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Permalink

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Journal

Transportation Research Record Journal of the Transportation Research Board, 2628(1)

ISSN

0361-1981

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Publication Date

2017

DOI

10.3141/2628-07

Peer reviewed

TripEnergy: Estimating personal vehicle energy consumption given limited travel survey data

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Word Count: 6,199 words text + 4 figures + 1 table = 7,449 words

Submission Date: August 2, 2016

1 ABSTRACT

2 Estimating personal vehicle energy consumption is important for nationwide climate policy, local
3 and statewide environmental policy, and technology planning. Transportation energy use is com-
4 plex, depending on vehicle performance and the driving behavior of individuals as well as on travel
5 patterns of cities and regions. Previous studies typically combine large samples of travel behav-
6 ior with fixed estimates of per-mile fuel economy or use detailed models of vehicles with limited
7 samples of travel behavior. Here we introduce a model for estimating privately operated vehicle
8 energy consumption, TripEnergy, that accurately reconstructs detailed driving behavior across the
9 U.S. and simulates vehicle performance for different driving conditions. TripEnergy consists of
10 a demand model, linking GPS drive cycles to travel survey trips, and a vehicle model, efficiently
11 simulating energy consumption across different types of driving. Because of its ability to link
12 small-scale variation in vehicle technology and driver behavior with large-scale variation in travel
13 patterns, we expect it to be useful for a variety of applications, including technology assessment,
14 cost and energy savings from eco-driving, and the integration of electric vehicle technologies into
15 the grid.

1 INTRODUCTION

2 Personal vehicles in the United States consumed an estimated 1.7×10^{19} joules of secondary energy
3 in 2014 (1) during over 200 billion trips (2). This demand arose from a population of vehicles and
4 drivers using various transportation technologies and following diverse travel patterns. Quantifying
5 energy consumption and related environmental impacts at the scale of countries, regions, and cities,
6 and relating those aggregates to micro-scale determinants, is critical for developing sustainable
7 transportation strategies.

8 A variety of methods have been used to estimate the energy use of single trips or larger
9 populations. Top-down methods such as energy sales accounting provide data on large-scale envi-
10 ronmental impacts but not the low-level determinants needed to evaluate, for example, the effects
11 of future technological changes on total energy use. Bottom-up methods such as dynamometer
12 testing and microsimulation provide high-fidelity representations of specific vehicle performance
13 and driver behavior, but rely on data that is not available at the macro scale needed to understand
14 the societal impacts of policies.

15 Relating aggregated energy-related impacts, such as greenhouse emissions, to low-level
16 factors is similarly critical. Privately operated vehicles (POVs) are one of the primary emitters of
17 greenhouse gases in the U.S., and reductions to the energy- and carbon-intensity of transportation
18 are a major component of mitigation scenarios (3, 4). Future emissions will be affected by cur-
19 rent policies such as fuel economy standards (5), technology developments such as battery electric
20 vehicles (6), and demographic changes such as urbanization (7). Evaluating the plausibility of
21 emissions targets means relating them to required levels of technology, infrastructural, or behav-
22 ioral changes necessary to meet these goals.

23 In this paper we present a tool for estimating POV energy consumption that is designed
24 to be applicable to this wide range of uses. The method, TripEnergy, produces accurate estimates
25 for energy aggregates consistent with top-down inventories (e.g. total gasoline consumption), but
26 computes them from the bottom-up based on second-by-second reconstructions of driving pat-
27 terns across the U.S. and an energy model that works with specific, existing vehicles. As a result,
28 TripEnergy can model the effects on aggregate energy use from changes to vehicle technology
29 and driving behavior. TripEnergy can estimate energy requirements for individual trips for a wide
30 variety of vehicle models, and can operate probabilistically, producing a distribution of possible
31 energies for each trip. Energy requirements can be flexibly aggregated by region, trip purpose, ve-
32 hicle type, and a large number of socioeconomic variables. The tool produces coherent results with
33 different levels of detail in its inputs, for a wide range of vehicle models, and in a computationally
34 tractable way. It allows more coverage and accuracy than models based only on GPS surveys or
35 direct vehicle modeling, but can address a wider range of questions than possible with fleetwide
36 emissions models.

37 BACKGROUND

38 Here we present a summary of some widely used methods for estimating POV energy consumption.
39 TripEnergy is not intended to replace any of the methods below, but to add new capabilities in
40 modeling fleetwide POV energy use.

41 Bottom-up methods

42 Bottom-up methods give energy consumption for individual trips based on direct measurement or
43 simulation. Many studies rely on published measurements of energy consumption per distance to

1 translate miles of travel into estimates of energy or emissions. In the U.S., the EPA requires fuel
2 economy labeling of all new personal vehicles. These are derived from a series of dynamometer
3 tests (8) in which a vehicle is driven through several standardized drive cycles (9). These estimates
4 have been used, for example, to study range requirements in electric vehicles using GPS data
5 (10, 11), or to estimate the fuel price elasticity of energy use (12).

6 To capture greater variation in operating conditions than in EPA drive cycles, some re-
7 searchers have supplemented EPA results with direct energy readings from a vehicle's onboard
8 computer (13, 14). Microsimulation has also been used to capture variation in operating condi-
9 tions. Various software packages simulate vehicle operation over an input drive cycle (15, 16).
10 One use of these simulations has been to capture energy consumption during the use phase of life
11 cycle assessments (17), allowing the effects of typical driving conditions on life cycle impacts to
12 be studied.

13 While widely useful, these methods are not suitable for all research questions. Methods
14 based on a single miles per gallon (MPG) estimate cannot directly capture variations in energy use
15 with driving style (18) or climate (19). By using a single energy intensity value, these methods will
16 introduce biases for congested city driving, for example, or moderate speed highway driving, con-
17 ditions that are likely to have particularly high or low energy intensity (17, 20, 21). Dynamometer
18 testing and onboard measurement can provide data for these more extreme conditions, but data
19 collection is impractical for analyses of very large numbers of trips and vehicle types.

