Environmental Science & Technology

Policy Analysis

pubs.acs.org/est

Greenhouse Gas Implications of Fleet Electrification Based on Big Data-Informed Individual Travel Patterns

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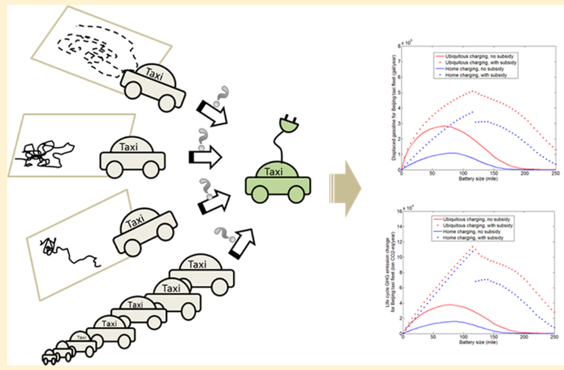
Supporting Information

ABSTRACT: Environmental implications of fleet electrification highly depend on the adoption and utilization of electric vehicles at the individual level. Past research has been constrained by using aggregated data to assume all vehicles with the same travel pattern as the aggregated average. This neglects the inherent heterogeneity of individual travel behaviors and may lead to unrealistic estimation of environmental impacts of fleet electrification. Using "big data" mining techniques, this research examines real-time vehicle trajectory data for 10,375 taxis in Beijing in one week to characterize the travel patterns of individual taxis. We then evaluate the impact of adopting plug-in hybrid electric vehicles (PHEV) in the taxi fleet on life cycle greenhouse gas emissions based on the characterized individual travel patterns. The results indicate that 1) the largest gasoline displacement (1.1 million gallons per year) can be achieved by adopting PHEVs with modest electric range (approximately 80 miles) with current battery cost, limited public charging infrastructure, and no government subsidy; 2) reducing battery cost has the largest impact on increasing the electrification rate of vehicle mileage traveled (VMT), thus increasing gasoline displacement, followed by diversified charging opportunities; 3) government subsidies can be more effective to increase the VMT electrification rate and gasoline displacement if targeted to PHEVs with modest electric ranges (80 to 120 miles); and 4) while taxi fleet electrification can increase greenhouse gas emissions by up to 115 kiloton CO_2-eq per year with the current grid in Beijing, emission reduction of up to 36.5 kiloton CO_2-eq per year can be achieved if the fuel cycle emission factor of electricity can be reduced to 168.7 g/km. Although the results are based on a specific public fleet, this study demonstrates the benefit of using large-scale individual-based trajectory data (big data) to better understand environmental implications of fleet electrification and inform better decision making.



INTRODUCTION

Fossil fuel-based transportation contributes significantly to global greenhouse gas (GHG) emissions and urban air pollution.[1] Fleet electrification through either plug-in hybrid vehicles (PHEVs) or battery electric vehicles (BEVs) is widely considered as a promising alternative to reduce the dependence on fossil fuels, mitigate GHG emissions, and improve air quality in urban areas. While PHEV/BEV technology has developed rapidly in recent years, there exist great uncertainties in terms of market acceptance. Previous studies evaluated factors that impact PHEV/BEV adoption, including infrastructure support, economies of scale, word of mouth effects (influence from other people's perception of electric vehicles), age of current vehicle, consumer income, and travel patterns.[2−10]

In particular, consumer travel patterns (i.e., travel behavior) have increasingly received significant attention, because they directly determine whether PHEV/BEV is acceptable to consumers and how it is utilized for daily travels.[11−13] However, previous research has predominately used aggregated travel pattern data,[10,14] such as the often cited National Household Travel Survey (NHTS), which assumes that everyone follows the same travel pattern as the aggregated average and neglects the heterogeneity of individual users and their specific travel patterns. Recent attempts to differentiate the impacts of individual travel patterns on PHEV/BEV market acceptance have also been constrained by the size of travel pattern samples (usually in the dozens or hundreds)[12,13] due to the difficulty in collecting travel behavior data from the private fleet.

Fortunately, the rapid development of information and communications technology has increasingly made a massive amount of travel behavior data available at a much larger scale. The availability of these "big data" (commonly referring to large-scale data sets[15]) on individual travel patterns, especially for public fleets, represents untapped opportunities to better understand how individual travel behavior affects the PHEV/BEV market acceptance and the associated environmental impacts.

Received: March 5, 2013
Revised: July 12, 2013
Accepted: July 19, 2013
Published: July 19, 2013

