Potential for widespread electrification of personal vehicle travel in the United States

Zachary A. Needell,[1,2] James McNerney,[1] Michael T. Chang,[1] and Jessika E. Trancik[1,3]

[1]*Institute for Data, Systems, and Society,*
Massachusetts Institute of Technology,
Cambridge, Massachusetts 02139, United States

[2]*Department of Civil and Environmental Engineering,*
Massachusetts Institute of Technology,
Cambridge, Massachusetts 02139, United States

[3]*Santa Fe Institute, Santa Fe, New Mexico 87501, United States*

(Dated: June 28, 2016)

Abstract

Electric vehicles can contribute to climate change mitigation if coupled with decarbonized electricity, but only if vehicle range matches travelers' needs. Evaluating electric vehicle range against a population's needs is challenging because detailed driving behavior must be taken into account. Here we develop a model to combine information from coarse-grained but expansive travel surveys with high-resolution GPS data to estimate the energy requirements of personal vehicle trips across the U.S. We find that the energy requirements of 87% of vehicle-days could be met by an existing, affordable electric vehicle. This percentage is markedly similar across diverse cities, even when per-capita gasoline consumption differs significantly. We also find that for the highest-energy days, other vehicle technologies are likely needed even as batteries improve and charging infrastructure expands. Car-sharing or other means to serve this small number of high-energy days could play an important role in the electrification and decarbonization of transportation.

Transportation accounts for 28% of U.S. energy use and 34% of U.S. greenhouse gas emissions, the majority coming from light duty vehicles making personal trips—people commuting to work, driving to social events, and performing errands in cars and light trucks [1, 2]. The United States has committed to reducing carbon emissions by 26% to 28% from 2005 levels by 2025 [3], even while total vehicle miles traveled are expected to stay constant or increase [1, 4, 5]. Battery electric vehicles (BEVs) could contribute to reducing transportation related greenhouse gas emissions, offering some emissions savings even with today's fossil-fuel dominated electricity supply mix [6–8]. If coupled with a decarbonized electricity supply mix, BEVs could dramatically cut transportation emissions [9–11]. Indeed the extent and pace of the transition to BEVs may determine whether the U.S. meets its emissions reduction goals [12].

There are several potential barriers to achieving the widespread electrification of transportation, however, including infrastructure integration challenges and various factors limiting consumer purchases of electric vehicles [13, 14]. Transportation electrification would expand the demand for electricity and could significantly change the temporal and spatial patterns of demand [15], potentially producing stress on existing infrastructure [16]. Supporting these changes may require an expansion of electricity supply infrastructure and innovation in how the electrical grid is managed. Relying primarily on nighttime charging would alleviate some of these integration concerns because vehicles could plug in at home when some power plants sit idle [6], and would avoid the need for ubiquitous charging infrastructure or battery swap stations [17]. Where available, workplace charging using on-site solar generation could offer an alternative, noninvasive charging option during the week, which may be particularly helpful if vehicles cannot charge at home [18, 19]. Once-daily charging would, however, require BEVs that cover the energy needs of an entire day's travel.

The limited range of BEVs is perhaps the most significant barrier to the large-scale adoption of BEVs [11], even with daytime charging available. Both real and imagined range constraints—defined by the vehicle range, available charging infrastructure, and the range requirements of drivers—can lead to 'range anxiety' that limits the adoption of BEVs [20]. Quantifying range constraints, which is the subject of this paper, may help alleviate this anxiety [21]. Addressing range anxiety is a necessary though not sufficient condition for the widespread growth in adoption of BEVs. Satisfying consumer preferences for vehicle performance and aesthetics will also be important, as will financing options to offset the purchase price of BEVs [22].

Several previous studies examine the range requirements of personal vehicle travel. For example, a study following 255 Seattle households found that a vehicle with 100-mile range would meet the needs of most single-car households while requiring behavioral modification on no more than 5 % of days [23]. These studies and other research on aggregate travel behavior in the U.S. [24, 25] provide insight on vehicle range requirements. But a question remains: How do these requirements compare to the range achievable by BEVs? BEV range has been shown to depend sensitively on the second-by-second velocity profile followed by the vehicle [26], and other factors such as ambient temperature and associated climate control auxiliary use [27].

Past studies of travel demand uncovered significant geographic variation in the energy requirements of transportation [28], with per capita energy consumption differing up to 50% across U.S. cities, in inverse correlation with factors such as population density and per-capita spending on public transit [29, 30]. These conclusions might suggest, at first glance, that BEV adoption potential would also vary considerably across cities and that high energy consuming cities would have lower BEV adoption potential because of a dependence on long-distance trips in personal vehicles.

Here, we evaluate BEV range and adoption potential against driving patterns across the United States, drawing on information in various datasets to cover millions of trips across the U.S. and to incorporate the effects of second-by-second velocity profiles and hourly ambient temperature. This paper thus presents a comprehensive yet high-fidelity analysis of vehicle range constraints to BEV adoption. We find that a large percentage of personal vehicle daily energy requirements across the U.S. as a whole, and within major cities, can be met by a relatively inexpensive BEV on the market today. Our cross-city comparison shows that the constraint imposed on BEV adoption potential by vehicle range is, in fact, remarkably similar across different cities. The Nissan Leaf, our representative vehicle, falls below the average and median lifetime cost of the 94 most popular vehicles on the U.S. market today [31]. We estimate that this vehicle can meet the energy requirements of 87% of vehicle-days across the U.S., and 89-94% in 12 of the most populous metropolitan areas, even if relying only on nighttime charging. This 87% of vehicle-days accounts for 61% of personal vehicle gasoline consumption in the U.S. Improvements to the energy density, specific energy, and cost per unit energy capacity of batteries would increase these daily vehicle and gasoline substitution percentages. But a number of very high energy days, as evidenced by a heavy-tailed distribution of daily vehicle energy requirements, translates to diminishing returns to battery improvement.

