5399−5408.
(52) The National Household Travel Survey (NHTS) 2009; http://nhts.ornl.gov/download.shtml#2009 (accessed Oct. 9, 2013).

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