   dx.doi.org/10.1021/es401008f | Environ. Sci. Technol. 2013, 47, 9035−9043

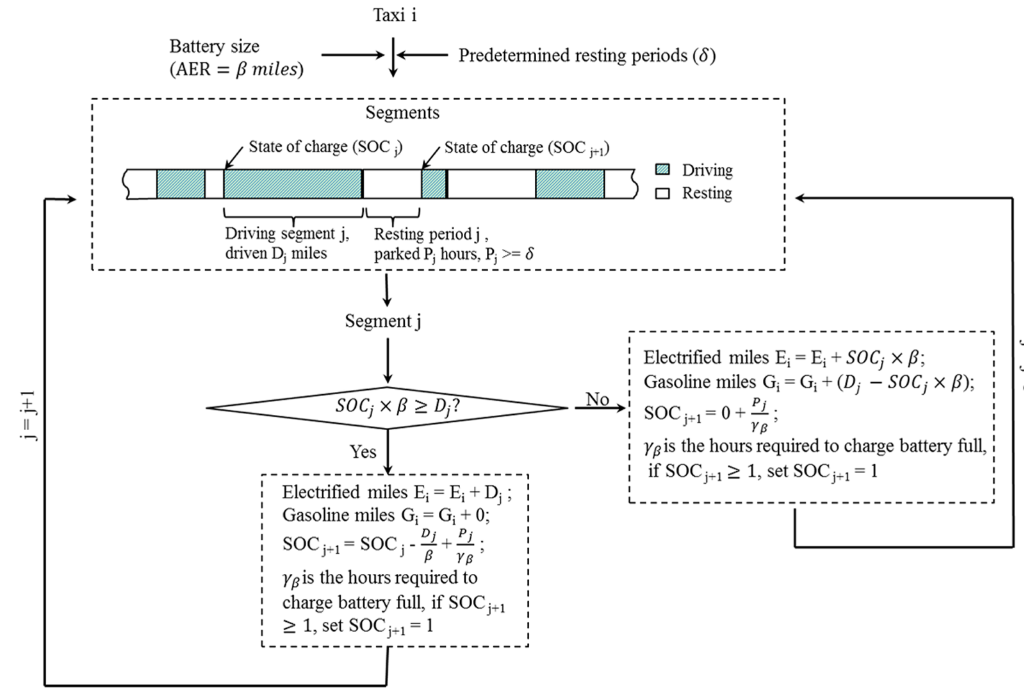


Figure 1. Charging algorithm for PHEVs.

This research examines a large-scale data set containing real-time trajectories of 10,375 taxis in Beijing for one week[16−18] to explore the impacts of individual travel patterns to PHEV acceptance and associated implications on GHG emissions. Public fleets such as taxis, city buses, and government fleets are likely to be early adopters of electric vehicles in China.[19] Given that this data set represents approximately 15% of Beijing's taxi fleet, the results provide useful information on the feasibility and environmental implications of fleet electrification, which is promoted by the Chinese government in large cities.[20] More generally, the method of this study is applicable to other cities for which similar data are available. This research represents the first of a series of studies exploring the role of big data in environmental systems analysis for the emerging PHEV/BEV systems.

■ MATERIALS AND METHODS

Data. The data set used in this study contains real-time trajectories of 10,357 taxis in Beijing over one week (February 2 to 8, 2008) retrieved using global positioning system (GPS) devices installed in taxis.[16,17] Each trajectory data point includes a unique taxi ID, the time (to the seconds) of the recording, and the position (longitude and latitude) of the taxi at the specific time. Depending on the GPS device setup in each vehicle, the frequency of recording ranges from five seconds to ten minutes but stays consistent for the same vehicle. To clean up the raw data, we apply a filter to eliminate 1) empty data points, 2) duplicate data points, 3) taxis with less than seven data points, and 4) unreasonable off-the-chart positions. The weather conditions during the week were mostly sunny and cloudy, with high temperature ranging from 0 to 2 °C (32 to 36 °F), low temperature ranging from −8 to −6 °C (18 to 20 °F), and no precipitation (typical February weather for Beijing).[21−24] The sixth day of the week (February seventh) was the New Year's Day based on the lunar calendar, a Chinese national holiday. The impact of the holiday and weather conditions on the results is analyzed in the sensitivity analysis and also discussed in the Limitation section.

Driving Segments and Charging Opportunities. Taxis are different from private vehicles in the way that taxis do not have uniformly regular parking time. Some taxi drivers take evening and late night shifts; some choose to pick up early morning businesses; and some drivers pair up to drive the same taxi in rotation to minimize costs. Therefore, "daily driving distance" is not a good metric to characterize taxi trips, because taxis may have significantly different starting and ending times of each "day" and the length of a "day" may also be different from taxi to taxi (e.g., one-driver taxi versus two-driver taxi).

To address this issue, we introduce the concept of "driving segments". A driving segment is the total distance driven between two major resting periods when the vehicle is parked with a predetermined length threshold. One segment may contain several separate trips, which is similar to "trip chains" used in previous studies.[12] The resting periods between segments represent charging opportunities.

In this study, we range the predetermined resting threshold from 30 min to eight hours to test the impact of charging opportunities on PHEVs adoption. For example, 4-h segments mean that each segment contains trips between two resting periods of at least four hours each. In other words, charging opportunities are only available if the vehicles have a resting time of four hours or longer. In this paper, we focus the discussion on two extreme cases: the "home-charging only" scenario and the "ubiquitous charging" scenario. The home-charging only scenario represents a relatively conservative case that vehicles can only be charged at home thus requiring a longer resting period (we use eight hours in this study). On the other hand, the ubiquitous charging scenario represents an optimistic case that public charging stations are ubiquitously available, allowing drivers to charge their vehicles as long as they have more than half an hour of resting time.

Charging Algorithm. We develop a charging algorithm to model PHEV charging activities based on taxi trajectories

(Figure 1). For each taxi (taxi i), based on the predetermined resting period (δ), the trajectory can be translated into a series of driving segments and resting periods in temporal sequences. At the beginning of each driving segment (segment j), the condition of the vehicle's battery is represented by "state of charge (SOC_j)", which means the remaining capacity of the battery relative to the all-electric range (AER). SOC_j depends on the battery size of the PHEV, driving distance, and charging opportunities of all segments prior of segment j. "Battery size" in this study refers to vehicle on-road AER in miles and PHEVs in this study utilize a serial configuration. Based on SOC_j and battery size, we then decide whether available battery electricity is able to cover the travel needs of the entire segment. If yes, the total distance driven in this segment (D_j) is added to the electrified mileage of taxi i (E_i). The SOC is then updated with electricity consumed in this segment and available charging time during resting period j. If available electricity is not enough to cover the entire driving segment, the battery will be entirely depleted and the remaining mileage will be fueled by gasoline. Because the battery has been depleted, the SOC at the beginning of the next driving segment $j+1$ (SOC_{j+1}) will depend on the available charging time in resting period j. Then the same process goes for the next segment (segment $j+1$). When all segments are analyzed, we can compute the portion of the trips of taxi i that can be electrified if using a PHEV with a battery with given AER under given charging opportunity conditions.