Probabilistic model of BEV range

The model presented here provides a probabilistic view of BEV range. This model, 'TripEnergy', draws on information from the National Household Travel Survey (NHTS) [2] database on the distance and duration of trips taken by a representative sample of drivers across the U.S., data on regional temperature at an hourly time scale ([32], Supplementary Figure 2), GPS datasets giving second-by-second velocity profile information across a diverse set of trips (e.g. [33], Supplementary Note 1, Supplementary Figure 1, Supplementary Table 1), and the results of vehicle fuel economy tests [34] (Supplementary Table 2). Using a conditional bootstrap procedure, we match NHTS trips to a set of possible drive cycles (Figure 1, Supplementary Figure 3) and use information on the time and location of trips to estimate climate control auxiliary energy use (Methods and Supplementary Note 2). The model has been calibrated and validated through extensive testing (Supplementary Note 3, Supplementary Figures 10-12).

The results demonstrate the importance of considering driving behavior in estimating BEV range (Figure 2). While the U.S. Environmental Protection Agency (EPA) publishes estimated ranges for particular vehicles (Supplementary Table 3), the realized range—the distance that can be driven on one charge—is influenced by several factors and can vary from trip to trip. These factors include the use of auxiliary power for heating or cooling and the velocity profile of the trips taken. These factors can have a large impact on vehicle range (Figures 1-2, Supplementary Figure 6). Given EPA-estimated average fuel economy of 116 MPGe, battery capacity of 24 kWh, allowed depth of discharge of 80% (in keeping with the Leaf's 'long life mode' [35], Supplementary Note 1), and charging losses of 10%, we would predict the 2013 Nissan Leaf to have a range of 73 miles. Our model predicts 74 miles as the median range—the distance for which half of all vehicle-days could be covered on one charge. However, variation in trip velocity profiles and auxiliary power use produces a distribution

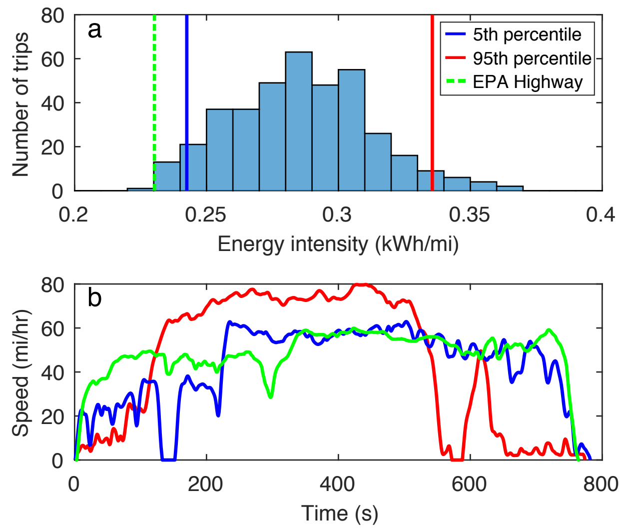

FIG. 1. Energy intensities and velocity histories of trips with similar distances and durations. Trips shown are similar to the EPA highway (HWFET) drive cycle in terms of distance and duration but have differing energy intensities, demonstrating the importance of considering velocity histories in determining trip energy requirements. **a**, Fuel economy distribution (kWh per mile) for the 2013 Nissan Leaf, for trips in the GPS database that have a distance and duration similar to the EPA HWFET. **b**, Velocity profiles of the three trips marked on the above plot.

of ranges (Figure 2), and our model predicts that 1 out of 20 of 58-mile vehicle-days could not be covered by existing batteries, and 1 out of 20 of 90-mile vehicle-days could.

Furthermore, application of the model reveals that the BEV's median range changes nonlinearly with battery capacity, because velocity profiles tend to differ between short and long distance travel days. As an example, increasing the battery's specific energy to an Advanced Research Projects Agency-Energy (ARPA-E) target value of 200 kWh/kg [36] while keeping its mass constant would increase usable battery capacity by 186% to 55 kWh. Doing so would increase the Leaf's median range to 173 miles, an increase of only 131%. The sub-linear relationship between range and battery capacity is due to the longer vehicle-days containing more long distance highway driving—trips for which BEVs have a lower fuel economy than for inner city trips [26, 37, 38] (Supplementary Figure 9). This finding—the quantification of this sub-linear relationship—illustrates the value of a model that captures changing vehicle efficiency with the velocity profile and a comprehensive characterization of real-world travel behavior.

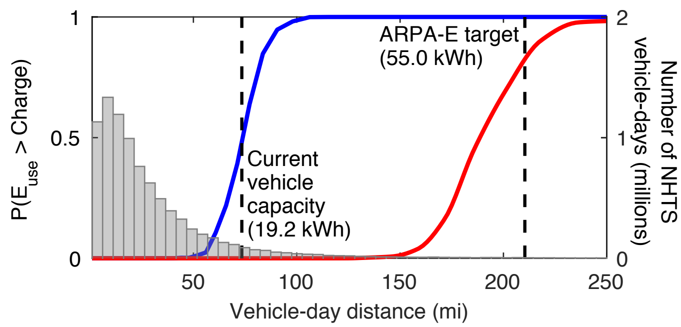

FIG. 2. Probabilistic model of BEV range given observed nationwide travel behavior. The probability that a vehicle traveling a given daily distance exceeds a battery energy threshold is shown for a current and future improved battery technology. Blue line: current usable battery capacity of 19.2 kWh in a vehicle modeled after the 2013 Nissan Leaf. Red line: identical vehicle with the same battery mass but 55.0 kWh usable battery capacity, based on an ARPA-E battery specific energy target. Dotted lines: ranges for the current battery capacity (19.2 kWh) and the ARPA-E target capacity (55.0 kWh) based on the EPA estimated average vehicle fuel economy. Grey bars: histogram of nationwide vehicle-day driving distance.