20 **Top down methods**

21 Top-down methods can provide accurate assessments of energy consumption in aggregate. These
22 methods use data on energy sales and trace backward to when and how energy was used for trans-
23 portation. In the U.S. for example, the Federal Highway Administration (FHWA) (22) collects
24 data on statewide and national gasoline consumption from gas tax receipts, and converting barrels
25 of oil to energy consumption and CO₂ emissions. For well-mixed greenhouse gases this approach
26 is often deemed accurate enough for modeling and inventory purposes. Other uses of top-down
27 accounting include extrapolating future trends in gasoline consumption from fleet-average fuel
28 economy and vehicle miles traveled (23), and constructing localized emissions inventories. For
29 example, Gately et al. use roadway level VMT data to create a high-resolution spatial inventory of
30 U.S. transportation-related greenhouse gas emissions (24).

31 For evaluating vehicle technologies, however, top-down inventories lack critical details,
32 such as the effects of driving conditions on vehicle performance (25). As inventories often lack a
33 picture of travel behavior and traveler needs, they cannot address some policy questions related to
34 meeting users' technology needs, charging infrastructure, and impacts of charging on the electric
35 grid.

36 **Hybrid methods**

37 Combining large and representative sample sizes with realistic trip patterns has been an ongoing
38 goal of transportation modeling. Some methods accomplish this by using the output of travel
39 demand models as proxies for real-world data. These include four-step network flow models and
40 more complex activity-based or car-following models. Simulated trips can be fed into software
41 such as MOVES (26) and combined with information on expected fleet composition, weather,
42 and other variables to estimate energy and emissions for cities or regions. MOVES calculates the
43 expected emissions intensity of a given vehicle-mile of travel using distributions of energy intensity

1 for different road types and travel speeds, resulting in energy consumption estimates for particular
2 roadways (27). Other approaches have been to generate synthetic drive cycles from travel demand
3 models and combine them with vehicle simulation (21, 28), or to directly link microscopic travel
4 demand simulations with detailed vehicle models (29).

5 These simulations are a common way to estimate the energy impacts of changes to the
6 transportation network or travel demand. However, they are not typically designed to address
7 technological change or modifications to driving behavior. Energy consumption in these models
8 is often calibrated using a small number of drive cycles and real-world vehicles (30), limiting the
9 range of technology and driving conditions captured. A more problematic issue is that many hybrid
10 methods produce estimates of the emissions or energy intensities of each link of the road network,
11 rather than driver- or vehicle-based intensities. A road-based energy accounting makes it difficult
12 to observe the energy need of individual vehicles over the course of a day.

13 **MODEL REQUIREMENTS & APPLICATIONS**

14 The tool that we describe in the next section aims to meet two general requirements. First, it
15 produces accurate energy estimates, for a wide range of vehicles, when applied to realistic driving
16 behavior. Second, it produces estimates for individual trips, for national aggregates, and for various
17 levels of aggregation in between.

18 Energy requirements vary greatly from trip to trip due to variations in vehicle technology,
19 driving style (18), and ambient temperature (19). Accounting for these variations allows fuel
20 economy to vary in a realistic way with trip characteristics, allowing a number of applications
21 that require location-, time-, and trip-resolved energy estimates. Additionally, because trip-by-
22 trip energy consumption is highly variable, we would like our method to be able to produce a
23 probabilistic picture of energy intensity, which is often more relevant to users' needs.

24 The most accurate estimate of an individual POV trip's energy consumption is likely to
25 come from microsimulation or onboard instrumentation, while the best measure of national energy
26 use comes from accounting of fuel sales. Bridging these data types allows analyses that run across
27 scales, i.e. involving both small scale technology performance and large scale energy demand. An
28 example would be a comparison of the fuel economy and energy use of suburban residents to those
29 in the inner core of a city.

30 Our tool needs to perform well despite limitations in the scope and accuracy of data on
31 travel behavior and vehicle characteristics. Data collection from onboard recorders or GPS devices
32 provides detailed information about driving and energy use, but is infeasible to gather at the large
33 scales provided by nationally-representative travel surveys. Furthermore, every vehicle type has
34 distinct performance characteristics that strongly influence energy use.

35 The TripEnergy model presented below was developed to meet these needs while address-
36 ing the limitations in data. It combines data from the National Household Travel Survey (NHTS)
37 (2), several GPS-based travel surveys (31–33), EPA emissions test parameters and results (8, 34),
38 and historical weather data (35). TripEnergy is able to model a wide range of vehicles because it
39 draws on widely available EPA vehicle test results, unlike many microscopic emissions simulators
40 that rely on extensive data collection from a few vehicles. TripEnergy consists of a vehicle model,
41 designed to capture variations in POV performance under a range of driving conditions, and a
42 demand model, designed to reproduce travel patterns across the U.S. at high resolution.

1 **Applications**

2 Meeting the requirements described in the last section enables a variety of applications that are
3 not easily done with existing methods. Here we outline some of these applications for researchers,
4 policy makers, consumers, and industry.

5 *Enriched BEV range estimates*

6 Official range estimates for BEVs are designed to be accurate on average, but make little allowance
7 for variation in driving conditions. Estimates are currently based on predictions of a vehicle's
8 average fuel economy under city and highway-style driving. But potential customers may also
9 wish to know a 'worst case' range. TripEnergy could calculate this, for example, as a range below
10 which a trip or series of trips would exceed battery capacity with a given low probability. Since
11 range varies with ambient temperature, range estimates could be tailored to a region's climate
12 and disaggregated seasonally. Ranges estimates could also be compared to typical daily driving
13 distances in a given city or area where the vehicle is sold.

14 *BEV charging effects on the electric grid*

15 TripEnergy could help electricity providers and regulators predict the impacts on the electric grid
16 of a fleet of electric vehicles charging. The timing and intensity of grid demand could be predicted
17 based on daily driving distances, when trips start and stop, and weather. This ability would let
18 electricity providers and regulators better understand the secondary effects of widespread BEV
19 adoption, such as weather-related spikes in residential and transportation energy consumption.