Fuel Cost Saving and Electrification Rate. The main incentive for drivers to adopt PHEVs is potential fuel cost savings. To explore the heterogeneity of fuel cost saving potentials at the individual level, we calculate the probability distribution of fuel cost savings and payback time for the cost of batteries for Beijing's taxi fleet. Factors affecting fuel cost savings include gasoline cost, electricity cost, battery cost depending on battery size and unit price, fuel economy, charging opportunities, and charging speed (charging voltage and ampere, also depending on the size of batteries). In this study, we use electricity price of $0.078/kWh (0.488 CNY/kWh), gasoline price of $1.29/L (8.06 CNY/L), fuel economy at charge depleting mode of 0.35 kWh/mile (based on 2013 Chevy Volt),[25] fuel economy at charge sustaining mode of 35 mile/gal (city travel of 2013 Chevy Volt),[25] charging voltage at 240 V, charging current at 16A,[14] and charging efficiency of 88%.[14] Fuel economy of gasoline vehicles is assumed to be the same as PHEV charge sustaining mode (35 mile/gal). Currencies are converted based on an exchange rate of 6.23 CNY/USD. It is also assumed that all vehicles have a fully charged battery (SOC = 100%) at the beginning of the simulation. We range battery size from 0 to 250 miles, battery cost from $500/kWh (current level) to $100/kWh (future target),[26] and charging opportunity from "home-charging only" to "ubiquitous charging" to explore their impacts on fuel cost savings for individual vehicles and the overall electrification rate. We assume that the price difference between a PHEV and comparable conventional gasoline vehicle is solely due to the cost of battery which increases linearly with the capacity of the battery. The size of batteries is represented by AER in miles, which is the maximum distance a fully charged vehicle can drive on electricity. To evaluate battery cost payback time, we use a discount rate of 5% to calculate the net present value (NPV) of future fuel cost savings. The impacts of these assumptions are tested by conducting a sensitivity analysis.

Adoption. Adoption of PHEVs can be overestimated using electrification rate calculated solely based on daily vehicle mileage traveled (VMT) and the size of batteries.[12] The cost of battery also plays a key role, because drivers who do not drive enough mileage to make payback of the battery cost within the vehicle lifetime are less likely to adopt PHEVs. In addition, drivers whose travel patterns allow little charging opportunities are also less likely to adopt PHEVs or less likely to utilize PHEVs even if they adopt. Therefore, we use a payback model to allow drivers to adopt PHEVs only if they can payback the cost of batteries within eight years (maximum service time of taxis in China[27]). If the payback time is longer than eight years, we assume the driver will decline switching to PHEV and this taxi will stay as conventional gasoline vehicle. The utilization of PHEVs is modeled using the travel pattern detected for each individual vehicle. The fleet level VMT electrification rate is then the ratio of total electrified mileage to total mileage traveled.

Government Subsidy. We study two types of government subsidies in this research. The first is a one-time refund depending on the size of batteries. The Chinese government is currently offering a subsidy of $482/kWh (3,000 CNY/kWh) with a maximum cap of $8,026 (50,000 CNY) for PHEVs and $9,631 (60,000 CNY) for BEVs.[28] Several local governments (e.g., Shanghai) also offer an additional subsidy of $8,026 (50,000 CNY) for each PHEV. We examine the impact of a government subsidy to fleet level VMT electrification with subsidies ranging from $0 to $803/kWh (5,000 CNY/kWh) with a cap of $16,051 (100,000 CNY) per vehicle. The other subsidy studied is the "electricity subsidy" that government subsidizes electricity to enlarge the fuel cost savings for PHEVs. The current electricity price is $0.078/kWh (0.488 CNY/kWh) in Beijing. We study an electricity subsidy range between $0 and $0.064/kWh (0.4 CNY/kWh). We set the upper limit at $0.064/kWh (0.4 CNY/kWh) because if drivers do not pay for fuels at all or even receive money from charging, their travel patterns might be significantly altered (e.g., driving more). We assume the electricity subsidy will be constant for eight years.

Greenhouse Gas Emissions. In general, PHEVs can eliminate or reduce tailpipe emissions, but the life cycle GHG emissions may or may not decrease, depending on the energy mix of the power grid. The life cycle GHG emissions of a vehicle come from two parts: the vehicle cycle and the fuel cycle. The vehicle cycle includes the production and end-of-life management of vehicles and batteries, while the fuel cycle includes the extraction, production, transportation, and consumption of the fuels. GHG emissions associated with the production of a medium-sized passenger car in China is approximately 6,675 kg CO_2-eq/vehicle.[29] It is assumed that vehicle manufacturing of PHEVs and conventional gasoline vehicles are identical except that PHEVs need additional battery production. This assumption can be justified by the fact that smaller internal combustion engines (ICEs) in PHEVs can account for the difference due to electric motors and additional control equipment.[30] GHG emissions from the Li-ion battery production are approximately 120 kg CO_2-eq/kWh battery capacity.[30] The fuel cycle emissions are tightly tied to the carbon intensity of electricity production. China has six large power grids. Beijing belongs to the North China Grid with GHG emission factor of 236.7 g CO_2-eq/km traveled.[31] GHG emissions of conventional gasoline vehicles are approximately 224.4 g CO_2-eq/km.[31] We scale up our results obtained from the present data set to reflect total emissions of the entire taxi fleet electrified by PHEVs with different battery size, assuming eight years of taxi service time. We discuss the implications of future grid mix change, although the change of grid mix over time is not included in the modeling.