Daily energy requirements and BEV adoption potential

We apply the model to personal vehicle travel across the U.S. Two metrics are presented here. The first is the daily vehicle adoption potential (DAP), which is defined as the percentage of vehicles per day that could be covered on one charge. The second metric is the gasoline substitution potential (GSP), which is the percentage of gasoline consumption that could be replaced by BEVs charging once a day (See Supplementary Note 4). These metrics quantify a technical potential that is limited by range constraints for utilizing a battery electric vehicle on a representative day, with only once-daily charging available. Individual days may diverge from these results, particularly those when many people are traveling long distances (e.g. Thanksgiving [39]). For BEV ownership to rise to these levels, convenient options should be available to meet travelers' needs on all days.

Figure 3 shows the energy distribution for personal vehicle-days in the U.S., as well as the DAP and GSP for the U.S. in aggregate. Results are also shown for the 12 metropolitan areas with the largest number of NHTS respondent households. We find a DAP of 87.0% for the U.S. in aggregate. The corresponding GSP is 60.9%, lower than the DAP because the 13.0 % of trips not covered by the BEV account for a disproportionate amount of energy

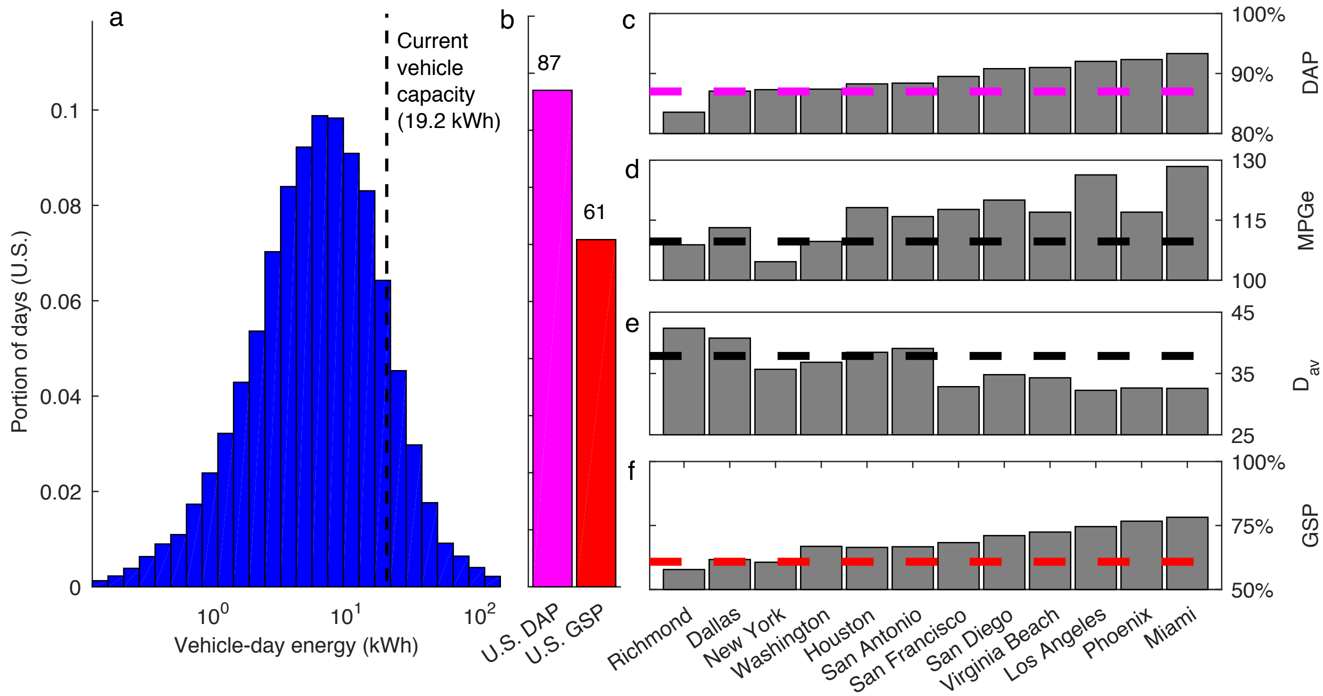

FIG. 3. Nationwide and city-specific BEV energy requirements evaluated against battery capacity. Energy capacity and requirements are calculated for the 2013 Nissan Leaf. **a**, Histogram of BEV vehicle-day energy consumption for the entire U.S. (blue bars) compared to the usable battery capacity (dotted line). **b**, daily vehicle adoption potential (DAP, purple) and gasoline substitution potential (GSP, red) across the U.S. **c**, City-wide values for daily vehicle adoption potential (DAP). **d**, Average fuel economy (in miles per gallon equivalent). **e**, Average vehicle-day driving distance (in miles); **f**, Gasoline substitution potential (GSP). Horizontal dotted lines represent U.S. averages.

consumption.

Rural areas in aggregate have an DAP and GSP that is below the U.S. average, while urban areas have an above average DAP and GSP. The aggregate rural DAP is 80.8% and GSP is 52.2%. The average urban DAP across the U.S. is 89.1%, varying from 84-93% in the 12 cities examined in detail (Figure 3). The average urban GSP is 64.5%, ranging from 58-78% in individual cities. These results support the idea of cities as natural initial markets for BEVs [10, 26].

In addition to the DAP and GSP, the average distance and fuel economy of trips is revealing. The rank ordering of cities in terms of DAP and GSP does not individually match that of either distance or fuel economy, as shown in Figure 3, again illustrating the importance of considering variations in fuel economy in addition to distance in characterizing trip energy requirements.

Variation Across Cities

The comparison of BEV range constraints applied to individual cities reveals a remarkable degree of similarity in the BEV daily adoption potential across diverse locations, varying from 84% to 93% (Figure 3, Supplementary Table 4). This is in contrast with per capita travel energy consumption, which varies by a factor of 1.6 across cities. These results can be understood by examining the shapes of the energy distributions in individual cities (Figure 4) and several factors affecting per capita energy consumption (Figure 5).