20 *Energy savings from changes to driving behavior*

21 The model presented here would allow drivers and policymakers to better understand the potential
22 for energy savings from changes in driving behavior. Studies have shown that some savings can
23 be achieved simply by reminding travelers about the energy and emissions impacts of their travel
24 choices (36). TripEnergy is computationally inexpensive and could be run on a smartphone, with
25 estimates for planned or past trips displayed to drivers in real time, with city, neighborhood, or
26 social-network level comparisons.

27 *Energy savings from changes to vehicle performance and technology*

28 We recently used TripEnergy to study how improvements to battery capacity would affect BEV
29 range, showing that expected battery improvement will practically eliminate the difference be-
30 tween urban and rural areas in the portion of vehicle-days that are covered on a single charge
31 (37). The same approach could be used to study how much energy savings could be realized from
32 improvements to vehicle mass or drag, for example, with results that can be made specific to par-
33 ticular locations. TripEnergy draws on a richer variation in driving conditions than can be obtained
34 from standardized drive cycles, making it more suitable to assessing the benefits of potential im-
35 provements under real-world usage. This ability could help vehicle manufacturers evaluate vehicle
36 designs quickly.

37 **MODEL**

38 TripEnergy consists of a demand model, which pairs trips from a travel survey with plausible
39 second-by-second drive cycles and external temperature, and a vehicle model, which computes
40 energy use given a drive cycle, ambient temperature, and specified vehicle type (Fig. 1.). These

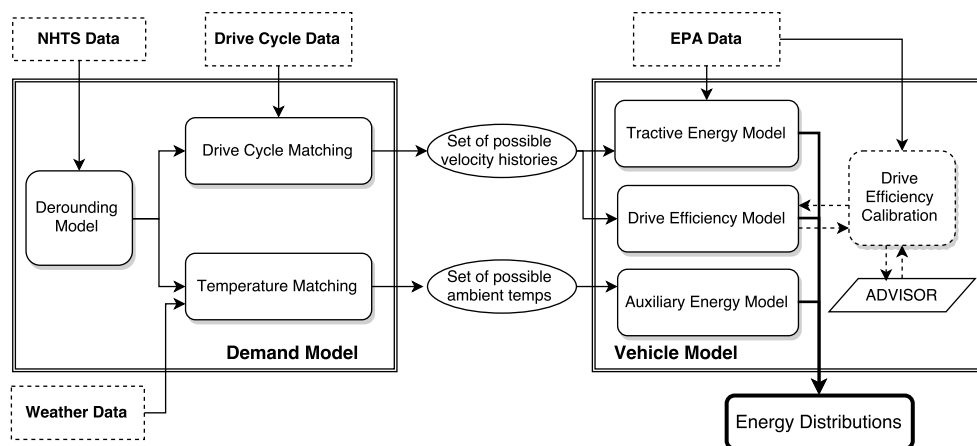


FIGURE 1 : TripEnergy model diagram, showing the demand model (left) and vehicle model (right). The demand model combines travel survey data (e.g. National Household Travel Survey) with higher resolution GPS-based drive cycles and weather data to reconstruct a second-by-second picture of vehicle operating conditions that determine energy use. The vehicle model, calibrated by EPA dynamometer test results, converts this information into an estimate for a trip’s energy consumption. A similar diagram appears in the Supplementary Information of Needell et al. (37).

1 components separate the factors influencing energy consumption into two groups – vehicle charac-
 2 teristics such as mass, drag coefficients, and powertrain efficiency, and trip characteristics, particu-
 3 larly speed and weather conditions. Treating these factors as independent is a minor simplification
 4 that lets us supplement broad survey data with the detailed description of trips needed to estimate
 5 energy consumption.

6 Here we outline the core structure and functioning of the model. Extensive details on all
 7 components below, and additional validation, can be found in the Supplementary Information of
 8 Needell et al. (2016) (37).

9 Demand Model

10 The demand model begins with a user selecting a population of trips for study from the National
 11 Household Travel Survey (NHTS) (2). NHTS is the most comprehensive source of data on travel
 12 behavior in the U.S., compiled by the Federal Highway Administration about once every ten years.
 13 The 2009 survey covers about 1 million personal vehicle trips in the U.S., using a weighting scheme
 14 to ensure that results are demographically and geographically representative. NHTS provides a
 15 wide variety of data on individual trips, including region, number of passengers, trip purpose,
 16 and many socioeconomic variables. Using these variables many different subsets of trips can be
 17 isolated for analysis depending on the application.

18 Trip distances and times from NHTS are self-reported, and travel surveys have shown ev-
 19 idence of rounding and other reporting errors (38). To correct for rounding a model of traveler
 20 rounding was fit to the NHTS trip distance and time distributions, providing the probability $p(x|\tilde{x})$
 21 that a rounded distance or time \tilde{x} was originally x . As described in (37) this function can then be
 22 used to estimate the distribution of the original unrounded distances and times.

23 The purpose of the demand model is to augment the data in the NHTS with detailed in-
 24 formation needed to estimate a range of energy values an observed trip could have had. In the

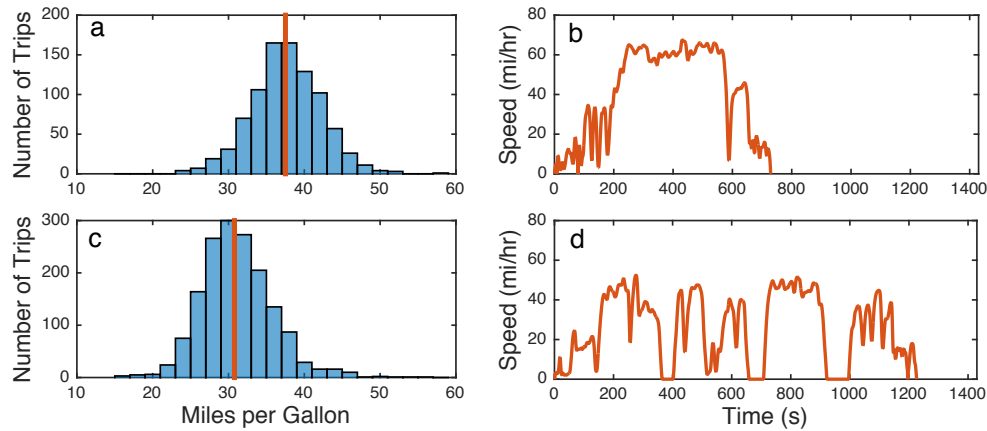


FIGURE 2 : Example of the effect of trip duration on the fuel economy of the 2014 Ford Focus. The right column shows two drive cycles corresponding to 8-mile trips, with durations of 10 minutes (b) and 22 minutes (d). The left column (a,c) shows the distribution of fuel economy values for similar trips in the GPS dataset as chosen by the demand model. The drive cycles shown in the right column correspond to the medians of these distributions, as indicated by the orange vertical lines. As expected the fuel economy of the faster trip is typically (though not always) higher.