RESULTS AND DISCUSSION

Travel Patterns. The data set after the filtration contains trajectories of 9,951 taxis with a total of 16.2 million data points and 7.7 million miles traveled. Figure S1 provides an overall sense of the data set by visualizing an individual vehicle's average speed between sampling points. An animation of the trajectories of all taxis can be found at http//vimeo.com/65922939/. More than 60% of taxis have over 1,000 data points. The definition of "segment" determines the distribution of distance traveled in each segment as well as charging opportunities between segments (Figure 2), especially for those

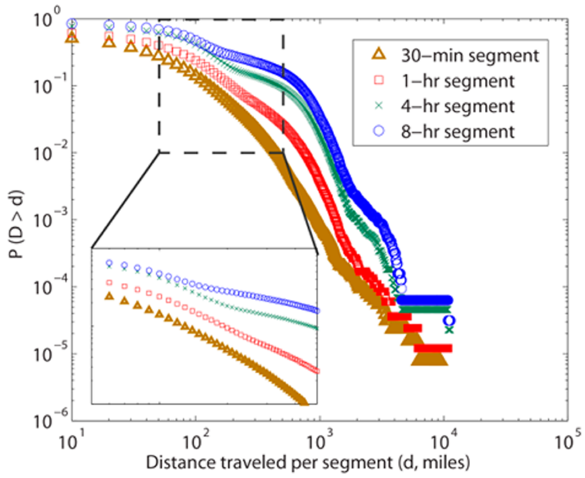


Figure 2. Complementary cumulative probability distribution of per-segment distance with different charging opportunities.

with per-segment travel distance between 100 and 2,000 miles, representing approximately 80% of the total VMT. Unexpectedly, segment travel distance distributions for 4-h segments and 8-h segments are much similar. In particular, the 4-h segment distribution is almost identical to the 8-h one for segments between 50 and 100 miles of travel distance and then gradually diverge as the per segment travel distance increases (Figure 2 insert). Tamor et al. observed similar results with household vehicle travels in Minnesota.[12]

Fuel Cost Saving. Individual taxis can have very different fuel cost savings from adopting PHEVs with the same battery size depending on individual travel patterns. Figure 3a shows the complementary cumulative probability distribution of fuel cost savings from PHEV adoption, representing the probability of a randomly picked vehicle to have more fuel cost savings than the corresponding x-axis value. If the taxi fleet adopts PHEVs with 40-mile battery range (PHEV40), 90% of the taxis can save more than \$5 per week, and 10% of them can save more than \$40 per week. When PHEVs with 240-mile battery range (PHEV240) are adopted by the fleet, 90% of the drivers can save more than \$26 per week, and 10% of them can save more than \$79 per week.

From a perspective of each vehicle's relative fuel cost savings, 90% of the taxis can save more than 5% of their fuel cost, while 10% can save more than 57% with PHEV40. With PHEV240, 90% of the taxis can save at least 24% of the total fuel cost, while 35% can save at least 77% (Figure 3a insert). There is no correlation between absolute fuel cost reduction and percentage saving of total fuel cost for individual taxis (Figure S2). The percentage of fuel cost saving by PHEVs with a large battery is significant. However, a larger battery also increases upfront vehicle cost and therefore delays the payback time of the battery. Figure 3b presents the probability distribution of payback time for PHEVs with different battery size. It is notable that a significant portion of the vehicles (38% for PHEV40 and 99% for PHEV240) will not be able to payback the additional battery cost from fuel cost savings over the lifetime of the vehicle (i.e., eight years) at the current battery cost of \$500/kWh. This indicates that fuel cost savings itself is not enough to achieve high PHEV adoption. Unit battery cost reduction can significantly shorten the payback time, especially for large batteries (Figure S3). A government subsidy also becomes critical in promoting PHEV adoption at least at the early stage of the market penetration.

Electrification Rate. The fraction of total VMT electrified is related to both PHEV battery size and unit cost of the battery, as presented in Figure 3c. When battery unit cost is relatively high (\$300/kWh to \$500/kWh), the overall electrification rate increases initially with the increased battery size but decreases after passing a tipping point. This is because that, when battery unit cost is high, large batteries mean high upfront vehicle premiums so that only a few vehicles with higher fuel cost saving potentials will adopt PHEVs where the electrification rate peaks represent the optimal battery size under each scenario. At current battery cost (\$500/kWh), the optimal battery size is approximately 80 miles for this fleet. It is worth noting that the overall electrification rate stabilizes at around 40% when the battery unit cost is reduced to \$200/kWh, indicating that battery cost is no longer a barrier to increase the electrification rate. Results in Figure 3c are based on a ubiquitous charging scenario (30-min segments). When charging opportunity is limited to home-charging only, the same trend holds, but the overall electrification rate decreases (Figure 3d). These factors cannot be easily assessed using aggregated data, and the electrification rate could be overestimated (Figure S6).

Subsidy. Government subsidies can significantly increase the fleet VMT electrification rate by offsetting high battery costs. Figure 4a shows that a moderate government subsidy can increase the overall electrification rate from 27% to as high as 45% with unit battery cost at \$500/kWh. Similar to Figure 3c, tipping points can also be observed in Figure 4a that the electrification rate first increases and then declines with increasing battery size if holding the government subsidy rate constant. Figure 4a also shows that, with the same battery size, a higher government subsidy rate only has marginal impacts on the electrification rate after reaching a threshold (dependent to battery size) due to the subsidy cap of \$16,051 per vehicle.