Probability distributions for vehicle-day energy for 12 cities are shown in Figure 4a. We observe that these functions diverge across cities as vehicle-day energy increases. In other words, the distribution of BEV vehicle-day energy requirements becomes increasingly different across cities as we increase the upper threshold on allowed vehicle-day energy requirements. For an energy threshold defined by the Nissan Leaf's battery capacity, cities appear more similar than they do for a threshold defined by the ARPA-E target [36]. This suggests that while a representative affordable BEV today can be expected to face relatively similar energy requirements among cities, the differences in tail behavior will cause the mean per-vehicle-day energy use to diverge as battery improvements increase overall DAP towards 100% (Figure 4 a,b).

The factor of 1.6 variation in per capita energy consumption shown in Figure 4b is explained by several factors. One determinant is the factor of 1.3 variation in daily energy requirements (calculated for the BEV). Another important determinant, however, is the difference in the tendency of the population to own and use personal vehicles. Figure 5 shows several statistics capturing this factor. Cities differ considerably in terms of the tendency to use different modes of transport [29], and in the propensity to use personal vehicles on any given day.

Taken together the factors discussed above explain an apparent inconsistency: the significant difference in the per capita transportation energy consumption and the much more limited difference in the adoption potential of a vehicle modeled after the Nissan Leaf across diverse cities. The large variation in energy consumption per capita is explained by some cities relying much less on personal vehicles for travel than others, while the smaller variation in BEV adoption potential is explained by similar energy requirements across cities for those vehicles that are driven. Furthermore the small number of high energy trips in the tail affect the mean of the vehicle-day energy distribution but do not greatly affect DAP.

The comparison between New York and Houston provides a striking example of this phenomenon (Figure 5). By most measures of travel behavior, New York and Houston are very different cities. Figure 5 shows differences in city layout, transportation mode choice, vehicle ownership, and vehicle use. New York City contains an extensive dense central area, whereas Houston sprawls over a similar area at more moderate densities. New York has the highest transit ridership and lowest personal vehicle ridership of all cities in the NHTS, whereas Houston is among the most car-dependent of major U.S. cities. Despite these major differences, however, the DAP and GSP for these two cities are remarkably similar, with DAP differing by 1% and GSP by 6%. When vehicles are driven in these two cities, the percentages of vehicle-days served by current BEV technology are remarkably similar. This means that both cities, despite their differences, show substantial BEV daily adoption potential.

Benefits of Battery Improvement

How might DAP and GSP increase with improvements to batteries? The vehicle-day energy distributions presented here allow for a quantification of the marginal benefits of improving BEV battery capacity (Figure 6). Improvements in battery capacity (at constant mass, and volume) increase the number of vehicle-days that could be replaced by BEVs, but the results show important nonlinearities. An increase in the Leaf's battery specific energy from its 2013 value of 88 Wh/kg by a factor of 2.3 to the U.S. ARPA-E specific energy target of 200 Wh/kg would increase DSP to 98% and GSP to 88%. Further improvements in GSP would require still greater increases in specific energy, with a GSP of 95% requiring an increase in battery specific energy by a factor of six to approximately 420 Wh/kg. To maintain vehicle affordability and thereby enable widespread BEV adoption, the cost per battery capacity should stay constant or even decrease while battery energy density and specific energy increase. Commercial progress is being made towards this end. For example, the 2017 Chevrolet Bolt BEV is intended to be widely affordable and offers a 60 kWh battery with a specific energy of 138 Wh/kg (Supplementary Note 1). The 2018 Tesla Model 3 promises comparable range to the Bolt at a similar price point, though with different aesthetics and performance features.

The distinction between urban and rural areas is revealing in this context. While urban areas show a significantly higher GSP than rural areas (52.2% in rural and 64.5% in urban areas on average), the returns to further improvement in batteries is greater in rural areas than urban ones. Increasing battery specific energy and energy density to meet the ARPA-E target would almost eliminate the difference in GSP between urban and rural areas. Batteries with this capacity would allow BEVs to replace approximately 80% of gasoline consumption if fully adopted in both locations.

The relationship between DAP and battery capacity is important to consider in assessing potential long-term limits to BEV adoption. The sub-linearity of DAP versus battery capacity suggests that a complete daily electrification of personal vehicles presents a significant technical challenge, and that other powertrain technologies will be needed for some time even as batteries and charging infrastructure advance.

Discussion

Our results show that current, affordable BEV technology is able to replace 87% of vehicles driven on a given day without recharging. This would allow for a reduction of gasoline consumption by approximately 60%. These findings support the concept that cities are especially suited for early BEV adoption [10, 26], given that nearly all cities studied rated as well or better than the national average in two metrics of BEV performance (DAP and GSP). However, we show quantitatively that a substantial portion of vehicle-days, and a larger portion of gasoline consumption, could not be replaced by the modeled BEV. These vehicle-days tend to involve longer travel distances and higher-speed driving, and they tend to be more common for residents of rural rather than urban areas.

These results provide fundamental insight on travel behavior in cities, adding to regularities that have previously been identified in behavior and energy consumption in cities [41, 42]. We find that daily energy consumption is distributed remarkably similarly across cities for the majority of vehicles. A small portion of vehicle-days which have particularly high energy requirements do vary in frequency and intensity across cities, and these days cause a disproportionate amount of the variation between individual cities when all vehicle days are considered. Further, a major factor in the differences between cities are how likely someone is to drive on any given day. These factors together give rise to differences in the per capita energy consumption across cities.