1 drive cycle matching component, we link each trip with a set of similar GPS drive cycles. The
 2 drive cycle matching draws from a GPS database with 117,588 drive cycles collected over several
 3 regional travel studies (31–33). Similar GPS trips are defined as ones that fall within a set window
 4 around the original trip in distance and duration. We found this procedure sufficiently differentiates
 5 between different types of trips with different energy requirements, as illustrated in Figure 2.

6 Trips are also linked with a range of external temperatures. Using an approach similar to
 7 Yuksel et al. (14), each NHTS trip is first paired with a weather station in the Typical Meteorological
 8 Year (TMY3) database based on its reported location (its Core Based Statistical Area if one is
 9 reported, otherwise its state). A range of possible temperatures is chosen from the TMY3 database
 10 according to the reported month and time-of-day of the trip.

11 The set of all linked driving conditions measure a range of plausible operating conditions
 12 of the POV trip observed in the NHTS. Each combination of drive cycle, temperature, and de-
 13 rounding can be fed into the vehicle model described below, leading to a probability distribution
 14 for energy requirements of each NHTS trip.

15 Vehicle Model

16 For convenience, we decompose a trip’s total energy use E_{use} into drive energy E_{drive} needed
 17 for vehicle motion and auxiliary energy E_{aux} used for other purposes, primarily climate control.
 18 Thus we have $E_{use} = E_{drive} + E_{aux}$. To compute E_{drive} , we factor it into final energy \mathcal{E}_{tr} , also
 19 known as tractive energy, actually delivered to the wheels and a drive efficiency factor η_{drive} :
 20 $E_{drive} = \mathcal{E}_{tr} / \eta_{drive}$. (To distinguish pre-conversion energies, measured at the battery or gas tank,
 21 from final energies delivered to wheels and auxiliary systems, we write the former in normal font
 22 and the latter in script.)

23 A trip’s tractive energy can be computed from drive cycles received from the demand model
 24 using standard models of vehicle motion, with tractive power output of a vehicle given as a function

1 of its speed and acceleration: $P_{tr}(v) = av + bv^2 + cv^3 + (1 + \varepsilon)mv\frac{dv}{dt}$. The coefficients a , b , and c
 2 are dynamometer or coastdown coefficients published by the EPA for many vehicles (34), m is
 3 vehicle mass, and ε is a factor accounting for the rotational inertia of a vehicle, assumed to be 1.05
 4 here. Positive values of P_{tr} (corresponding to energy being drawn by the engine) can be integrated
 5 over a drive cycle to compute tractive energy \mathcal{E}_{tr} for the trip.

6 Conversion losses are significant for all POVs. (An internal combustion engine is ther-
 7 modynamically limited to efficiencies η_{drive} typically less than 0.4.) The nonlinear relationship
 8 between engine operating conditions and fuel consumption can be modeled as a polynomial func-
 9 tion (39). Rakha et al. (40) present a related method using EPA test result data to fit this function.
 10 Our approach is similar, and uses a fitting approach first proposed by Lutsey (41) that exploits data
 11 from EPA CAFE fuel economy tests. A trip's total energy consumption ΔE_B and tractive energy
 12 consumption E_{tr} can be calculated from reported unadjusted MPG ratings, the CAFE drive cycles,
 13 and a vehicle's dynamometer coefficients. Using the formulation for total energy described above,
 14 η_{drive} can then be calculated for a particular CAFE drive cycle as

$$\eta_{drive} = \frac{\mathcal{E}_{tr}}{\Delta E_B - \frac{\mathcal{E}_{aux}}{\eta_{aux}}}. \quad (1)$$

15 Using the CAFE city and highway drive cycles, we can estimate two values of η_{drive} . Since η_{drive}
 16 varies with driving behavior, we use a two-parameter function for η_{drive} based on the drive cycle
 17 that is calibrated to exactly reproduce energy consumption over the two CAFE drive cycles. The
 18 form of this function is based on physical intuition and modeling in ADVISOR (described in more
 19 detail in Needell et al (37)), but follows the intuition that internal combustion engines are more
 20 efficient at higher speeds and torques, while BEV powertrain and regenerative braking efficiencies
 21 are roughly constant over a wide range of speed and torque.

22 Similarly, pre-conversion auxiliary energy is factored into final auxiliary energy delivered
 23 to auxiliary systems and the auxiliary efficiency: $E_{aux} = \mathcal{E}_{aux}/\eta_{aux}$. In typical driving most aux-
 24 iliary energy use comes from climate control (42). The external temperature received from the
 25 demand model determines how hard climate controls must work to maintain cabin temperature
 26 within a comfortable range. We model HVAC energy consumption with a steady-state heat bal-
 27 ance model: $P_{thermal} = k|\Delta T|$, with the thermal constant k taken to be 350 W/C deg. HVAC power
 28 depends on the thermal load to maintain cabin temperature and the coefficient of performance of
 29 the climate control system used (e.g. a heat pump, radiant heater, or air conditioner). We add a
 30 constant power of 250 W to power other auxiliaries such as dashboard lights and power steering
 31 (43). The efficiency η_{aux} is taken to be a constant for each powertrain type. (Equal to 0.185 for
 32 ICEVs, 0.81 for BEVs, which take into account typical powertrain efficiency and power conversion
 33 losses. See Needell et al. (37) Supplementary Information.)