In addition to the subsidy rate based on battery capacity, the total amount of subsidies is also relevant to policy making. The contour lines in Figure 4a represent the total government expenditures to subsidize the fleet electrification. It is interesting to note that the same amount of subsidies can achieve very different electrification results with different subsidy rates and battery sizes. Figure 4a suggests that PHEVs with a battery size of 80 to 120 miles can potentially reach to a maximal electrification rate of 45% with relatively low subsidies at a modest rate of \$300 to \$400/kWh. In the home-charging scenario, a modest government subsidy at \$385/kWh

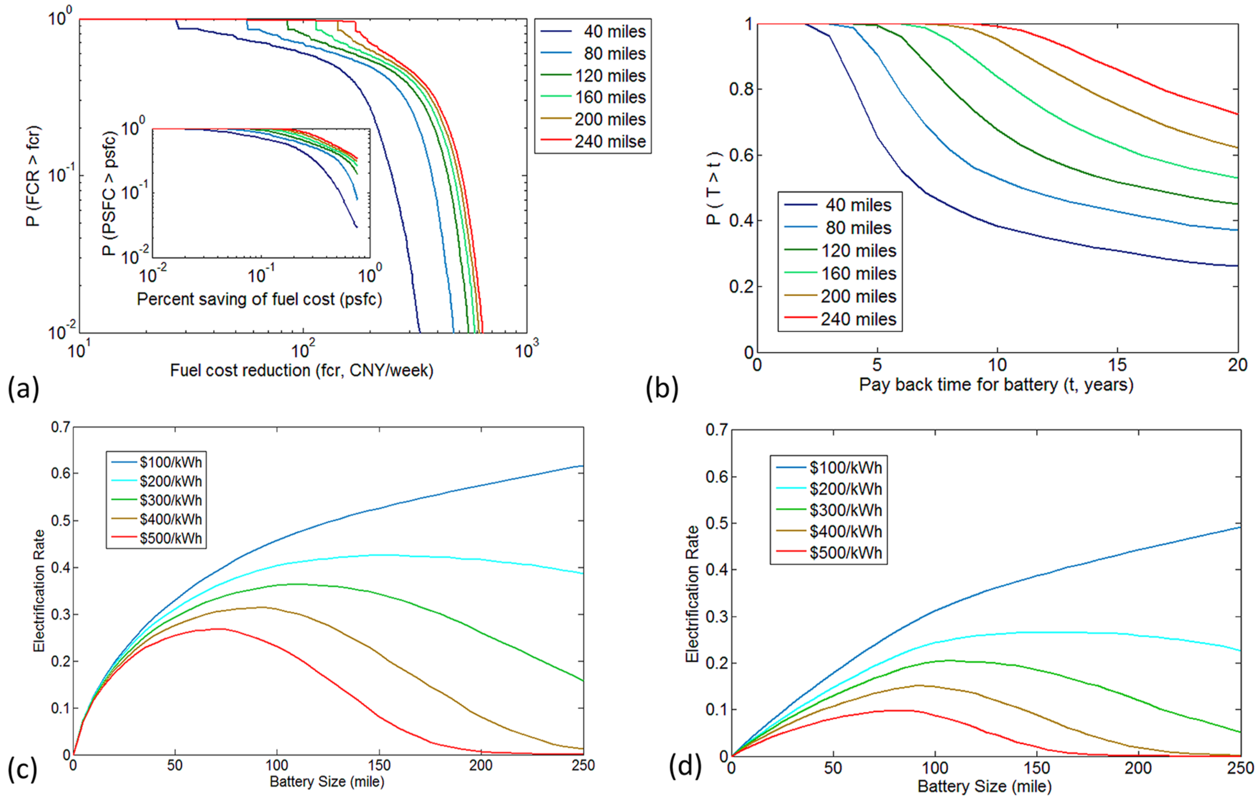


Figure 3. **a**) Complementary cumulative probability distribution of weekly fuel cost savings with PHEVs regarding different battery sizes modeled with ubiquitous charging. Inserted graph shows percent savings of total fuel cost. **b**) Complementary cumulative probability distribution of payback time for PHEVs with different battery size modeled with ubiquitous charging and battery cost at \$500/kWh. **c**) Electrification rates of total fleet VMT based on acceptance criteria of paying back battery cost within eight years for the ubiquitous charging scenario (charging opportunities exist when resting for longer than half an hour). **d**) Electrification rates of total fleet VMT based on acceptance criteria of paying back battery cost within eight years for home-charging only scenario (charging opportunities exist resting for longer than eight hours).

is able to increase the overall electrification rate from 10% to 31% at current battery cost (Figure 4b). When the unit subsidy is above \$385/kWh, the electrification rate declines rapidly after the battery size exceeds 115 miles. This is because the per-vehicle subsidy limit is reached and fuel cost savings required to breakeven with battery cost increase dramatically (Figure S4).

Government can also incentivize PHEV adoption and utilization by subsidizing electricity cost for charging. The electricity price in Beijing is currently \$0.078/kWh.[32] Figure 4c and Figure 4d show fleet VMT electrification with electricity subsidies up to \$0.064/kWh. We assume individual travel behavior does not change with electricity subsidies, which may underestimate the electrification rate if drivers actively seek charging opportunities. Figures 4c and 4d also show that subsidizing electricity is less effective than subsidizing battery cost to promote fleet electrification but is also relatively less expensive. If designed well, the same budget can achieve a similar level of electrification rate choosing either subsidy option. The advantage of subsidizing electricity is that it requires a substantially less amount of money each year for a longer period of time, while the purchasing subsidy requires greater upfront capital.