Increasing BEV battery capacity will allow for greater DAP and GSP, and our results enable the assessment of this potential against climate policy targets, under current and future improved battery performance. For example, meeting existing policy targets would require a reduction of transportation sector emissions of 26-28% from 2005 levels by 2025 [1, 3]. Even considering the current electric grid mix [43], today's BEV technology is capable of meeting this target. Achieving the GSP for current BEV technology by 2025 would yield an estimated 29% reduction (Figure 3) from 2005 emissions levels (based on an average U.S. electricity carbon intensity and 0.92% yearly VMT increase [44], see Supplementary Note 4, Supplementary Table 5).

Transportation emissions reduction targets for later years may be more ambitious, for example reaching 56 and 80% below 1990 emissions levels by 2040 and 2050 [45–47]. Given current battery capacity, modeled after the 2013 Nissan Leaf, carbon emissions from the remaining gasoline vehicles would be enough to exceed the 2040 target, meaning current technology could not provide enough reductions even with entirely carbon-free electricity. However, the Leaf with 55 kWh usable battery capacity (meeting ARPA-E target battery specific energy of 200 Wh/kg [36]) could enable nearly full BEV adoption without confronting range constraints (DAP=98.3%) and could meet the 2040 target in tandem with a 44% reduction in the average carbon intensity of electricity. By 2050, even with complete electrification of transportation, meeting the 80% emissions reduction target would require a reduction of 65% in grid emissions intensity. These examples of rough calculations demonstrate the power of the model for assessing battery technology and electricity CO_2eq emissions intensity against climate policy targets.

The results presented here represent theoretically achievable values of DAP and GSP given BEV range constraints. Realizing these levels of BEV adoption would require that prospective BEV owners have access to personally-operated or other vehicles with longer range that can meet their needs on all days, including high-energy ones [24]. Even with substantial battery improvements, other powertrain technologies may be needed to cover those days with the highest energy consumption. This need may persist for some time, even with expanded (and improved [17, 48, 49]) charging infrastructure. Predicting high-energy days and providing convenient solutions—such as commercial programs for sharing internal combustion engine vehicles (ICEVs) to complement within-household car sharing and alternative transportation modes—may therefore be critical for increasing BEV ownership.

Many other considerations will also affect realized adoption levels, including consumer preferences for vehicles, and financing options to offset the higher purchase price of BEVs [21, 31], as well changes to travel demand over time. These factors will also be important to consider in evaluating BEV technology and transportation policy to achieve emissions reductions.

METHODS

The TripEnergy model draws on information contained in travel data with varying resolution and coverage, as well as data on ambient temperatures. This information is used in a travel demand component and then a vehicle energy component in order to determine the trip by trip energy requirements of travel across the United States. We describe TripEnergy and the methods used in this paper here, and provide further information in Supplementary Note 2.

Data

Data inputs include information on travel behavior and ambient temperature. We use two sources of data to estimate trip velocity profiles: the National Household and Transportation Survey (NHTS) and GPS data sets from several U.S. cities. The 2009 NHTS [2] contains approximately 1.1 million trips from 150,000 households. The GPS data (Supplementary Note 1) contains speed histories of approximately 120,000 trips from nine cities across the U.S. Considering both of these datasets provides information on both the travel behavior of drivers across the U.S. and on representative high-resolution velocity profiles. The representative nature of the GPS drive cycles has been validated as described in Supplementary Note 3.

Vehicle model

To produce the energy distributions used in this paper, we model both vehicle performance and driving demand to determine personal vehicle energy consumption. For the vehicle performance aspect of our model, we calculate tractive energy requirements and the internal efficiency of a given velocity profile, the former using EPA test dynamometer coefficients and the latter estimated based on CAFE test results in a method based on Lutsey [50] (see Supplementary Note 2, Supplementary Figures 7-8 for further discussion). In order to estimate the amount of auxiliary energy used, we use the National Solar Radiation Database's Typical Meteorological Year database [32] to produce a distribution of possible ambient temperatures for the trip based on its time of day, month, and location, which is converted to HVAC energy consumption via a simple energy balance model. The model uses factory-rated battery capacity estimates, and does not consider consumer-reported deviations from these reported values due to battery degradation over time.

Demand model

We base overall travel demand in our model off of the NHTS, using a de-rounding algorithm (see Supplementary Note 2, Supplementary Figures 4 and 5) to remove rounding biases from the self-reported data. Because the NHTS does not contain high-resolution vehicle speed data, we use a conditional bootstrap procedure to probabilistically match each NHTS trip with a representative set of possible GPS velocity histories. A sample application of this process is shown in Figure 1. The tractive energy from the vehicle model and the auxiliary energy from the climate model are combined to produce a probability distribution of the energy needs of the NHTS trips.

Corresponding Author

Correspondence to Jessika E. Trancik (trancik@mit.edu)

Acknowledgments

We thank Marco Miotti for his contributions to the auxiliary power component of the TripEnergy model, and Fabian Riether for his contributions to characterizing the model robustness. We thank John Heywood and Stephen Zoepf for their feedback on the vehicle model. This work was supported by the New England University Transportation Center at MIT under DOT grant No. DTRT13-G-UTC31, the MIT Leading Technology and Policy Initiative, the Singapore-MIT Alliance for Research and Technology, the Charles E. Reed Faculty Initiatives Fund, and the MIT Energy Initiative.

Author Contributions

J.E.T. designed the study; J.M., M.T.C., Z.A.N., and J.E.T. built the model; Z.A.N., M.T.C., J.M., and J.E.T. performed the analysis; J.E.T., Z.A.N., and J.M. wrote the paper.

Additional Information

Supplementary information is available online. Reprints and permissions information is available online at `www.nature.com/reprints`. Correspondence and requests for materials should be addressed to J.E.T.

[1] U.S. Department of Energy, Energy Information Administration (EIA). Annual energy outlook with projections to 2040 (2014).

[2] Federal Highway Administration. *2009 National Household Travel Survey*. U.S. Department of Transportation (2011).