34 MODEL VALIDATION

35 The model reproduces several intuitive aspects of vehicle performance under different operating
 36 conditions. We describe these aspects below.

37 Overall fuel economy without adjustment factors

38 EPA fuel economy estimates (8) are derived by multiplying raw, unadjusted values measured dur-
 39 ing CAFE tests by adjustment factors (9), which bring fuel economy into better agreement with
 40 values experienced in real-world driving (18). The need for adjustment factors is thought to arise

1 from differences between the drive cycles used in the tests and real-world drive cycles. How-
 2 ever, the method here produces estimates close to adjusted fuel economies without the need for
 3 adjustment factors. After using the EPA test results to calibrate drive efficiency, the model can
 4 be applied to a broad set of realistic drive cycles that are representative of real-world driving to
 5 measure fleetwide performance. The model has been calibrated on two ICEVs and two BEVs and
 6 shows similar values to what the EPA estimates after making adjustments. (Table 1.)

	2011 Ford Explorer		2013 Nissan Leaf		2014 Tesla Model S		2014 Ford Focus	
	EPA	Calculated	EPA	Calculated	EPA	Calculated	EPA	Calculated
Highway	34.7	34.7	146.4	146.4	121.5	121.5	50.4	50.4
City	21.9	21.9	184.2	184.2	118.6	118.6	33.5	33.5
Overall	20	22.2	116	109.7	95	85.7	30	31.8

TABLE 1 : Comparison of fuel economies predicted by our model with EPA-published fuel economies. The EPA city and highway fuel economies shown here are raw, unadjusted values, while the overall fuel economy is the adjusted value (see text). Predicted highway and city fuel economies are based on the EPA city and highway drive cycles, while the overall fuel economy is based on an average over all POV trips in the NHTS. The efficiency component of our model is calibrated to match the city and highway CAFE test results. A similar table appears in the Supplementary Information of Needell et al. (37).

7 Reproducing EV and ICEV performance behavior

8 BEVs and hybrid electric vehicles (HEVs) tend to perform best in urban driving, where low-speed,
 9 start-and-stop driving predominates and regenerative braking can salvage the most energy possi-
 10 ble. Conventional ICEVs perform best during moderate speed highway driving, where powertrain
 11 efficiency is high and energy losses from braking are minimized (17). The model here reproduces
 12 these performance patterns. (Figure 3.) We see a strong dependence on average speed in agree-
 13 ment with expected performance for both vehicle types. We see a secondary dependence on trip
 14 distance where, for a given average speed, fuel economy tends to increase with trip distance for an
 15 ICEV but decrease for a BEV. This occurs because longer distance trips tend to include more
 16 highway driving.

17 In addition, the method here can be used to study variability in fuel economy given the dis-
 18 tance of a trip. Variability in fuel economy is not easily probed by other methods, yet is important
 19 because it makes vehicle range uncertain. Fuel economy is most variable for short trips in ICEVs
 20 and slow trips in BEVs. In another paper (37), we exploit this capability of TripEnergy to evaluate
 21 the way BEV range is different for rural and urban drivers.

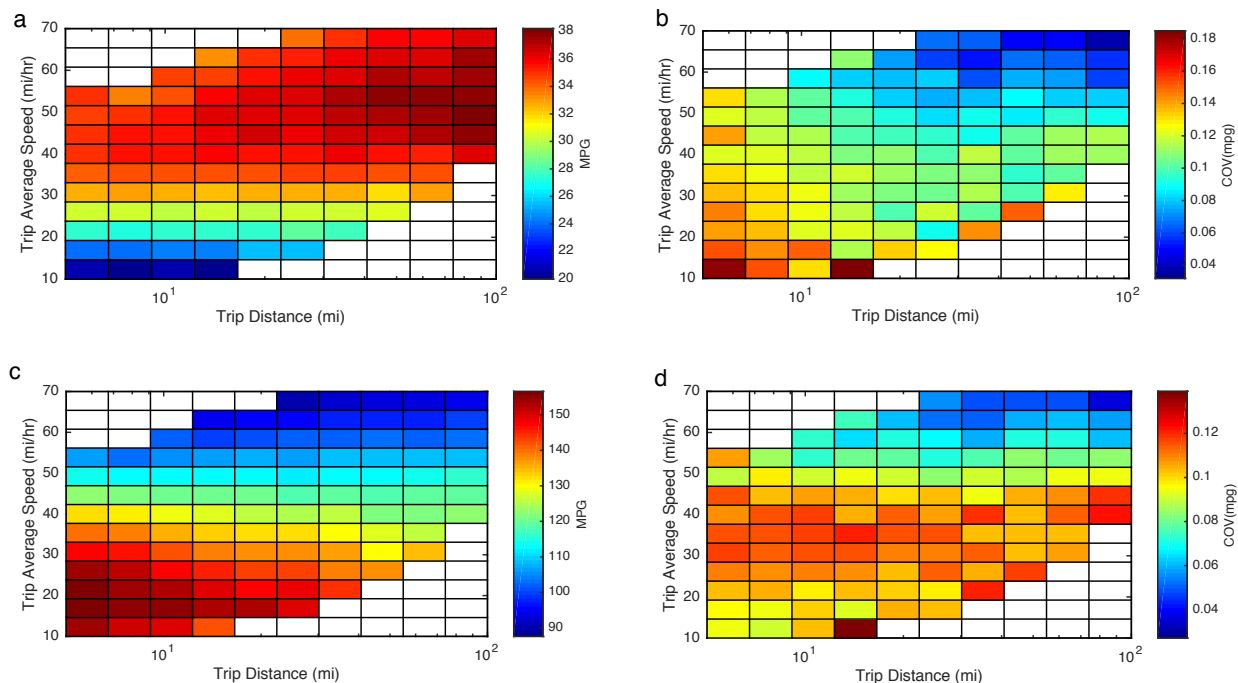


FIGURE 3 : Differences in ICEV and BEV fuel economy performance by trip distance and average speed. Top plots are for the 2014 Ford Focus (an ICEV) and bottom plots are for the 2013 Nissan Leaf (a BEV). The left column shows the average fuel economy, in units of miles per gallon (MPG) for the Focus (a), and miles per gallon equivalent (MPGe) for the Leaf (c), for trips in a given distance and average speed bin. The right column shows the variability in fuel economy within a bin, as captured by the coefficient of variation of fuel economy. (The standard deviation of fuel economy divided by the average.) The ICEV realizes its highest fuel economy for moderately high speed, long distance trips, while the BEV realizes its highest fuel economy for moderately slow, short trips.