GHG Emissions. Previous research examines environmental implications of PHEVs adoption often on a per-vehicle or per-VMT basis assuming specific battery size or VMT. This approach does not reflect the role of individual travel patterns and battery size variations in determining the fleet electrification rate which in turn determines environmental impacts. For example, considering two identical PHEVs with the same battery size and total annual VMT but different travel patterns, the vehicle that takes shorter trips between charging events tends to charge more often and can displace more gasoline than the other taking longer trips between less frequent charging events. In addition, a larger battery can electrify more VMT (Figure S5) but also implies more life cycle energy input, material use, and GHG emissions from the battery production. Can the GHG emission reduction from VMT electrification offset the emissions from battery production? Figure 5a shows that the marginal electrification rate, defined as the amount of VMT electrified per vehicle due to one mile of additional battery range, diminishes in general with increasing battery size. Note that a government subsidy can actually reduce the marginal electrification rate by offering adoption incentives to vehicles that do not benefit much from PHEVs due to travel patterns. Similar to results shown in Figures 3c and 3d, with current battery cost, limited public charging infrastructure, and no government subsidy, the greatest amount of gasoline displacement (1.1 million gallons per year) can be achieved by modest battery size (approximately 80 miles); larger batteries do not necessarily mean more VMT electrification or gasoline displacement (Figure 5b). The sudden drop of marginal electrification rate in the home-charging with subsidy scenario in Figures 5a and 5b (also in 5c and 5d) at around 120-mile battery size is due to the fact that per-vehicle subsidy cap (\$16,051/vehicle) is reached, as explained earlier in discussing Figure 4b.

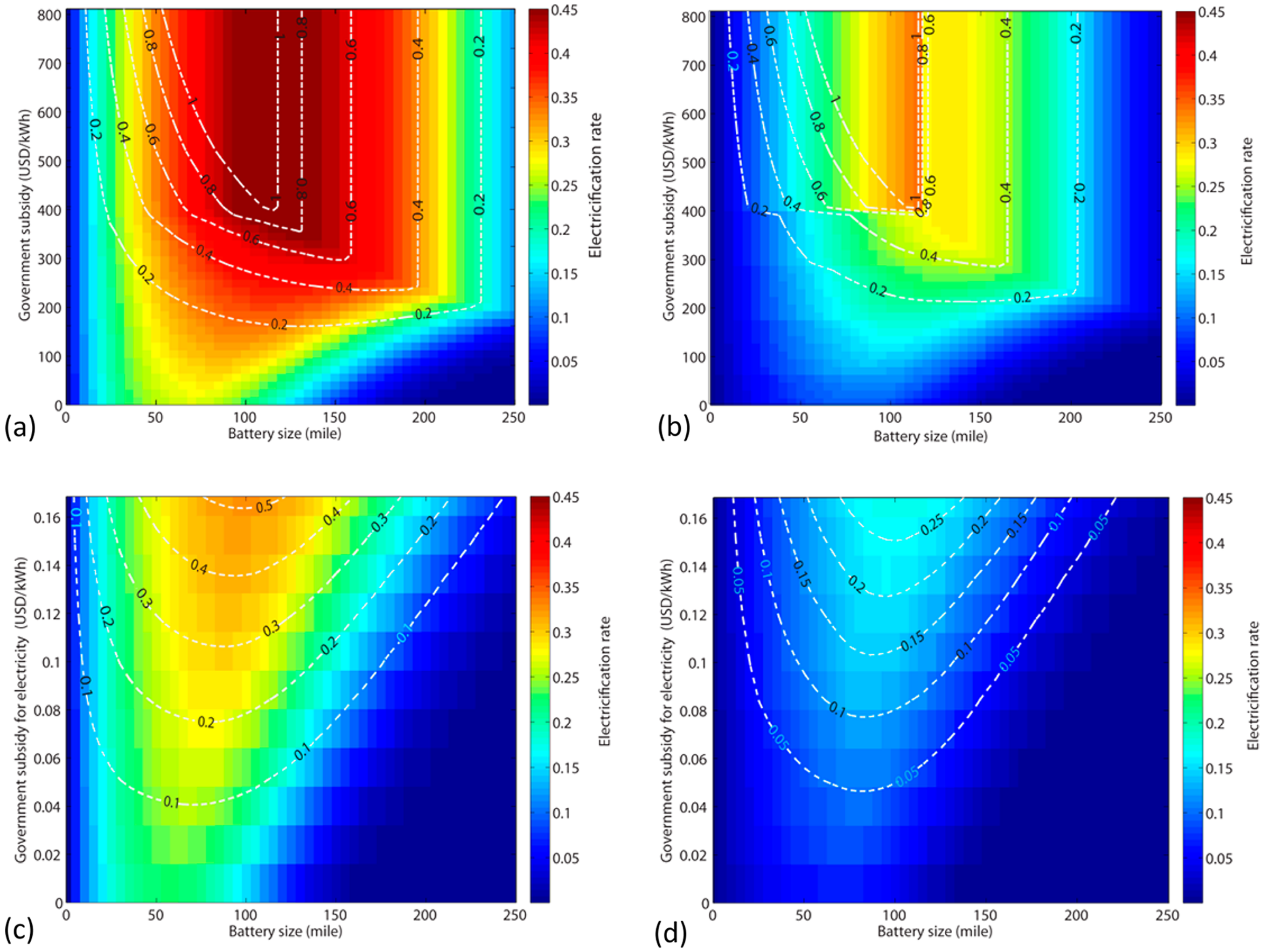


Figure 4. Impact of subsidies on fleet VMT electrification. One time purchasing subsidy from \$0 to \$803/kWh based on battery capacity with a maximum of \$16,051 per vehicle and unit battery cost at \$500/kWh under **a**) the ubiquitous charging scenario and **b**) the home-charging only scenario. Charging subsidy from \$0 to \$0.0644/kWh based on charged electricity for ten years under **c**) the ubiquitous charging scenario and **d**) the home-charging only scenario. Contour lines show total costs to government from subsidies in billion dollars.