[3] The White House, Office of the Press Secretary. U.S.-China Joint Announcement on Climate Change and Clean Energy Cooperation. White House Fact Sheet (2014). URL `http://www.whitehouse.gov/the-press-office/2014/11/11/fact-sheet-us-china-joint-announcement-climate-change-and-clean-energy-c`.

[4] Polzin, S. & Chu, X. Peak vehicle miles traveled and postpeak consequences? *Transp. Res. Record* 22–29 (2014).

[5] Sager, J., Apte, J. S., Lemoine, D. M. & Kammen, D. M. Reduce growth rate of light-duty vehicle travel to meet 2050 global climate goals. *Environ. Res. Lett.* **6**, 024018 (2011).

[6] Sioshansi, R., Fagiani, R. & Marano, V. Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. *Energy Policy* **38**, 6703–6712 (2010).

[7] Donateo, T., Ingrosso, F., Licci, F. & Laforgia, D. A method to estimate the environmental impact of an electric city car during six months of testing in an Italian city. *J. Power Sources* **270**, 487–498 (2014).

[8] Tamayao, M.-A. M., Michalek, J. J., Hendrickson, C. & Azevedo, I. M. Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO2 Emissions across the United States. *Environ. Sci. Technol.* **49**, 8844–8855 (2015).

[9] Williams, J. H. *et al.* The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. *Science* **335**, 53–60 (2012).

[10] Kennedy, C., Ibrahim, N. & Hoornweg, D. Low-carbon infrastructure strategies for cities. *Nat. Clim. Chang.* **4**, 343–346 (2014).

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

[12] Lipman, T. & Delucchi, M. A. *Sustainable transportation energy pathways*, chap. Comparing greenhouse gas emissions, 133–170 (UC Davis Institute of Transportation Studies, 2011).

[13] Tran, M., Banister, D., Bishop, J. D. K. & McCulloch, M. D. Realizing the electric-vehicle revolution. *Nat. Clim. Chang.* **2**, 328–333 (2012).

[14] Meinrenken, C. J. & Lackner, K. S. Fleet view of electrified transportation reveals smaller potential to reduce GHG emissions. *Appl. Energy* **138**, 393–403 (2015).

[15] Kelly, J. C., MacDonald, J. S. & Keoleian, G. A. Time-dependent plug-in hybrid electric vehicle charging based on national driving patterns and demographics. *Appl. Energy* **94**, 395–405 (2012).

[16] Green, R. C., Wang, L. & Alam, M. The impact of plug-in hybrid electric vehicles on distribution networks: a review and outlook. *Renew. Sust. Energ. Rev.* **15**, 544–553 (2011).

[17] 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* **52**, 429–438 (2013).

[18] Saber, A. Y. & Venayagamoorthy, G. K. Plug-in vehicles and renewable energy sources for cost and emission reductions. *IEEE Trans. Ind. Electron.* **58**, 1229–1238 (2011).

[19] Birnie, D. P. Solar-to-vehicle (S2V) systems for powering commuters of the future. *J. of Power Sources* **186**, 539–542 (2009).

[20] Franke, T. & Krems, J. F. What drives range preferences in electric vehicle users? *Transport Policy* **30**, 56–62 (2013).

[21] Egbue, O. & Long, S. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy* **48**, 717–729 (2012).

[22] Hidrue, M. K., Parsons, G. R., Kempton, W. & Gardner, M. P. Willingness to pay for electric vehicles and their attributes. *Resour. Energy Econ.* **33**, 686–705 (2011).

[23] Khan, M. & Kockelman, K. M. Predicting the market potential of plug-in electric vehicles using multiday GPS data. *Energy Policy* **46**, 225–233 (2012).

[24] Pearre, N. S., Kempton, W., Guensler, R. L. & Elango, V. V. Electric vehicles: How much range is required for a day's driving? *Transp. Res. Part C Emerg. Technol.* **19**, 1171–1184 (2011).

[25] Vyas, A. D., Santini, D. J. & Johnson, L. R. Potential of Plug-In Hybrid Electric Vehicles to Reduce Petroleum Use. *Transp. Res. Record* 55–63 (2009).

[26] Karabasoglu, O. & Michalek, J. Influence of driving patterns on life cycle cost and emissions of hybrid and plug-in electric vehicle powertrains. *Energy Policy* **60**, 445–461 (2013).

[27] Yuksel, T. & Michalek, J. Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States. *Environ. Sci. Technol.* **49**, 3974–3980 (2015).

[28] Newman, P. W. G. & Kenworthy, J. R. Gasoline Consumption and Cities. *J. Am. Plann. Assoc.* **55**, 24–37 (1989).

[29] Cervero, R. & Murakami, J. Effects of built environments on vehicle miles traveled: Evidence from 370 US urbanized areas. *Environ. Plan. A.* **42**, 400–418 (2010).

[30] Gately, C. K., Hutyra, L. R. & Sue Wing, I. Cities, traffic, and CO2: A multidecadal assessment of trends, drivers, and scaling relationships. *Proc. Natl. Acad. Sci. U. S. A.* **112**, 4999–5004 (2015).

[31] Miotti, M., Supran, G., Kim, E. & Trancik, J. E. Personal vehicle technologies evaluated against climate change mitigation targets. *Environ. Sci. Technol. (in the press)* (2016). http://dx.doi.org/10.1021/acs.est.6b00177

[32] Wilcok, S. & Marion, W. Users Manual for TMY3 Data Sets. Tech. Rep. NREL/TP-581-43156, National Renewable Energy Laboratory (2008).

[33] National Renewable Energy Laboratory. *California Household Transportation Survey.* U.S. Department of Energy, DOE-019-9889603959 (2012).

[34] US Environmental Protection Agency. Fuel economy test car list database files. Available http://www3.epa.gov/otaq/tcldata.htm (2015).

[35] Nissan. *2013 Leaf Owner's Manual* (2013).