1 Single trip energy and aggregate energy estimation

2 To test the accuracy of energy estimates we performed a cross-validation test in which one set
 3 of GPS trips were used to predict the energies of another set. One tenth of the GPS trips were
 4 chosen as a test set and the remainder used within the demand model as described above. To
 5 simulate survey data, distances and times in the test set were rounded as though they were part of
 6 the original survey data, with only the rounded distance and duration observable by TripEnergy.
 7 For comparison we performed the same test using a different method of drawing on the reference
 8 GPS data. We compute the average fuel economy of all reference trips and apply this fixed MPG
 9 value to all test trips. We call this the 'MPG Method'. Both estimates were compared with energy
 10 consumption calculated from the full GPS drive cycle, taken as the true values, with a constant
 11 auxiliary power of 300W assumed.

12 We show results for a BEV (the 2013 Nissan Leaf) with similar results for ICEVs. (Fig.
 13 4.) Both methods perform well at estimating total energy. Across ten folds, the root median square
 14 error was 1.2% for TripEnergy and 1.0% for the MPG method, with the MPG method results
 15 more variable. TripEnergy significantly outperforms the MPG method in estimating the energies

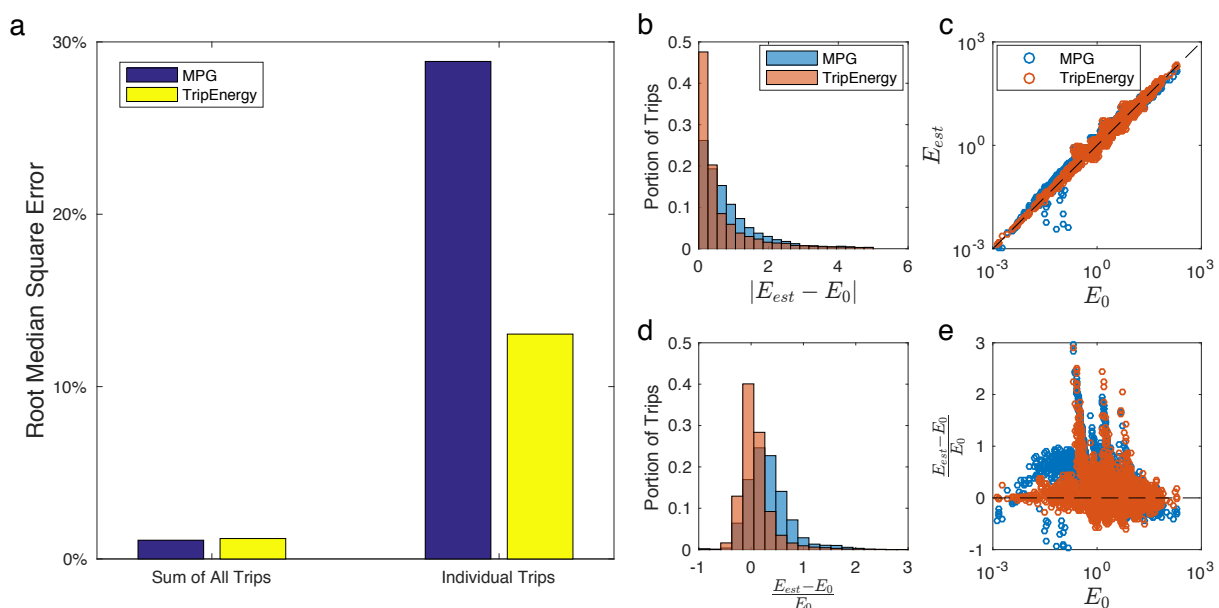


FIGURE 4 : Cross-validation of TripEnergy’s accuracy and comparison with a method based on average fuel economy (the MPG method). TripEnergy was used to estimate the energy of a test set of GPS trips using only the distance and duration of the trip. Energy estimates were also made using the MPG method. Both estimates were compared with energy consumption calculated from the full GPS drive cycle, taken as the true values. (a): Root median square percent error for the total energy of the test set of trips under 10-fold cross-validation, and for the energy of individual trips within the test set. Methods perform similarly well for estimating total energy, while TripEnergy significantly outperforms the MPG method for individual trips. Right: Four measures of individual trip errors. (b) histogram of absolute energy errors; (c): predicted energies (in MJ) versus true energies from a single fold; (d) histogram of relative errors; (e) relative errors versus true energies from a single fold. The MPG method systematically overestimates the energies of low energy trips and underestimates the energies of high energy trips.

1 of individual trips. Denoting the true energy of trip i by $E_{0,i}$ and its estimated energy by $E_{est,i}$, we
2 define the root median square percent error of trip energy estimates as $100 \cdot \sqrt{\text{median}_i \left(\frac{E_{est,i} - E_{0,i}}{E_{0,i}} \right)}$.
3 For TripEnergy we find a value of 13%, compared to 29% for the MPG method. TripEnergy is
4 especially successful at identifying the highest-energy trips, which for the Leaf tend to be long,
5 high speed trips with lower fuel economy.

6 **SUMMARY**

7 Personal vehicles contribute significantly to energy use and environmental impacts at local and na-
8 tional scales. Relating aggregate impacts to low-level determinants, such as vehicle technology and
9 driver behavior, is key to informing environmental policy and technology planning. The TripEn-
10 ergy model presented here accomplishes this by accurately reconstructing second-by-second driv-
11 ing behavior across the U.S., giving a detailed yet expansive view of travel patterns. A demand
12 model pairs trips from a nationally-representative travel survey with GPS-based drive cycles and
13 time- and location-based temperatures. This information is fed into a vehicle model that computes
14 energy use, and covers a wide range of vehicles. A realistic distribution of energy requirements for
15 single trips can be generated based on known information about a trip's distance, region, time and
16 date of travel. Aggregate energy estimates for large numbers of trips draw on travel surveys that
17 are representative of the traveling population.