Given that electricity in China is largely produced from coal, especially in the northern region where Beijing is located, displacing ICE vehicles using gasoline with electric vehicles using electricity can actually increase fuel cycle GHG emissions by 12.3 g CO_2-eq/km.[31] Figure 5c shows the life cycle emission changes of the fleet with PHEV adoption and utilization modeled based on different battery size as described above. Because emissions in the fuel cycle dominate in the life cycle of a vehicle,[33] life cycle GHG emissions increase and peak (at 38 kiloton CO_2-eq per year) without subsidies at around 80 miles (battery range) where the electrification rate is at the highest (Figure 3c and 3d). With government subsidies, life cycle GHG emissions increase up to 115 kiloton CO_2-eq per year due to increased electrification rate. GHG reduction can be achieved if the electricity grid of Beijing becomes less carbon-intensive. Currently, Beijing is planning on decarbonizing its grid through measures such as increasing natural gas power generation, improving efficiency of existing plants, and diversifying fuel sources with renewables.[37] If the fuel cycle emission factor of electricity can be reduced to 168.7 g/km (can be achieved by replacing 40% coal with natural gas in electricity generation and increasing efficiency of coal-fired power plants by 10%), emission reduction of up to 36.5 kiloton CO_2-eq per year can be achieved (Figure 5d). Government subsidy does not result in more GHG reduction at low battery range (less than 120 miles), because vehicles that benefit less from PHEVs due to travel patterns are encouraged by the subsidy to adopt PHEVs and emissions reduced from gasoline displacement are not enough to make up emissions due to battery manufacturing for these taxis.

Policy Implications. At current battery cost (approximately \$500/kWh), a larger battery does not necessarily imply higher rate of adoption, utilization, and electrification of PHEVs due to the heterogeneous individual travel patterns. The VMT electrification rate peaks when PHEV battery range is around 80 miles, which represents the optimal battery size for the fleet at current technology.

While the battery range is one of the major concerns from consumers' perception,[34] our results show that a larger battery actually decreases the VMT electrification rate when the unit battery cost is higher than \$200/kWh. Only when the unit battery cost is lower than \$200/kWh, extended electric drive range can increase the adoption and thus electrification rate. In addition, we find that charging opportunities (i.e., how frequently a driver can charge a vehicle) also play a key role in VMT electrification. Increasing charging speed only has

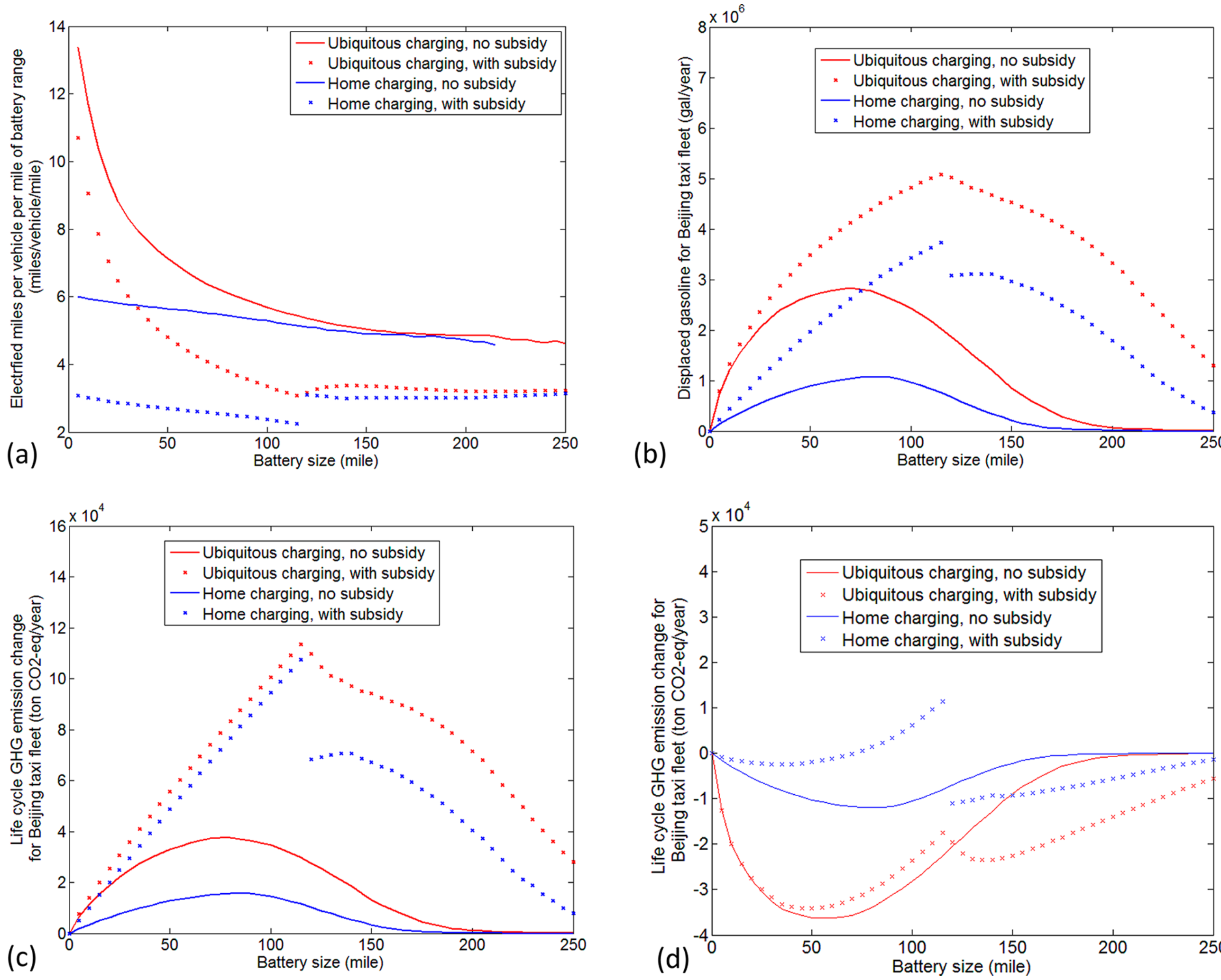


Figure 5. **a**) Marginal electrification rate (the amount of VMT electrified per vehicle due to one mile of additional battery range) and **b**) displaced gasoline with different PHEV battery size under different charging and subsidy scenarios. Life cycle GHG emission change with different PHEV battery size under different charging and subsidy scenarios using fuel cycle emission factor of **c**) North China grid (which Beijing belongs to) and **d**) a cleaner grid scenario with 40% natural gas power plants and 10% efficiency improvement in coal-fired power plants. These scenarios are all modeled with battery cost at \$500/kWh and subsidy at \$401/kWh if applicable.