[36] United States Department of Energy. Batteries for electrical energy storage in transportation (BEEST). ARPA-E Funding Opportunity Announcement (2009). URL `http://arpa-e.energy.gov/?q=arpa-e-programs/beest`.

[37] Bingham, C., Walsh, C. & Carroll, S. Impact of driving characteristics on electric vehicle energy consumption and range. *Intelligent Transport Systems, IET* **6**, 29–35 (2012).

[38] Raykin, L., Roorda, M. J. & MacLean, H. L. Impacts of driving patterns on tank-to-wheel energy use of plug-in hybrid electric vehicles. *Transp. Res. D Transp. Environ.* **17**, 243–250 (2012).

[39] Li, H., Guensler, R. L., Ogle, J. H., Jun, J. & Elango, V. V. Descriptive Analysis of Long-Distance Travel by Personal Vehicles Using 2004 Commute Atlanta Data. In *Transportation Research Board 86th Annual Meeting*, 07-1688 (2007).

[40] United States Census Bureau. 2013 American Community Survey 1-year estimate, Table B01003. Generated using American FactFinder: `http://factfinder2.census.gov`, 4/28/2015 (2014).

[41] Bettencourt, L. M. The origins of scaling in cities. *Science* **340**, 1438–1441 (2013).

[42] Bettencourt, L. & West, G. A unified theory of urban living. *Nature* **467**, 912–913 (2010).

[43] Argonne National Laboratory. GREET 1 model. https://greet.es.anl.gov/ (2014).

[44] Office of Highway Policy Information. FHWA Forecasts of Vehicle Miles Traveled (VMT): May 2015. Tech. Rep., Federal Highway Administration (2015). URL `http://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.pdf`.

[45] Den Elzen, M. & Höhne, N. Reductions of greenhouse gas emissions in Annex I and non-Annex I countries for meeting concentration stabilization targets. *Clim. Change* **91**, 249–274 (2008).

[46] Trancik, J. E., Chang, M. T., Karapataki, C. & Stokes, L. C. Effectiveness of a Segmental Approach to Climate Policy. *Environ. Sci. Technol.* **48**, 27–35 (2014).

[47] California. Sb-350, clean energy and pollution reduction act of 2015. State Law (2015). URL `https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201520160SB350`.

[48] Gil, A. & Taiber, J. A literature review in dynamic wireless power transfer for electric vehicles: Technology and infrastructure integration challenges. In *Sustainable Automotive Technologies 2013*, 289–298 (Springer, 2014).

[49] Chen, T. D. *et al. Management of a shared, autonomous, electric vehicle fleet: vehicle choice, charging infrastructure & pricing strategies*. Ph.D. thesis, University of Texas at Austin (2015).

[50] Lutsey, N. A technical analysis of model year 2011 US automobile efficiency. *Transp. Res. D Transp. Environ.* **17**, 361–369 (2012).