18 TripEnergy contributes to multiple communities studying personal vehicle travel, includ-
19 ing energy and environmental researchers, transportation researchers, policy makers, and vehicle
20 manufacturers. We expect the model to be particularly useful where (i) analyses depend on varia-
21 tions in vehicle performance and temporal, regional, or socioeconomic patterns of travel behavior,
22 and where (ii) impacts are likely to change with continued evolution in vehicle technology. Aiding
23 such analyses should help inform environmental policy and technology planning, while addressing
24 consumer's travel needs.

1 ACKNOWLEDGMENTS

2 We thank Fabian Riether for his contributions to model validation, and John Heywood and Stephen
3 Zoepf for their feedback on the vehicle model. This work was supported by the New England Uni-
4 versity Transportation Center at MIT under DOT grant No. DTRT13-G-UTC31, the MIT Leading
5 Technology and Policy Initiative, the Singapore-MIT Alliance for Research and Technology, the
6 Charles E. Reed Faculty Initiatives Fund, and the MIT Energy Initiative.

1 **REFERENCES**

- 2 [1] Bureau of Transportation Statistics, *National Transportation Statistics*. United States
3 Department of Transportation, http://www.bts.gov/publications/national_
4 [transportation_statistics/](http://www.bts.gov/publications/national_transportation_statistics/), 2016.
- 5 [2] Federal Highway Administration, *2009 National Household Travel Survey*. U.S. Department
6 of Transportation, 2011.
- 7 [3] Williams, J. H., B. Haley, F. Kahrl, J. Moore, A. D. Jones, M. S. Torn, and H. McJeon, *Path-*
8 *ways to Deep Decarbonization in the United States*. Energy and Environmental Economics,
9 Inc., 2014.
- 10 [4] Miotti, M., G. J. Supran, E. J. Kim, and J. E. Trancik, Personal vehicle technologies evaluated
11 against climate change mitigation targets. *Environ Sci Technol (In Press)*, [http://dx.doi.](http://dx.doi.org/10.1021/acs.est.6b00177)
12 [org/10.1021/acs.est.6b00177](http://dx.doi.org/10.1021/acs.est.6b00177), 2016.
- 13 [5] National Highway Traffic Safety Administration, *Obama Administration Finalizes Historic*
14 *54.5 mpg Fuel Efficiency Standards*. Press Release, 2012.
- 15 [6] Williams, J. H., A. DeBenedictis, R. Ghanadan, A. Mahone, J. Moore, W. R. Morrow III,
16 S. Price, and M. S. Torn, The technology path to deep greenhouse gas emissions cuts by
17 2050: the pivotal role of electricity. *Science*, Vol. 335, No. 6064, 2012, pp. 53–60.
- 18 [7] Creutzig, F., G. Baiocchi, R. Bierkandt, P.-p. Pichler, and K. C. Seto, Global typology of
19 urban energy use and potentials for an urbanization mitigation wedge. *Proc Natl Acad Sci U*
20 *S A*, Vol. 112, No. 20, 2014, pp. 6283–6288.
- 21 [8] United States Environmental Protection Agency, *Certified Vehicle Test Results Report Data*.
22 Available <http://www.epa.gov/otaq/crttst.htm>, 2015.
- 23 [9] *Fuel Economy Labeling of Motor Vehicle Revisions to Improve Calculation of Fuel Economy*
24 *Estimates*. Office of Transportation and Air Quality, US EPA, 2006.
- 25 [10] Gonder, J., T. Markel, A. Simpson, and M. Thornton, Using GPS Travel Data to Assess the
26 Real World Driving Energy Use of Plug- in Hybrid Electric Vehicles (PHEVs). In *Trans-*
27 *portation Research Board (TRB) 86th Annual Meeting*, 2007, May.
- 28 [11] Vyas, A. D., D. J. Santini, and L. R. Johnson, Potential of Plug-In Hybrid Electric Vehicles
29 to Reduce Petroleum Use. *Transp Res Rec*, , No. 2139, 2009, pp. 55–63.
- 30 [12] Basso, L. J. and T. H. Oum, Automobile Fuel Demand: A Critical Assessment of Empirical
31 Methodologies. *Transport Reviews*, Vol. 27, No. 4, 2007, pp. 449–484.
- 32 [13] Donato, T., F. Ingrosso, F. Licci, and D. Laforgia, A method to estimate the environmental
33 impact of an electric city car during six months of testing in an Italian city. *J Power Sources*,
34 Vol. 270, 2014, pp. 487–498.
- 35 [14] Yuksel, T. and J. Michalek, Effects of Regional Temperature on Electric Vehicle Efficiency,
36 Range, and Emissions in the United States. *Environ Sci Technol*, Vol. 49, 2015, pp. 3974–
37 3980.
- 38 [15] Assessment and Standards Division, Office of Transportation and Air Quality, *Advanced*
39 *Light-Duty Powertrain and Hybrid Analysis (ALPHA) Tool User’s Guide for Off-Cycle Credit*
40 *Evaluation*. U.S. Environmental Protection Agency, 2012.
- 41 [16] Markel, T., A. Brooker, T. Hendricks, V. Johnson, K. Kelly, B. Kramer, M. O’Keefe, S. Sprik,
42 and K. Wipke, ADVISOR: a systems analysis tool for advanced vehicle modeling. *J Power*
43 *Sources*, Vol. 110, No. 2, 2002, pp. 255–266.