marginal impacts with limited charging opportunities, because when charging opportunities are limited (e.g., home charging only), each charging event has a relatively long charging time which allows most of the vehicles being fully charged even at the current charging speed.

Subsidy can effectively increase the VMT electrification rate by filling the gap between fuel cost savings and the premium cost of PHEVs. Our results show that focusing on PHEVs with modest electric ranges (80 to 120 miles) can most efficiently boost VMT electrification with a fixed amount of budget. Different from a lump sum subsidy to incentivize consumers to buy PHEVs, subsidizing electricity cost can also encourage PHEV owners to drive more on electricity. Our study demonstrates that better understanding on individual travel patterns using large-scale trajectory data can help design better subsidy programs for PHEV/BEV adoption and utilization.

Last but not least, previous research on environmental impacts of PHEVs is often conducted based on average daily or annual VMT.[35,36] Our study demonstrates how individual travel patterns, charging opportunities, and battery size influence life cycle GHG emissions due to PHEV adoption and utilization at the individual vehicle level. It also sheds lights on the utilization of large-scale vehicle trajectory data for enhancing assessment of environmental impacts of PHEV/BEVs.

Sensitivity Analysis. To assess the impacts of various parameters on the results, we conduct a sensitivity analysis in reference to the baseline scenario. The baseline scenario has the following assumptions: home-charging only, no government subsidy, charging efficiency at 88%, electricity price at \$0.078/kWh, gasoline price at \$1.29/L, fuel economy for charging depletion mode at 0.35 kWh/mile, fuel economy for charging sustaining mode or conventional gasoline vehicle at 35 mile/gal, charging voltage at 240 V, charging current at 16A, range battery at 80 miles, and battery unit cost at \$500/kWh. The sources of these parameters are cited in the method section. We find that fuel cost reduction is more sensitive to charging opportunities than to charging speed. It is also more sensitive to gasoline cost and fuel economy than to electricity cost. Details of the sensitivity analysis and results are included in the Supporting Information (Tables S2 and S3). We also test the impact of the holiday on the electrification rate by separating the data into two subsets: before-holiday data and holiday data

dx.doi.org/10.1021/es401008f | Environ. Sci. Technol. 2013, 47, 9035−9043

and comparing results obtained by using the entire week's data with those using the subsets. Results show that all three data sets lead to results with similar trends (Table S5). Holiday data have higher electrification rates because taxis drive less during the holiday and have more time to charge. In addition, electrification rates based on the entire week's data are generally lower than those based on the subset data, especially at a larger battery range. This is due to the fact that segments crossing February fifth and sixth are cut into two shorter segments when data are separated into two subsets, which inflates the overall electrification rates.

Limitation. While the data used in this study have the merit of including a large number of vehicles, the time span of available data for each vehicle is limited to a week including a national holiday. Because taxi usage is reduced during the holidays, the present data set including taxi trajectories for the holiday may cause overestimation of the electrification rate. Given that weather conditions can also potentially impact the usage of taxis (e.g., more people may take taxis when it is raining), data with larger temporal coverage for a more representative period of time can improve this study. Nevertheless, the methodological framework developed in this study and key findings are still valid and valuable. This research also demonstrates the benefits of using individual travel patterns to study environmental implications of fleet electrification.

Another limitation of this study is that we assume the adoption criteria are the same (i.e., payback battery cost within eight years) for everyone and the entire fleet will choose PHEVs with the same battery size. While similar assumptions have been made in many studies (e.g., Tamor et al., 2013[12]), the heterogeneity of tolerance level and diversity of consumer choices are lost. Although the taxi fleet may have a tendency of using identical vehicles, individual drivers have different adoption criteria regarding payback time depending on their own risk tolerance levels and economic preferences. A survey of drivers' preferences can be supplementary to improve this study. Other factors impacting consumer choices (e.g., age of the current vehicle, drivers' economic conditions) are not considered in this study either, but our study can provide important guidance on developing realistic agent-based models with a more sophisticated design of agents (i.e., consumers) that have heterogeneous adoption criteria and vehicle choices.

In addition to the serial powertrain configuration considered in this study, the power-split configuration can also be used for PHEVs, especially for vehicles with smaller batteries. Because the power-split configuration uses a combination of electricity and gasoline to power the vehicle, the overall electrification rates will be lower than using the serial configuration.

Lastly, temporal changes of emission factors, fuel economies, energy prices, and VMT are not accounted for in this study. These parameters are modeled as constants through the eight-year lifetime of taxis. While changes are expected with the rapid development of China, projections of these parameters over time bear high uncertainties and are thus out of the scope of this study. For the purpose of this study, perhaps it is better to evaluate the impacts of fleet electrification in isolation of these uncertain parameters.

■ ASSOCIATED CONTENT

Supporting Information

Supplementary figures and tables presenting the results and sensitivity analysis. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This material is based upon work partially supported by the Department of Energy under Award Number DE-PI0000012. H.C. also acknowledges the support from the ERM Group Foundation. The authors thank Dr. Yu Zheng of Microsoft Research Asia for providing data and valuable insights.

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