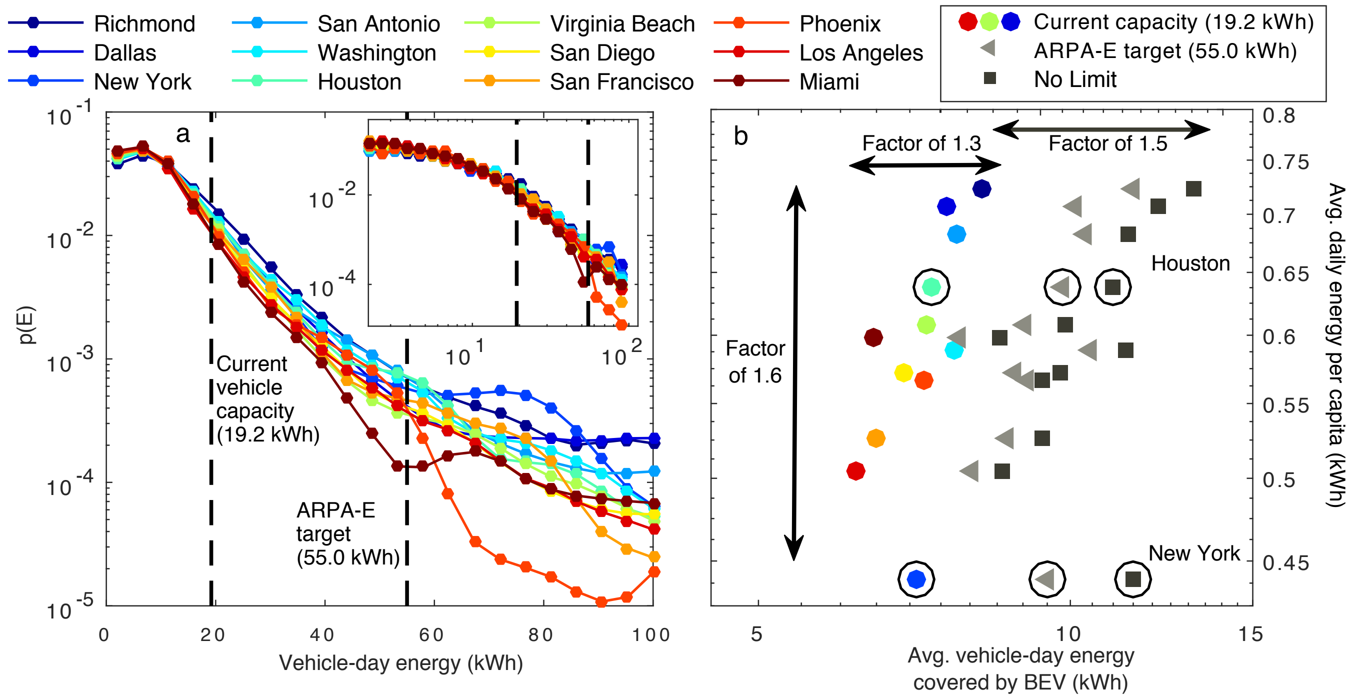

FIG. 4. Vehicle-day energy distributions in various cities and the differentiating effect of their heavy tails. **a**, Estimated vehicle-day probability distribution on a log-linear (Inset: log-log) scale. Vertical lines represent usable battery capacity for the 2013 Leaf with current battery technology (19.2 kWh) and the ARPA-E target battery specific energy but the same battery mass (55 kWh). **b**, Average daily energy consumption (in personal vehicles) per capita and average daily energy consumption per vehicle driven. The y-axis shows city-wide average energy consumption per capita, for the range of cities studied, assuming a BEV is used for all trips. The x-axis shows mean BEV energy consumption per vehicle-day given different battery constraints, which are each represented by different symbols. The mean BEV energy consumption in each city shifts to the right as the battery capacity increases and more high energy vehicle-days are included in the sample. The variability across cities also increases, from a factor of 1.3 for the current Leaf to 1.5 for a BEV with no range constraints. For illustration, New York and Houston are highlighted with open circles.

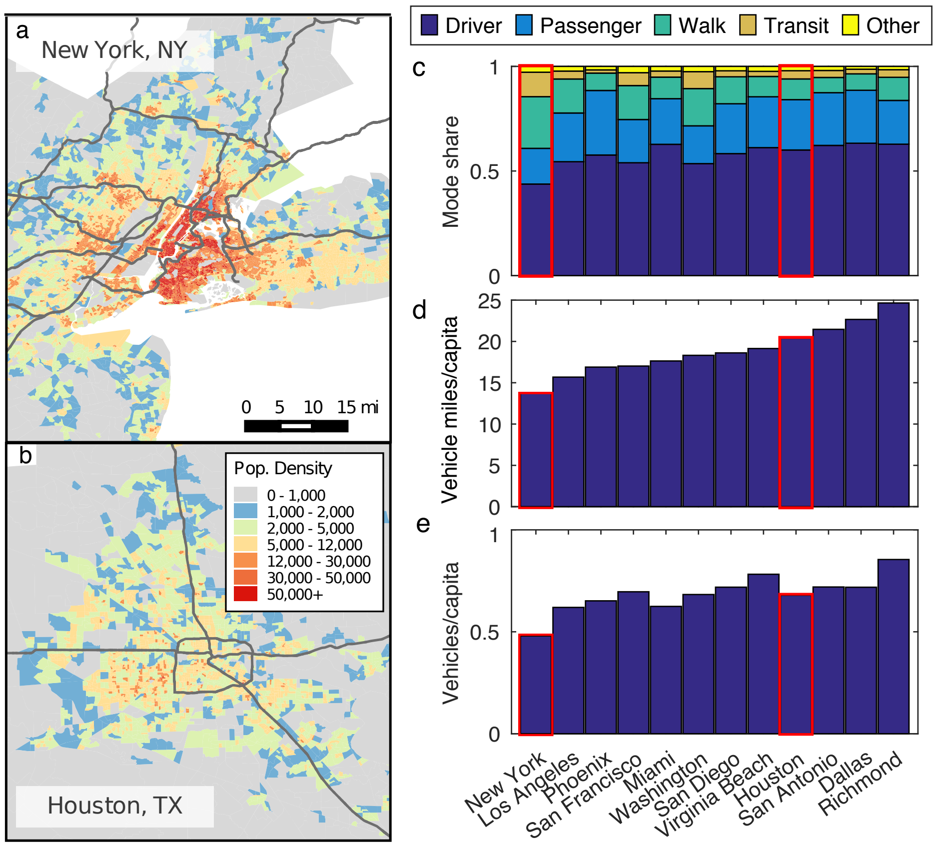

FIG. 5. Differences in travel behavior and vehicle use across cities. Population density maps of **a**, New York, and **b**, Houston (data from [40]), displayed in units of persons per square mile. **c**, Portion of total trips taken by each mode of transportation. **d**, Personal vehicle miles per capita. **e**, Vehicles per capita.

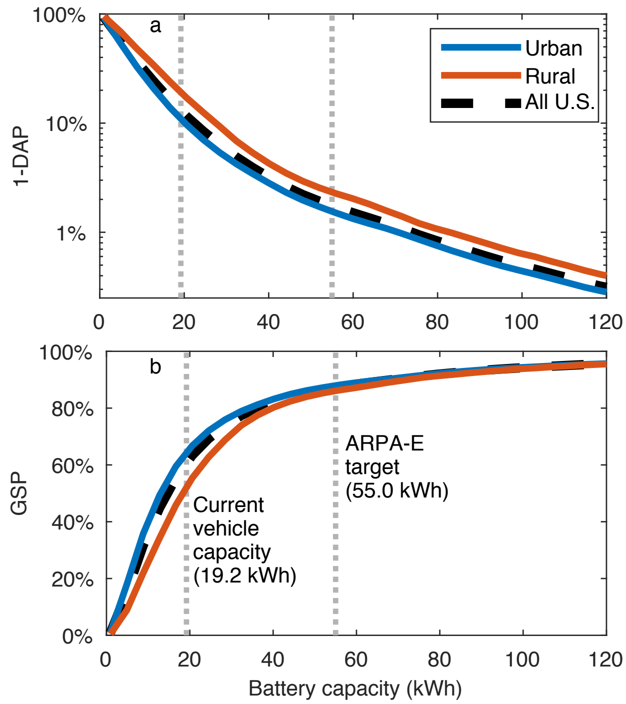

FIG. 6. Effects of increasing battery capacity (keeping battery mass constant) on BEV range constraints. **a**, Daily vehicle adoption potential, shown in the inverse to display the exponential decrease of the portion of vehicle-days exceeding one full charge. **b**, GSP, the portion of gasoline use that could be displaced by BEVs given full adoption of within-range vehicle-days. Dotted lines represent usable battery capacity for the 2011 Leaf (left) and for a similar vehicle assuming the ARPA-E specific energy target is reached (right).