- 1 [17] Karabasoglu, O. and J. Michalek, Influence of driving patterns on life cycle cost and emis-
2 sions of hybrid and plug-in electric vehicle powertrains. *Energy Policy*, Vol. 60, 2013, pp.
3 445–461.
- 4 [18] Berry, I. M., *The Effects of Driving Style and Vehicle Performance on the Real-World Fuel*
5 *Consumption of U.S. Light-Duty Vehicles*. Ph.D. thesis, Massachusetts Institute of Technol-
6 ogy, 2010.
- 7 [19] Carlson, R., M. Duoba, D. Bocci, and H. Lohse-Busch, On-Road Evaluation of Advanced
8 Hybrid Electric Vehicles over a Wide Range of Ambient Temperatures. *23rd Electric Vehicle*
9 *Symposium in Anaheim*, Vol. 275, 2007.
- 10 [20] Bingham, C., C. Walsh, and S. Carroll, Impact of driving characteristics on electric vehicle
11 energy consumption and range. *Intelligent Transport Systems, IET*, Vol. 6, No. 1, 2012, pp.
12 29–35.
- 13 [21] Raykin, L., M. J. Roorda, and H. L. MacLean, Impacts of driving patterns on tank-to-wheel
14 energy use of plug-in hybrid electric vehicles. *Transp Res D Transp Environ*, Vol. 17, No. 3,
15 2012, pp. 243–250.
- 16 [22] Office of Highway Policy Information, *Highway Statistics 2014*. Federal Highway Adminis-
17 tration, 2014.
- 18 [23] U.S. Department of Energy, Energy Information Administration (EIA), *Annual Energy Out-*
19 *look with projections to 2040*, 2014.
- 20 [24] Gately, C. K., L. R. Hutyra, and I. Sue Wing, Cities, traffic, and CO₂: A multidecadal assess-
21 ment of trends, drivers, and scaling relationships. *Proc Natl Acad Sci U S A*, 2015.
- 22 [25] Ericsson, E., Independent driving pattern factors and their influence on fuel-use and exhaust
23 emission factors. *Transp Res D Transp Environ*, Vol. 6, 2001, pp. 325–345.
- 24 [26] Assessment and Standards Division, Office of Transportation and Air Quality, *Population*
25 *and Activity of On-road Vehicles in MOVES2014*. Draft Report EPA-420-D-15-001, U.S.
26 Environmental Protection Agency, 2015.
- 27 [27] Transportation and Climate Division, Office of Transportation and Air Quality, *MOVES2014*
28 *Technical Guidance: Using MOVES to Prepare Emission Inventories in State Implementation*
29 *Plans and Transportation Conformity*. US EPA, 2015.
- 30 [28] Amirjamshidi, G. and M. J. Roorda, Development of Simulated Driving Cycles: Case study
31 of the Toronto Waterfront Area. In *TRB 92nd Annual Meeting Compendium of Papers*, Trans-
32 portation Research Board, 2013, 13-2648.
- 33 [29] Zhang, L., Y. Yin, and S. Chen, Robust signal timing optimization with environmental con-
34 cerns. *Transportation Research Part C: Emerging Technologies*, Vol. 29, 2013, pp. 55–71.
- 35 [30] Panis, L. I., S. Broekx, and R. Liu, Modelling instantaneous traffic emission and the influence
36 of traffic speed limits. *Science of the total environment*, Vol. 371, No. 1, 2006, pp. 270–285.
- 37 [31] DOE National Renewable Energy Laboratory, *California Household Transportation Survey*.
38 DOE-019-9889603959, 2012.
- 39 [32] Atlanta Regional Commission, *Regional Travel Survey: Final Report*, 2011.
- 40 [33] Texas Department of Transportation, *2002 - 2011 Regional Travel Surveys with GPS data for*
41 *Abilene, Austin, El Paso, Houston Galveston, Laredo, Rio Grande Valley, San Antonio, Tyler*
42 *Longview, and Wichita Falls*, 2002-2011.
- 43 [34] US Environmental Protection Agency, *Fuel Economy Test Car List Database Files*. Available
44 <http://www3.epa.gov/otaq/tcldata.htm>, <http://www.epa.gov/otaq/tcldata.htm>, 2015.

- 1 [35] Wilcok, S. and W. Marion, *Users Manual for TMY3 Data Sets*. National Renewable Energy
2 Laboratory, 2008.
- 3 [36] Gaker, D., D. Vautin, A. Vij, and J. L. Walker, The power and value of green in promot-
4 ing sustainable transport behavior. *Environmental Research Letters*, Vol. 6, No. 3, 2011, p.
5 034010.
- 6 [37] Needell, Z. A., J. McNerney, M. T. Chang, and J. E. Trancik, Potential for widespread elec-
7 trification of personal vehicle travel in the United States. *Nature Energy (In Press)*, 2016.
- 8 [38] Zhao, F., F. C. Pereira, R. Ball, Y. Kim, Y. Han, C. Zegras, and M. Ben-Akiva, Exploratory
9 Analysis of a Smartphone-Based Travel Survey in Singapore. In *Transportation Research*
10 *Board 94th Annual Meeting*, 2015, 15-4343.
- 11 [39] Saerens, B., H. Rakha, K. Ahn, and E. Van Den Bulck, Assessment of alternative polynomial
12 fuel consumption models for use in intelligent transportation systems applications. *Journal*
13 *of Intelligent Transportation Systems*, Vol. 17, No. 4, 2013, pp. 294–303.
- 14 [40] Rakha, H. A., K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck, Virginia tech comprehen-
15 sive power-based fuel consumption model: model development and testing. *Transportation*
16 *Research Part D: Transport and Environment*, Vol. 16, No. 7, 2011, pp. 492–503.
- 17 [41] Lutsey, N., A technical analysis of model year 2011 US automobile efficiency. *Transp Res D*
18 *Transp Environ*, Vol. 17, No. 5, 2012, pp. 361–369.
- 19 [42] Kambly, K. R. and T. H. Bradley, Estimating the HVAC energy consumption of plug-in elec-
20 tric vehicles. *J Power Sources*, Vol. 259, 2014, pp. 117–124.
- 21 [43] Geringer, B. and W. K. Tober, *Batterieelektrische Fahrzeuge in der Praxis: Kosten, Reich-*
22 *weite, Umwelt, Komfort*. Institut für Fahrzeugantriebe und Automobiltechnik, Technische
23 Universität Wien, 2012.